Three Components of Machine Learning

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Learning Goals

- develop intuition for how ML works

- become familiar with concept of

  - data points (features, labels)

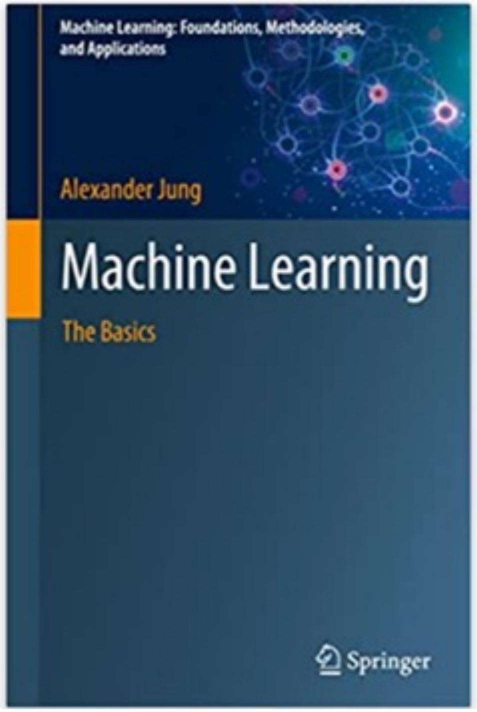
  - model (hypothesis space)

  - loss function (quality measure)

Reading.

- Chapter 1,2 of [MLBook]

AJ, "Machine Learning: The Basics", Springer, 2022.https://mlbook.cs.aalto.fi



NumPy

https://numpy.org/doc/stable/user/absolute_beginners.html

What is it all About ?

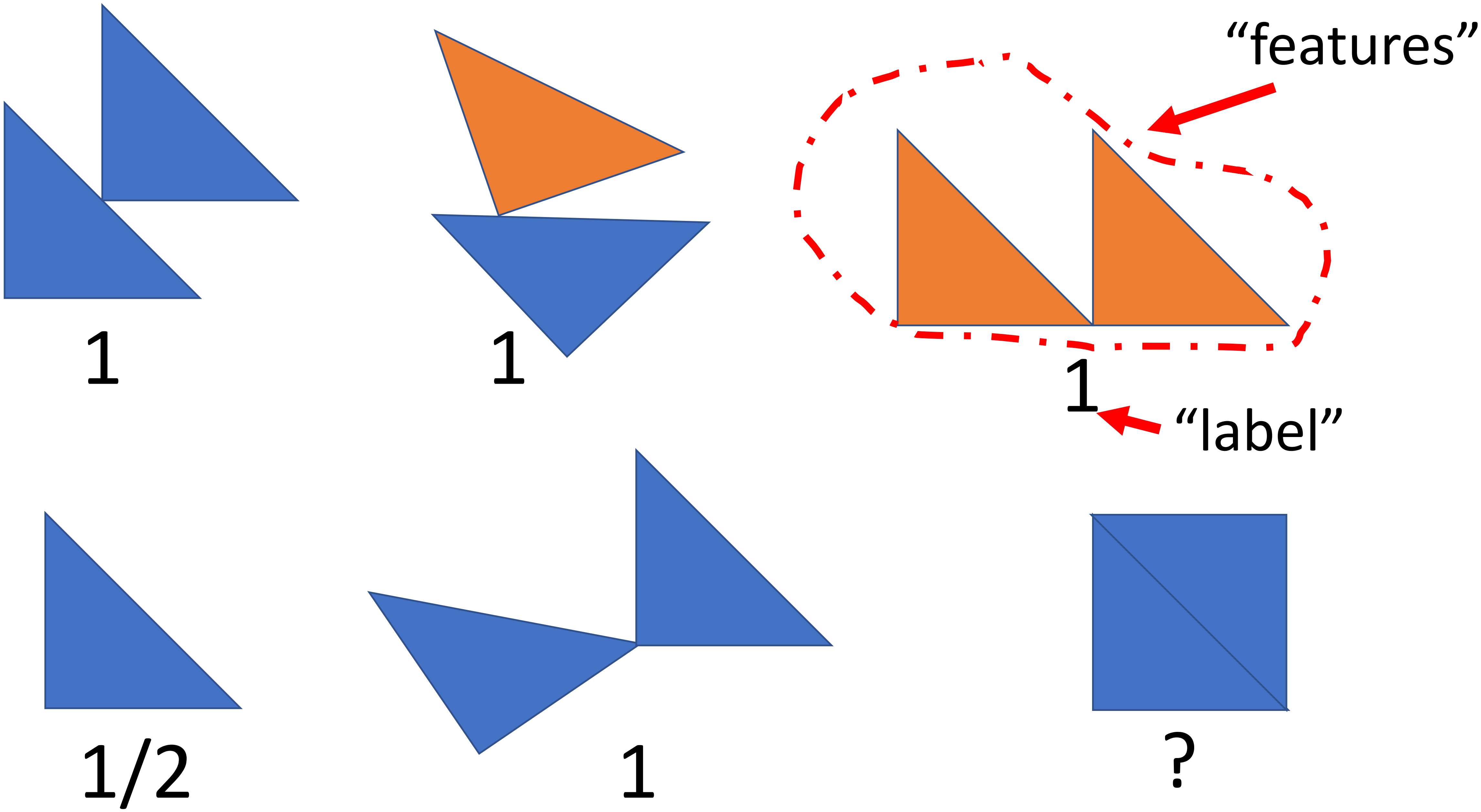
fit model to data to make accurate predictions or forecasts !

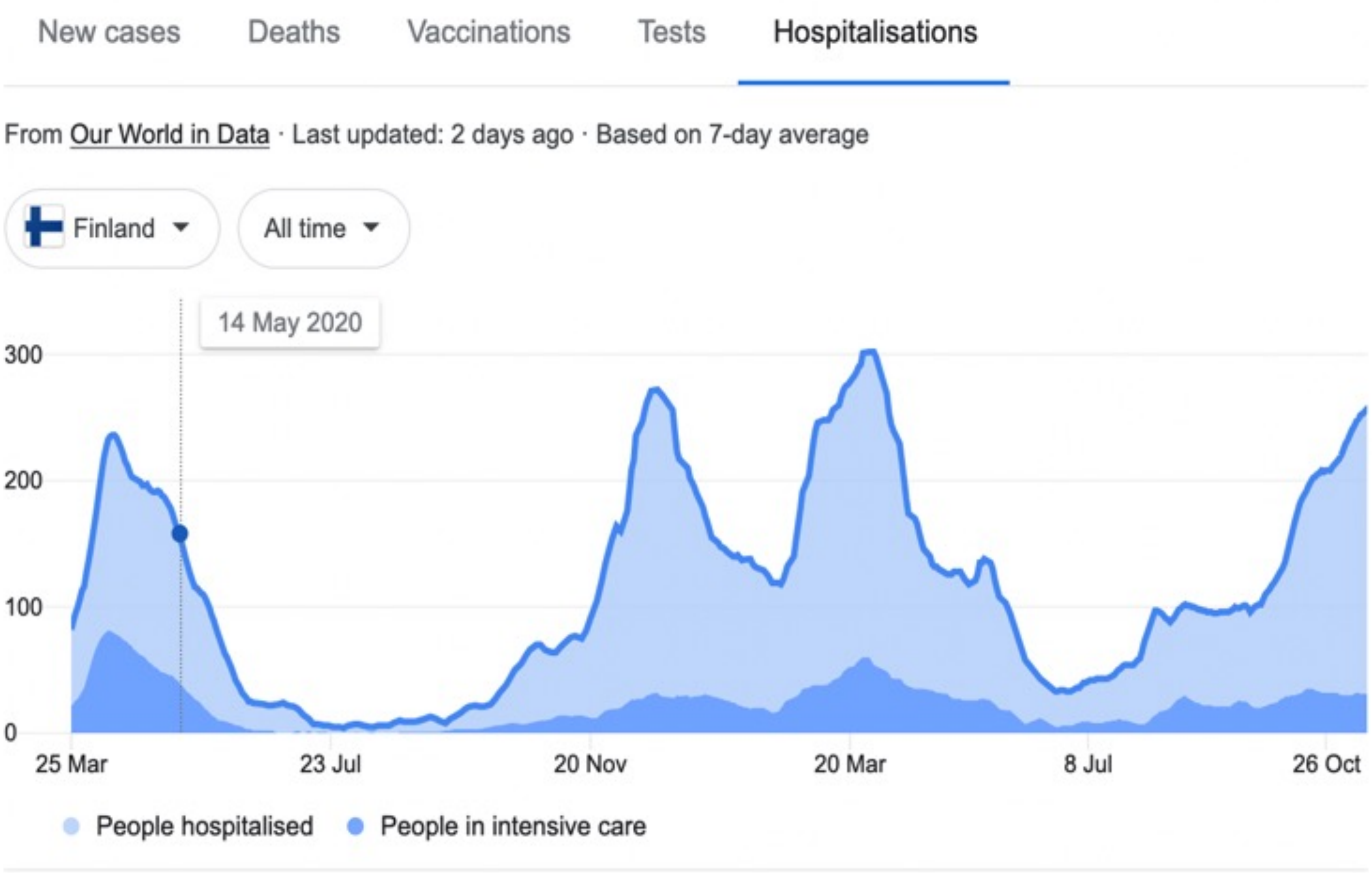
let’s look at some learning problems

1. element 2. 3. 4. 5. 6.

4, 5, 6, 7, 8, ?

“data point”


“features”
1
1
1
“label”
1/2
1
?


New cases
Deaths
Vaccinations
Tests
Hospitalisations
From Our World in Data · Last updated: 2 days ago · Based on 7-day average
Finland
All time
14 May 2020
300
200
100
0
25 Mar
23 Jul
20 Nov
20 Mar
8 Jul
26 Oct
People hospitalised
People in intensive care

?

?

INNOVATION

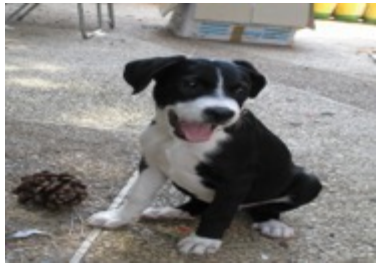
How Artificial Intelligence Completed Beethoven's Unfinished Tenth Symphony

On October 9, the work will be performed in Bonn, Germany, and a recording will be released

Ahmed Elgammal, The Conversation

September 24, 2021

features (pixel RGB values)



“Cat” “Dog” “Cat” ?

label

https://commons.wikimedia.org/

“feature”

min tmp: -10
max tmp: -3

min tmp: -3
max tmp: 4

min tmp: 1
max tmp: 5

data point

min tmp: -6
max tmp: ?

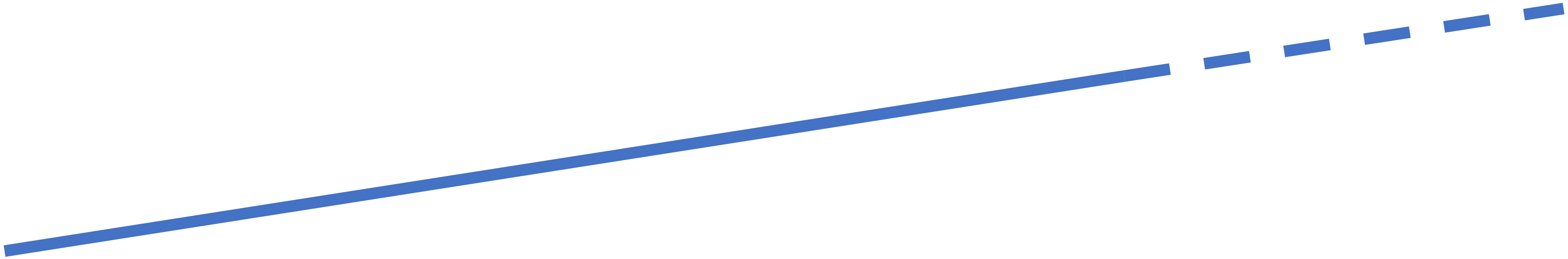
“label”

so, how does it work?

use hypothesis about data generation

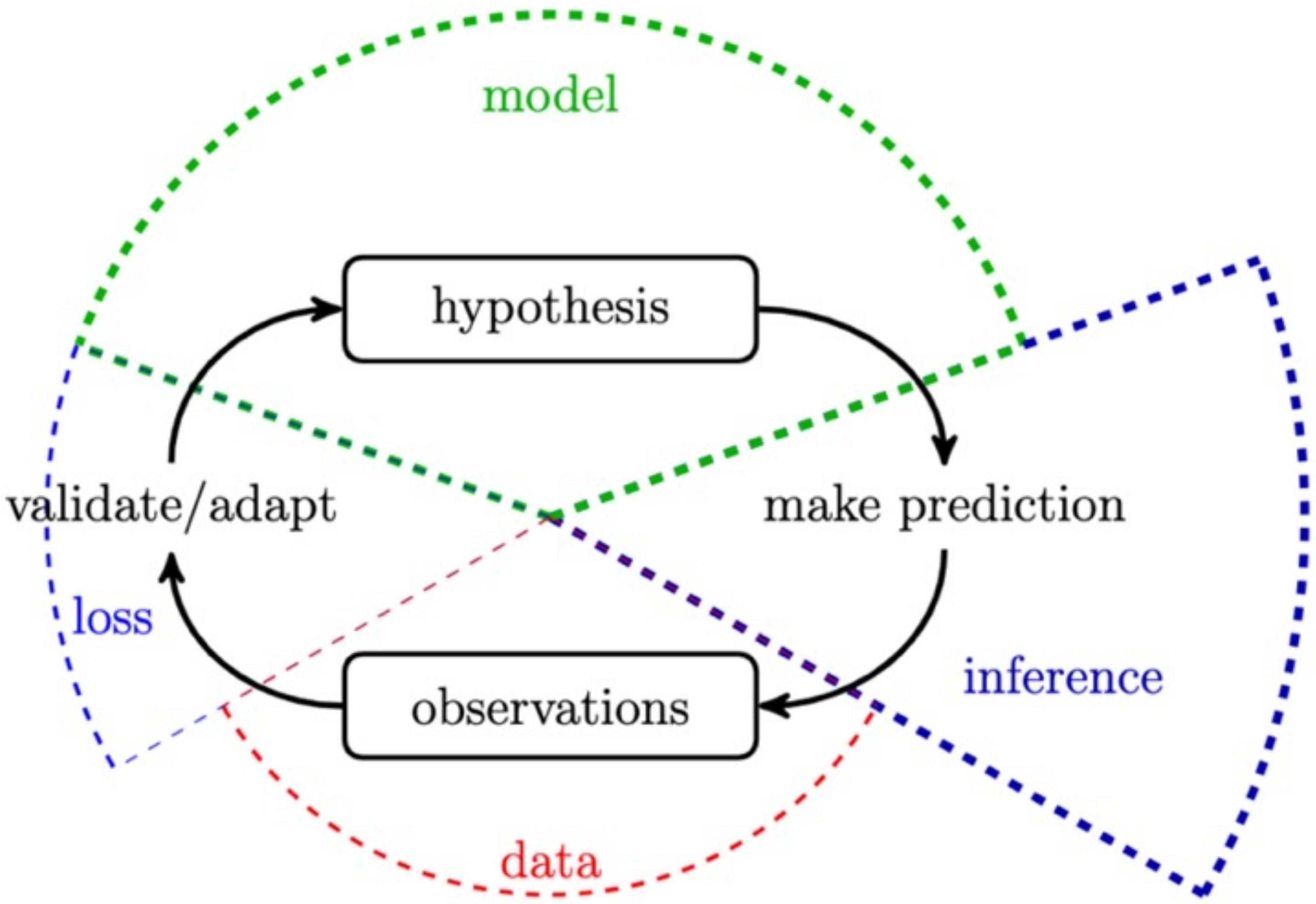
to make predictions (forecasts)

4, 5, 6, 7, 8, ?

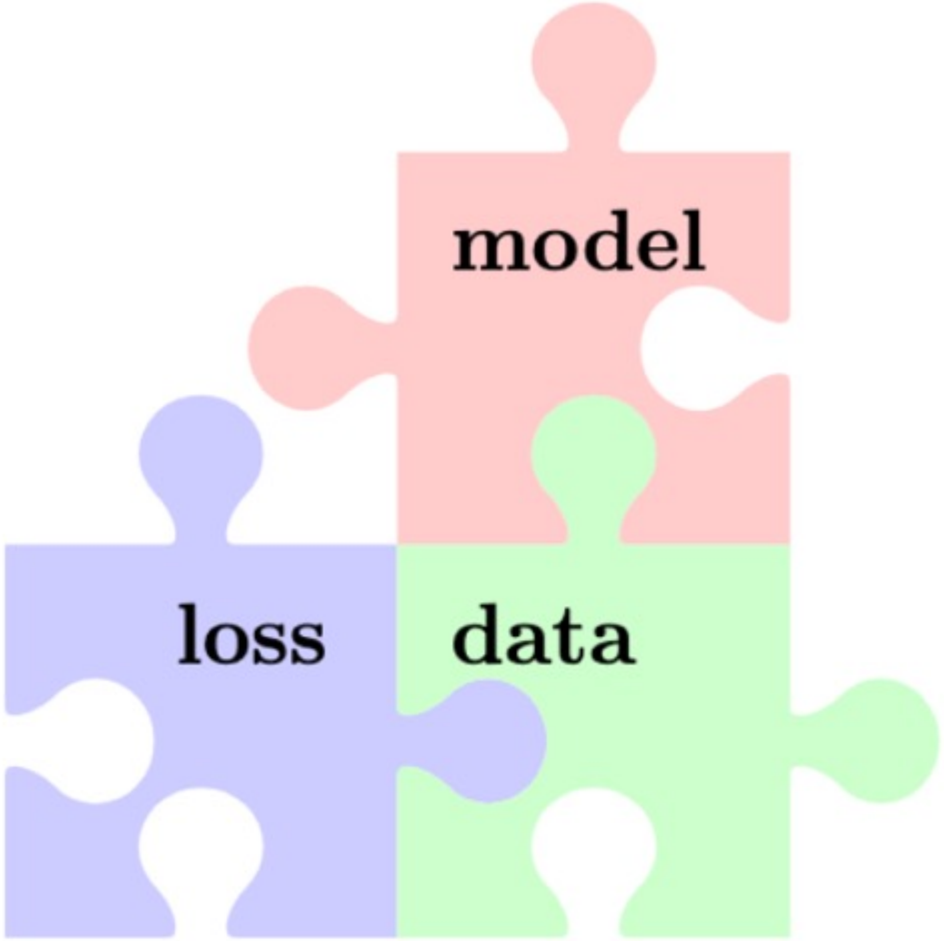


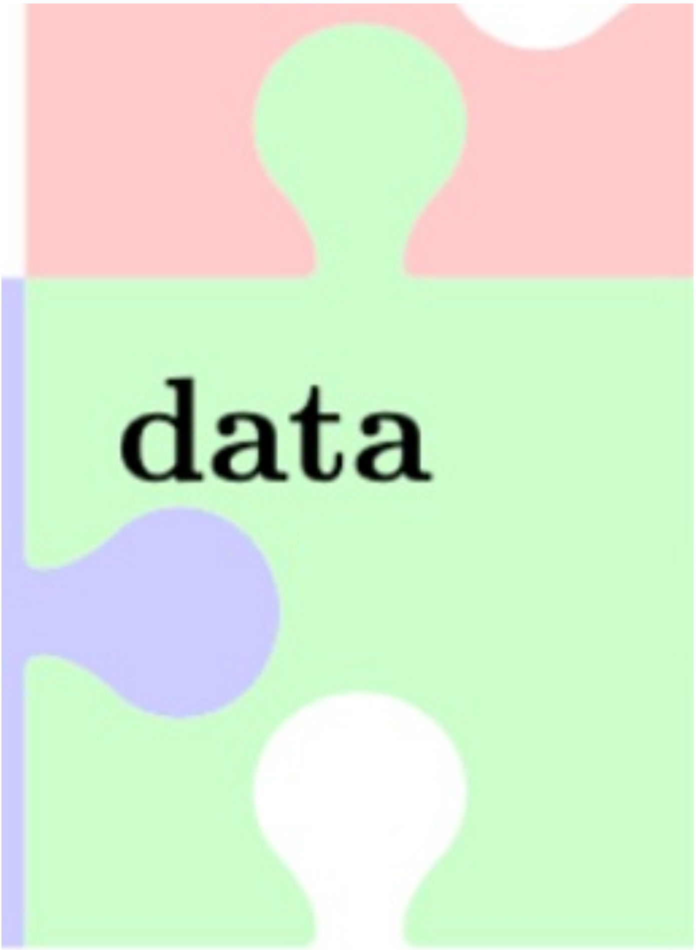
“hypothesis”

The Learning Cycle



Three Components of ML





“What I’m finding is that for a lot of problems, it’d be useful to shift our mindset toward not just improving the code but in a more systematic way of improving the data,” said Andrew Ng

https://read.deeplearning.ai/the-batch/issue-84/

data

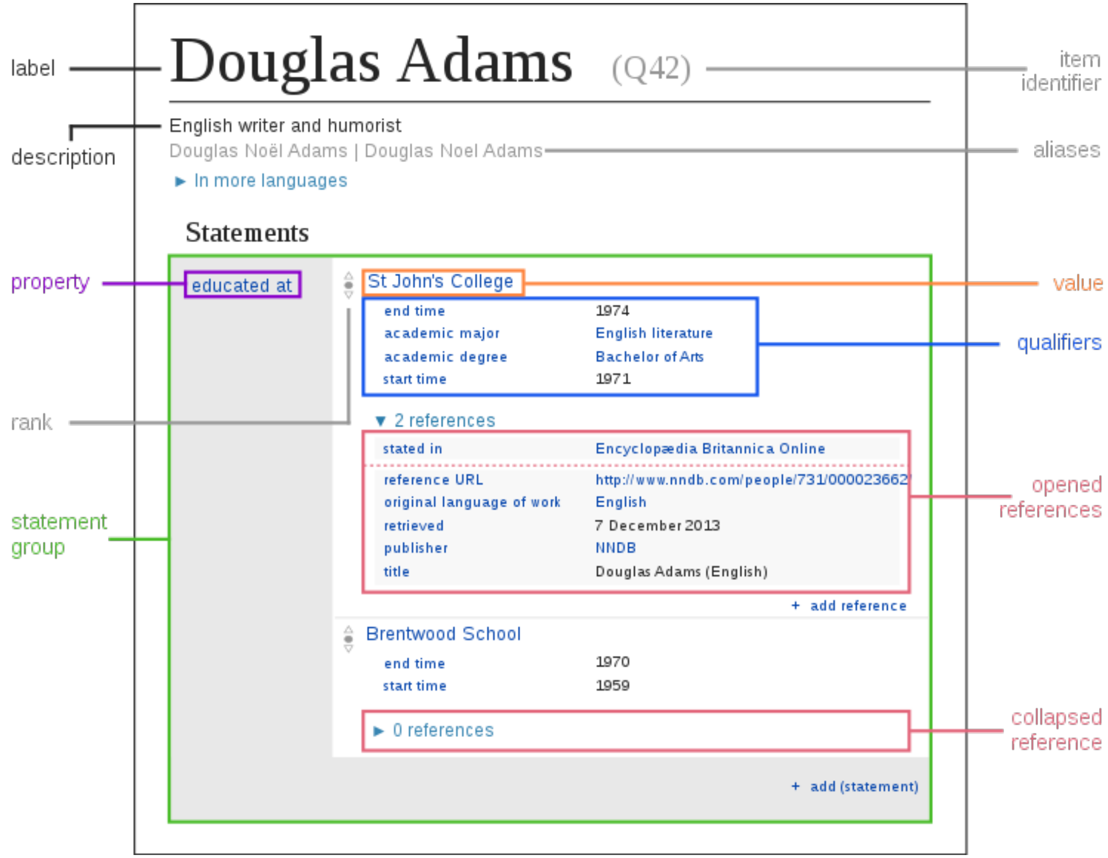
=

set of datapoints

What is a Datapoint?

some object that might carry relevant information

Datapoint = Some Item in Wikidata

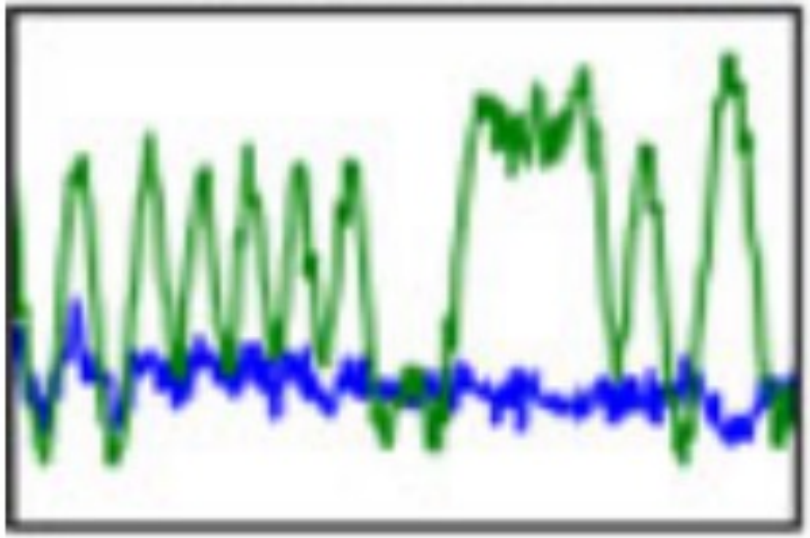


https://upload.wikimedia.org/wikipedia/commons/a/ae/Datamodel_in_Wikidata.svg

Datapoint = Some Period of Time

$\boxed{\text{1.1.2020 01:00 - 2.1.2020 13:00}}$

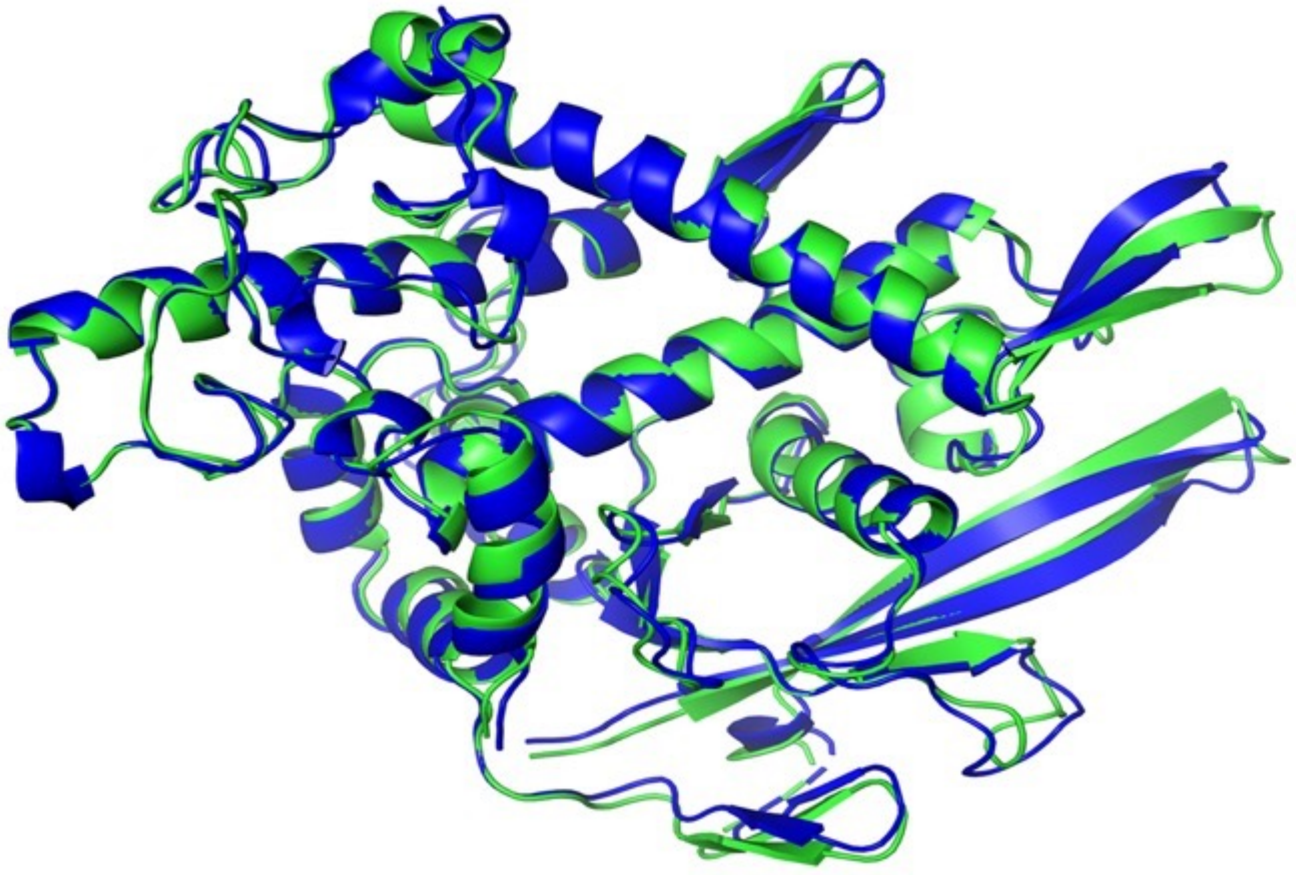
Datapoint = Some Wireless Signal



T. J. O’Shea, T. Roy and T. C. Clancy,
"Over-the-Air Deep Learning Based Radio Signal Classification,"
in *IEEE Journal of Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 168-179, Feb. 2018,
doi: 10.1109/JSTSP.2018.2797022.

Datapoint = Some Country

Datapoint = Some Protein



Datapoint = A Partial Differential Equation

$$\frac{\partial u}{\partial t}(t,x) + \frac{1}{2}\mathrm{Tr}\left(\sigma\sigma^{\mathrm{T}}(t,x)(\mathrm{Hess}_x u)(t,x)\right) + \nabla u(t,x)\cdot\mu(t,x) + f\left(t,x,u(t,x),\sigma^{\mathrm{T}}(t,x)\nabla u(t,x)\right) = 0 \qquad [1]$$

RESEARCH ARTICLE

Solving high-dimensional partial differential equations using deep learning

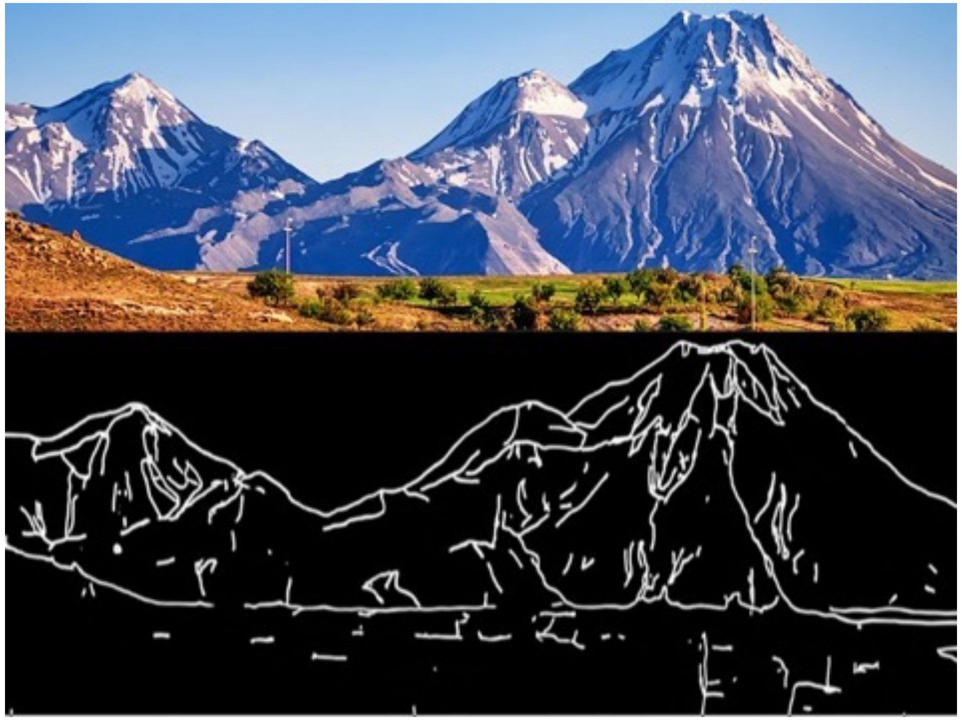
Jiequn Han, Arnulf Jentzen, and Weinan E
+ See all authors and affiliations

https://www.pnas.org/content/115/34/8505/tab-article-info

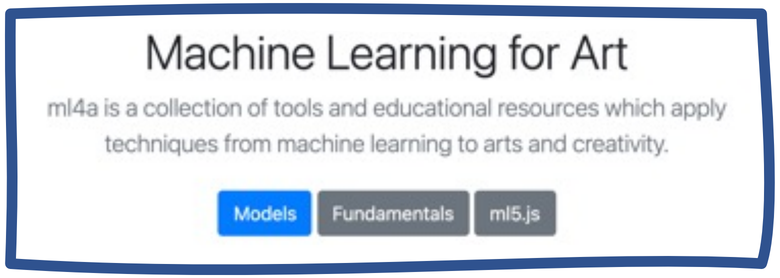
Datapoint = Some Bridge

https://commons.wikimedia.org/wiki/Category:Bridges

Datapoint = Image Sketch



https://ml4a.net/



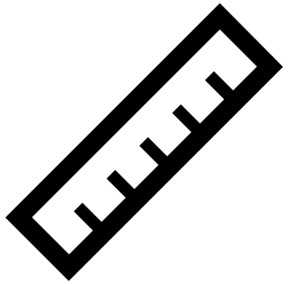
Features and Labels.

datapoint characterized by

- features: low-level properties; easy to measure/compute
- labels: high-level quantity of interest; difficult to measure/determine

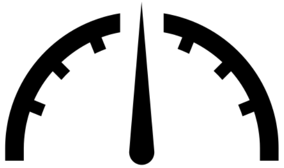
Numeric Features

we mainly use numeric features x1,…,xn to characterize a datapoint



stack features into feature vector

Python: use numpy array to store features



discuss feature learning methods later

Features of an Image.

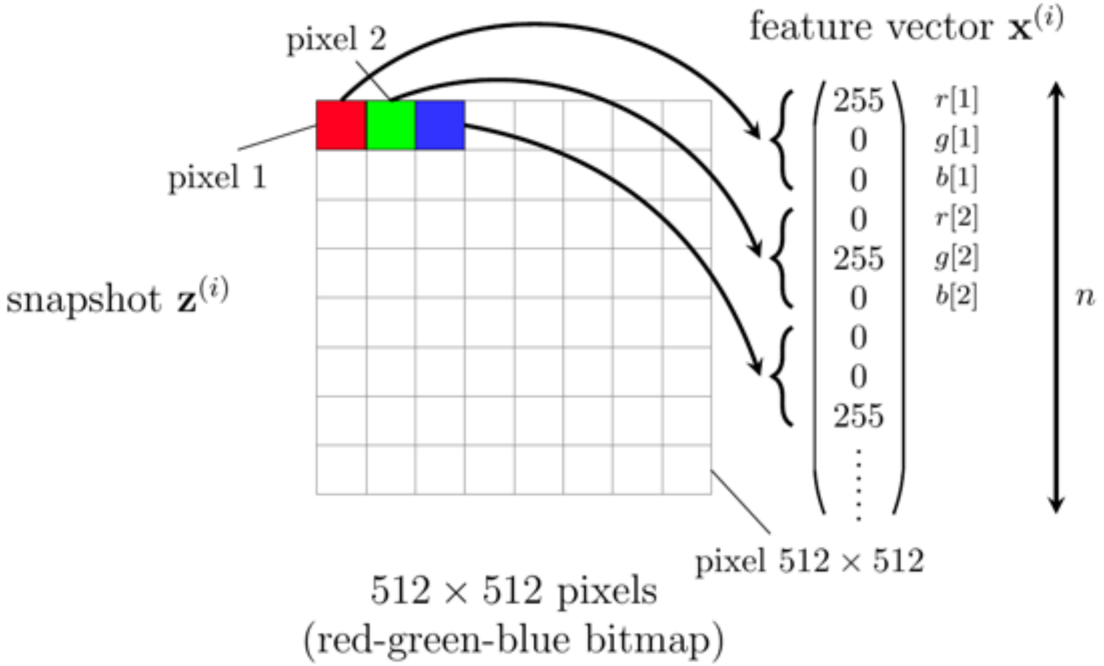


Figure 2.5: If the snapshot $\mathbf{z}^{(i)}$ is stored as a 512×512 RGB bitmap, we could use as features $\mathbf{x}^{(i)} \in \mathbb{R}^n$ the red-, green- and blue component of each pixel in the snapshot. The length of the feature vector would then be $n = 3 \times 512 \times 512 \approx 786000$.

Features of an Audio Recording.

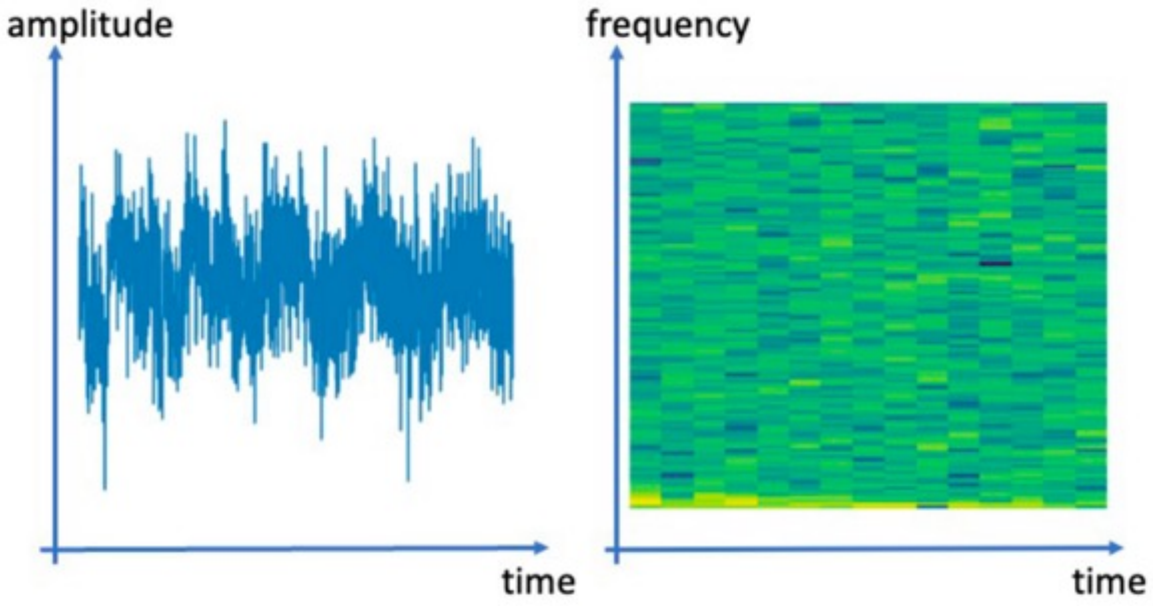


Figure 2.4: Two visualizations of a data point that represents an audio recording. The left figure shows a line plot of the audio signal amplitudes. The right figure shows a spectogram of the audio recording.

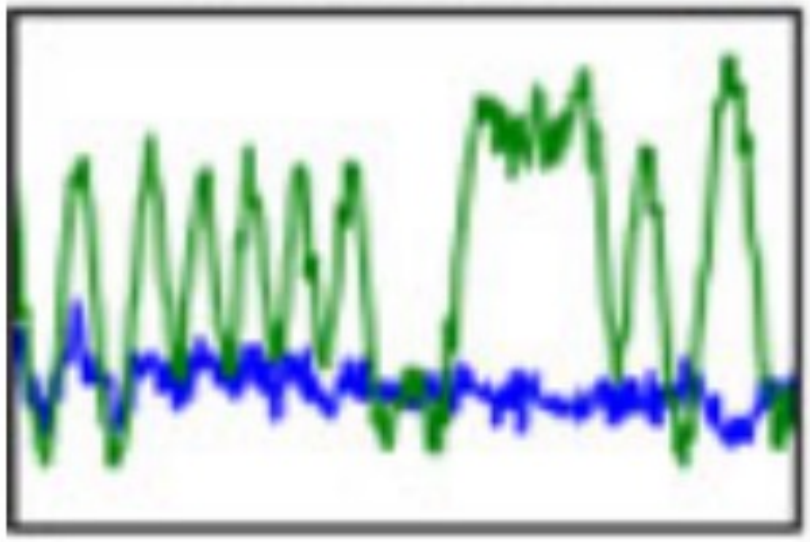
Datapoint = Period of Time

1.1.2020 00:00 - 1.1.2020 23:55

features: temperature recordings @ 01:00, 03:00, 05:00

label: temperature recording @ 23:00

Datapoint = Wireless Signal

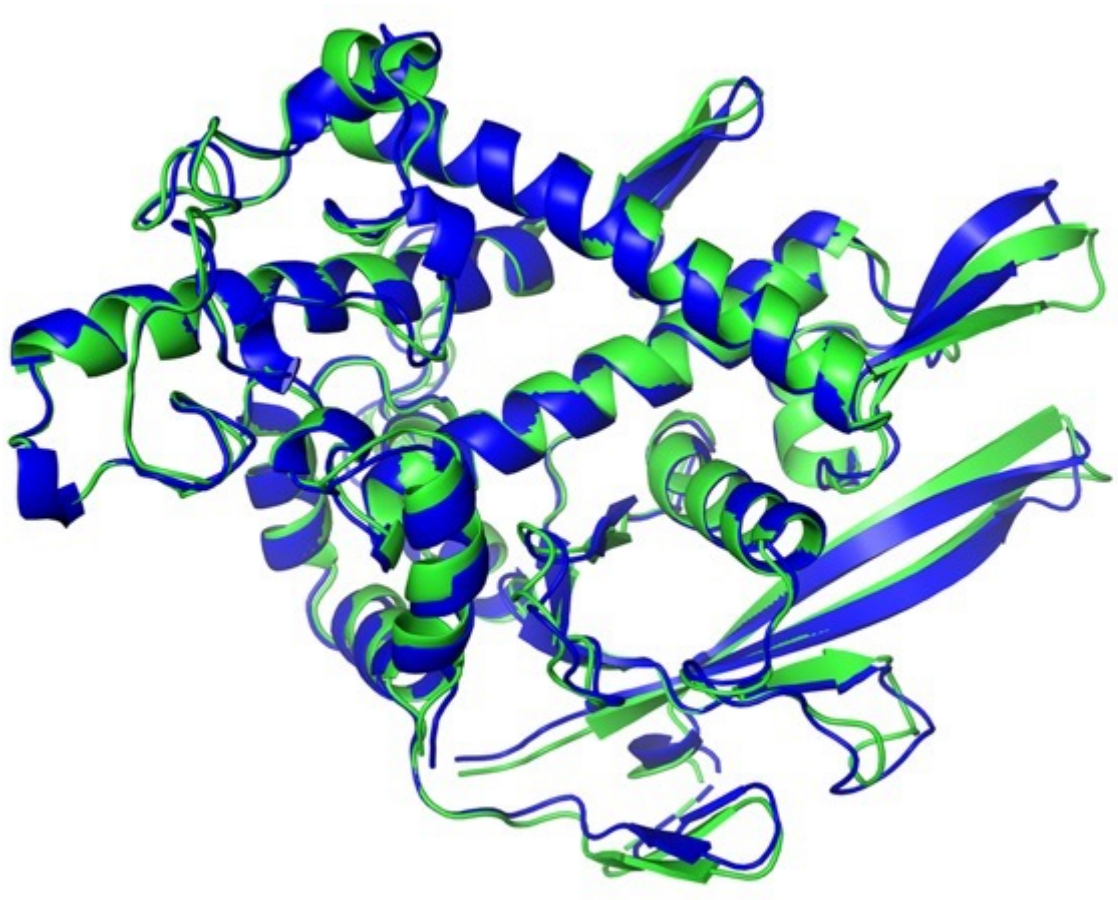


features:

label:

T. J. O'Shea, T. Roy and T. C. Clancy,
"Over-the-Air Deep Learning Based Radio Signal Classification,"
in *IEEE Journal of Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 168-179, Feb. 2018,
doi: 10.1109/JSTSP.2018.2797022.

Datapoint = A Protein



features:

label:

Datapoint = A Partial Differential Equation

$$\frac{\partial u}{\partial t}(t,x) + \frac{1}{2}\mathrm{Tr}\left(\sigma\sigma^{\mathrm{T}}(t,x)(\mathrm{Hess}_x u)(t,x)\right) + \nabla u(t,x)\cdot\mu(t,x) + f\left(t,x,u(t,x),\sigma^{\mathrm{T}}(t,x)\nabla u(t,x)\right) = 0 \qquad \textbf{[1]}$$

features:

label:

https://www.pnas.org/content/115/34/8505/tab-article-info

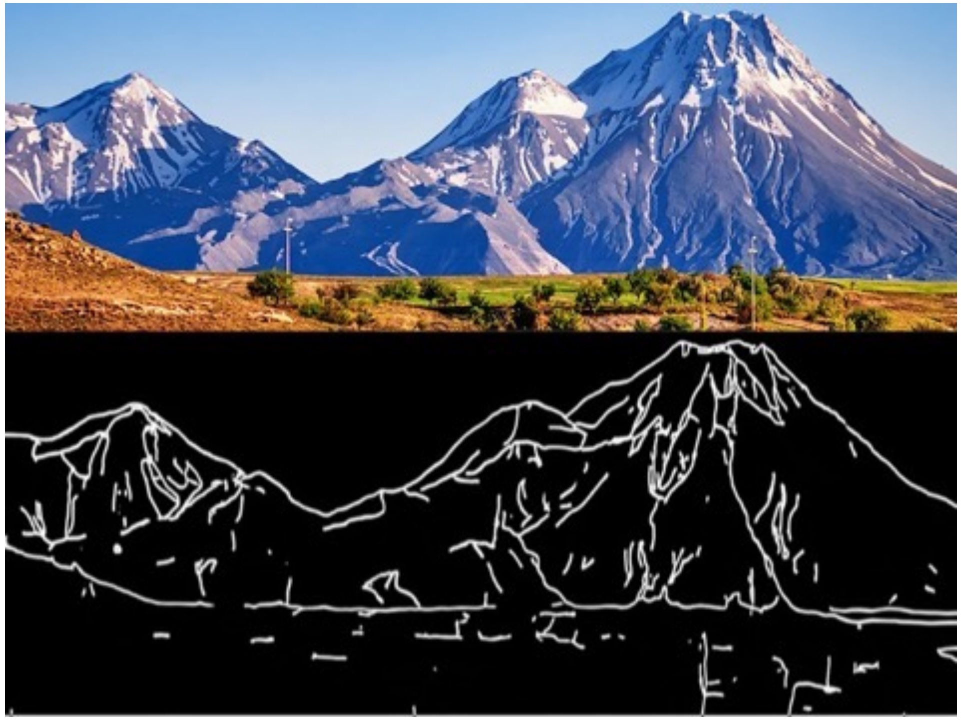
Datapoint = A Bridge

features:

label:

https://commons.wikimedia.org/wiki/Category:Bridges

Datapoint = Image Sketch



features:

label:

https://ml4a.net/

Datapoints, their Features and Labels are Design Choices!

raw data from FMI

https://en.ilmatieteenlaitos.fi/download-observations

Year	m	d	Time	precp	snow	airtmp	mintmp	maxtmp
2020	1	2	00:00	0,4	55	2,5	-2	4,5
2020	1	3	00:00	1,6	53	0,8	-0,8	4,6
2020	1	4	00:00	0,1	51	-5,8	-11,1	-0,7
2020	1	5	00:00	1,9	52	-13,5	-19,1	-4,6
2020	1	6	00:00	0,6	52	-2,4	-11,4	-1
2020	1	7	00:00	4,1	52	0,4	-2	1,3
2020	1	8	00:00	4,3	51	0,8	0,1	1,8
2020	1	9	00:00	-1	51	-0,6	-1,9	1,6
2020	1	10	00:00	-1	51	-6,2	-11	-1,4
2020	1	11	00:00	2,8	50	-4,8	-10,7	-2,1
2020	1	12	00:00	-1	53	-1,3	-3,5	0,9
2020	1	13	00:00	-1	53	-6,4	-12,9	-3,1
2020	1	14	00:00	9,7	52	-2,8	-9	-0,7
2020	1	15	00:00	-1	63	0,2	-0,7	0,6
2020	1	16	00:00	0,4	62	-3,9	-5,2	0,1
2020	1	17	00:00	2	62	-5,2	-8,4	-0,7

features

Year	m	d	Time	precp	snow	airtmp	mintmp	maxtmp
2020	1	2	00:00	0,4	55	2,5	-2	4,5
2020	1	3	00:00	1,6	53	0,8	-0,8	4,6
2020	1	4	00:00	0,1	51	-5,8	-11,1	-0,7
2020	1	5	00:00	1,9	52	-13,5	-19,1	-4,6
2020	1	6	00:00	0,6	52	-2,4	-11,4	-1
2020	1	7	00:00	4,1	52	0,4	-2	1,3
2020	1	8	00:00	4,3	51	0,8	0,1	1,8
2020	1	9	00:00	-1	51	-0,6	-1,9	1,6
2020	1	10	00:00	1	51	-6,2	-11	-1,4
2020	1	11	00:00	2,8	50	-4,8	-10,7	-2,1
2020	1	12	00:00	-1	53	-1,3	-3,5	0,9
2020	1	13	00:00	-1	53	-6,4	-12,9	-3,1
2020	1	14	00:00	9,7	52	-2,8	-9	-0,7
2020	1	15	00:00	-1	63	0,2	-0,7	0,6
2020	1	16	00:00	0,4	62	-3,9	-5,2	0,1
2020	1	17	00:00	2	62	-5,2	-8,4	-0,7

label

data point

data point, features and label
are design choices!

```
newdataset= somedata[somedata['date'] == '2021-06-01'] ;
print(newdataset)
```

```
          date   time  temperature
0   2021-06-01  00:00          6.2
1   2021-06-01  01:00          6.4
2   2021-06-01  02:00          6.4
3   2021-06-01  03:00          6.8
4   2021-06-01  04:00          7.1
5   2021-06-01  05:00          7.6
6   2021-06-01  06:00          7.5
7   2021-06-01  07:00          8.1
8   2021-06-01  08:00         10.3
9   2021-06-01  09:00         12.8
10  2021-06-01  10:00         15.0
11  2021-06-01  11:00         14.1
12  2021-06-01  12:00         16.5
13  2021-06-01  13:00         13.6
14  2021-06-01  14:00         14.2
15  2021-06-01  15:00         13.3
16  2021-06-01  16:00         14.5
17  2021-06-01  17:00         13.8
```

Key Parameters of a Data Set

number n of features

number m of data points "sample size"

Year	m	d	Time	precp	snow	airtmp	mintmp	maxtmp
2020	1	2	00:00	0,4	55	2,5	-2	4,5
2020	1	3	00:00	1,6	53	0,8	-0,8	4,6
2020	1	4	00:00	0,1	51	-5,8	-11,1	-0,7
2020	1	5	00:00	1,9	52	-13,5	-19,1	-4,6
2020	1	6	00:00	0,6	52	-2,4	-11,4	-1
2020	1	7	00:00	4,1	52	0,4	-2	1,3
2020	1	8	00:00	4,3	51	0,8	0,1	1,8
2020	1	9	00:00	-1	51	-0,6	-1,9	1,6
2020	1	10	00:00	-1	51	-6,2	-11	-1,4
2020	1	11	00:00	2,8	50	-4,8	-10,7	-2,1
2020	1	12	00:00	-1	53	-1,3	-3,5	0,9
2020	1	13	00:00	-1	53	-6,4	-12,9	-3,1
2020	1	14	00:00	9,7	52	-2,8	-9	-0,7
2020	1	15	00:00	-1	63	0,2	-0,7	0,6
2020	1	16	00:00	0,4	62	-3,9	-5,2	0,1
2020	1	17	00:00	2	62	-5,2	-8,4	-0,7
2020	1	18	00:00	19,6	65	-4,6	-7,3	-4,2
2020	1	19	00:00	0,7	81	-4,4	-8,8	-2,7
2020	1	20	00:00	2,8	79	-1,8	-10,5	1,2

Feature Deluge.

modern information technology provides huge number of raw features

- smartphones
- webcams
- social networks
- smart watch
- ….

use only most relevant features but not fewer.

missing relevant features bad for accuracy

using many irrelevant features wastes computation and might result in overfitting

```python
newdataset= somedata[somedata['date'] == '2021-06-01'] ;
print(newdataset)
```

```
          date   time  temperature
0   2021-06-01  00:00          6.2
1   2021-06-01  01:00          6.4
2   2021-06-01  02:00          6.4
3   2021-06-01  03:00          6.8
4   2021-06-01  04:00          7.1
5   2021-06-01  05:00          7.6
6   2021-06-01  06:00          7.5
7   2021-06-01  07:00          8.1
8   2021-06-01  08:00         10.3
9   2021-06-01  09:00         12.8
10  2021-06-01  10:00         15.0
11  2021-06-01  11:00         14.1
12  2021-06-01  12:00         16.5
13  2021-06-01  13:00         13.6
14  2021-06-01  14:00         14.2
15  2021-06-01  15:00         13.3
16  2021-06-01  16:00         14.5
17  2021-06-01  17:00         13.8
```

data point = some day at FMI station

feature = nr of hourly observations

want to predict maximum daytime temperature

missing relevant features bad for accuracy

```python
newdataset= somedata[somedata['date'] == '2021-06-01'] ;
print(newdataset)
```

```
          date   time  temperature
0   2021-06-01  00:00          6.2
1   2021-06-01  01:00          6.4
2   2021-06-01  02:00          6.4
3   2021-06-01  03:00          6.8
4   2021-06-01  04:00          7.1
5   2021-06-01  05:00          7.6
6   2021-06-01  06:00          7.5
7   2021-06-01  07:00          8.1
8   2021-06-01  08:00         10.3
9   2021-06-01  09:00         12.8
10  2021-06-01  10:00         15.0
11  2021-06-01  11:00         14.1
12  2021-06-01  12:00         16.5
13  2021-06-01  13:00         13.6
14  2021-06-01  14:00         14.2
15  2021-06-01  15:00         13.3
16  2021-06-01  16:00         14.5
17  2021-06-01  17:00         13.8
```

data point = some day at FMI station

feature = hourly temp. 00:00 – 15:00

want to predict temp at 16:00

using irrelevant features wastes comp. resources

Label is Design Choice!

YOU choose the label of a data point

by choosing/defining label you define the ML problem or learning task !

Regression. Numeric Labels.

	date	time	temperature
0	2021-06-01	00:00	6.2
1	2021-06-01	01:00	6.4
2	2021-06-01	02:00	6.4
3	2021-06-01	03:00	6.8
4	2021-06-01	04:00	7.1
5	2021-06-01	05:00	7.6
6	2021-06-01	06:00	7.5
7	2021-06-01	07:00	8.1
8	2021-06-01	08:00	10.3
9	2021-06-01	09:00	12.8
10	2021-06-01	10:00	15.0
11	2021-06-01	11:00	14.1
12	2021-06-01	12:00	16.5
13	2021-06-01	13:00	13.6
14	2021-06-01	14:00	14.2
15	2021-06-01	15:00	13.3
16	2021-06-01	16:00	14.5
17	2021-06-01	17:00	13.8

datapoint
“2021-06-01 at some FMI station”

label = tmp at 15:00

Binary Classification.

	date	time	temperature
0	2021-06-01	00:00	6.2
1	2021-06-01	01:00	6.4
2	2021-06-01	02:00	6.4
3	2021-06-01	03:00	6.8
4	2021-06-01	04:00	7.1
5	2021-06-01	05:00	7.6
6	2021-06-01	06:00	7.5
7	2021-06-01	07:00	8.1
8	2021-06-01	08:00	10.3
9	2021-06-01	09:00	12.8
10	2021-06-01	10:00	15.0
11	2021-06-01	11:00	14.1
12	2021-06-01	12:00	16.5
13	2021-06-01	13:00	13.6
14	2021-06-01	14:00	14.2
15	2021-06-01	15:00	13.3
16	2021-06-01	16:00	14.5
17	2021-06-01	17:00	13.8

datapoint
"2021-06-01 at some FMI station"

label =

- "hot" if tmp at 15:00 > 10
- "cold" if … <= 10

Multi-Class Classification

	date	time	temperature
0	2021-06-01	00:00	6.2
1	2021-06-01	01:00	6.4
2	2021-06-01	02:00	6.4
3	2021-06-01	03:00	6.8
4	2021-06-01	04:00	7.1
5	2021-06-01	05:00	7.6
6	2021-06-01	06:00	7.5
7	2021-06-01	07:00	8.1
8	2021-06-01	08:00	10.3
9	2021-06-01	09:00	12.8
10	2021-06-01	10:00	15.0
11	2021-06-01	11:00	14.1
12	2021-06-01	12:00	16.5
13	2021-06-01	13:00	13.6
14	2021-06-01	14:00	14.2
15	2021-06-01	15:00	13.3
16	2021-06-01	16:00	14.5
17	2021-06-01	17:00	13.8

datapoint
"2021-06-01 at some FMI station"

label =

- "nice morning" if tmp at 15:00 < 10 and tmp at 10:00 > 10
- "nice noon" if tmp at 15:00 > 10 and tmp at 10:00 < 10
- "nice day" if tmp at 15:00 > 10 and tmp at 10:00 > 10

Multilabel Problems – Multitask Learning

by choosing/defining label you define the ML task !

for same data, use different labels → multiple learning tasks

multi-label class. (special case of multi-task learning)

Multi-Label Regression.

	date	time	temperature
0	2021-06-01	00:00	6.2
1	2021-06-01	01:00	6.4
2	2021-06-01	02:00	6.4
3	2021-06-01	03:00	6.8
4	2021-06-01	04:00	7.1
5	2021-06-01	05:00	7.6
6	2021-06-01	06:00	7.5
7	2021-06-01	07:00	8.1
8	2021-06-01	08:00	10.3
9	2021-06-01	09:00	12.8
10	2021-06-01	10:00	15.0
11	2021-06-01	11:00	14.1
12	2021-06-01	12:00	16.5
13	2021-06-01	13:00	13.6
14	2021-06-01	14:00	14.2
15	2021-06-01	15:00	13.3
16	2021-06-01	16:00	14.5
17	2021-06-01	17:00	13.8

datapoint
“2021-06-01 at some FMI station”

label1 = tmp at 10:00

label2= tmp at 15:00

Multilabel Classification.

y_1= 1 or 0 if car present or not

y_2= 1 or 0 if person present or not

y_3= 1 or 0 if tree present or not

Features and Labels - Notation.

- consider m datapoints, indexed by i = 1,…,m
- i-th datapoint with features $x_1^{(i)}, \cdots, x_n^{(i)}$ and label $y^{(i)}$
- stack features of i-th data point into feature vector

$$\boldsymbol{x}^{(i)} = \left(x_1^{(i)}, \cdots, x_n^{(i)}\right)^{\boldsymbol{T}}$$

- represent date by feature matrix and label vector !

Feature Matrix.

$$\mathbf{X} = \left(\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \ldots, \mathbf{x}^{(m)}\right)^{T} = \begin{pmatrix} x_1^{(1)} & x_2^{(1)} & \ldots & x_n^{(1)} \\ x_1^{(2)} & x_2^{(2)} & \ldots & x_n^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{(m)} & x_2^{(m)} & \ldots & x_n^{(m)} \end{pmatrix} \in \mathbb{R}^{m \times n}$$

Label Vector.

$$\mathbf{y} = \left(y_1, y_2 \ldots, y_m \right)^{T} \in \mathbb{R}^{m}$$

NumPy Arrays

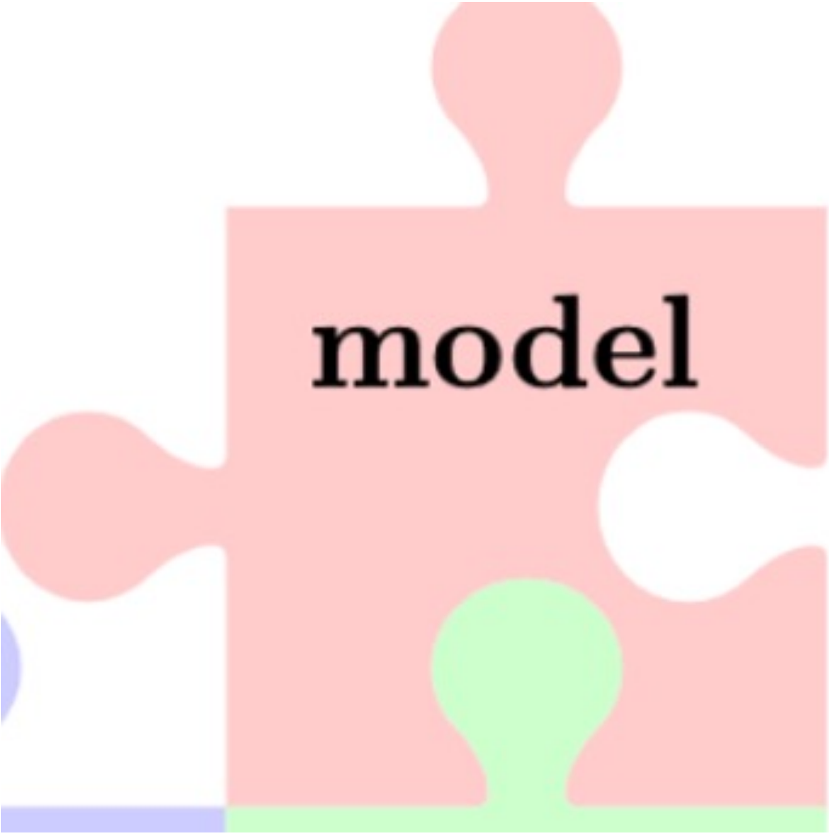
- feature matrix and label vector are numeric arrays
- Python library NumPy provides methods for num.arr.

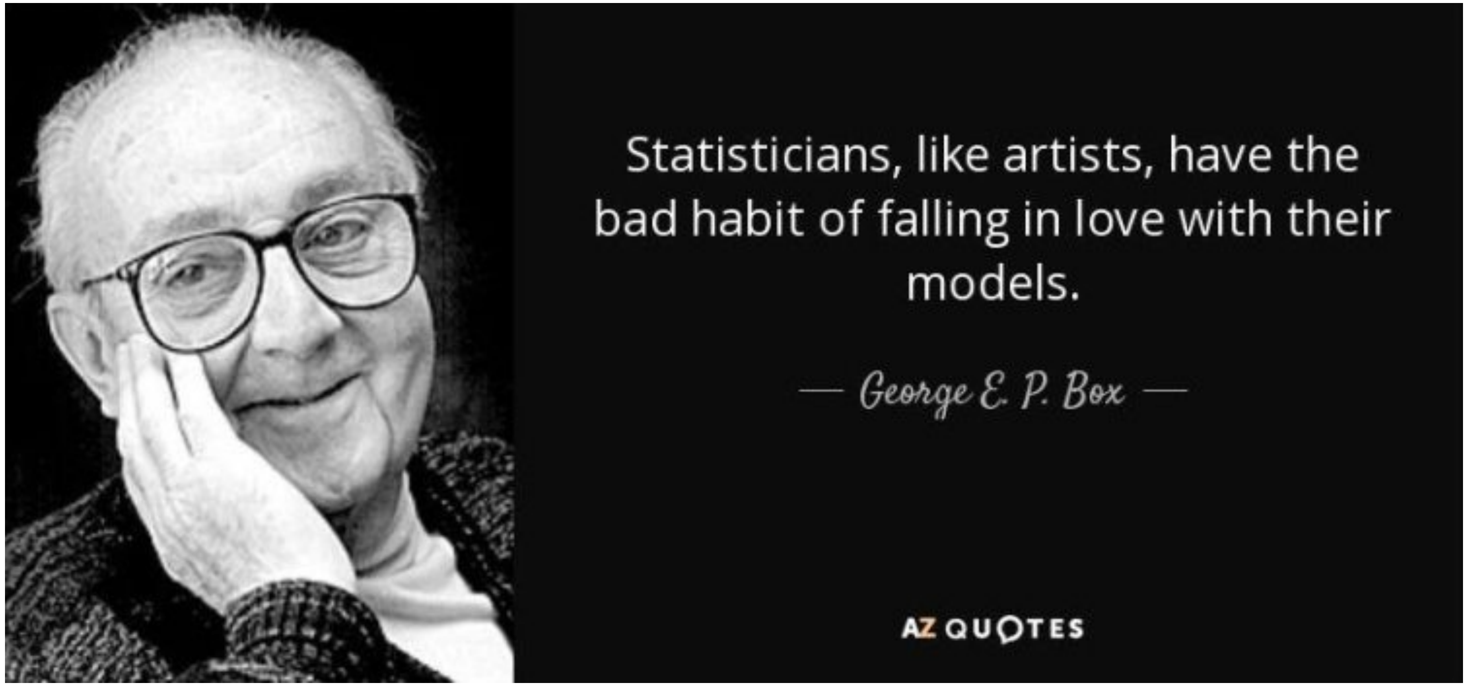
```
>>> import numpy as np
>>> from sklearn.linear_model import LinearRegression
>>> X = np.array([[1, 1], [1, 2], [2, 2], [2, 3]])
>>> # y = 1 * x_0 + 2 * x_1 + 3
>>> y = np.dot(X, np.array([1, 2])) + 3
```

“Data = X and y”

- represent data by feature mtx **X** and label vec. **y**

```
In [5]: from sklearn.datasets import load_iris
        dataset = load_iris()
        X = dataset.data
        y = dataset.target
```

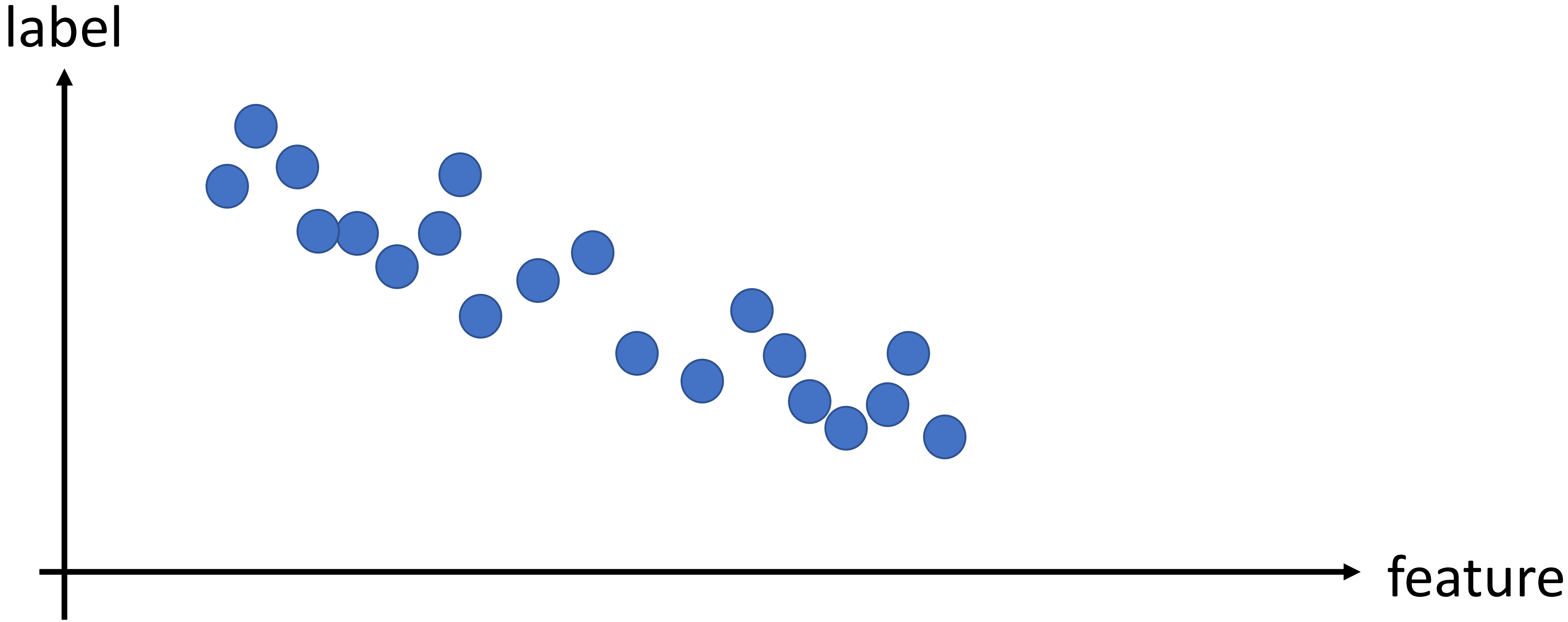

model


Statisticians, like artists, have the bad habit of falling in love with their models.
— George E. P. Box —
AZ QUOTES

Machine Learning.

"learn to predict the label of a data point solely from its features"

Scatterplot

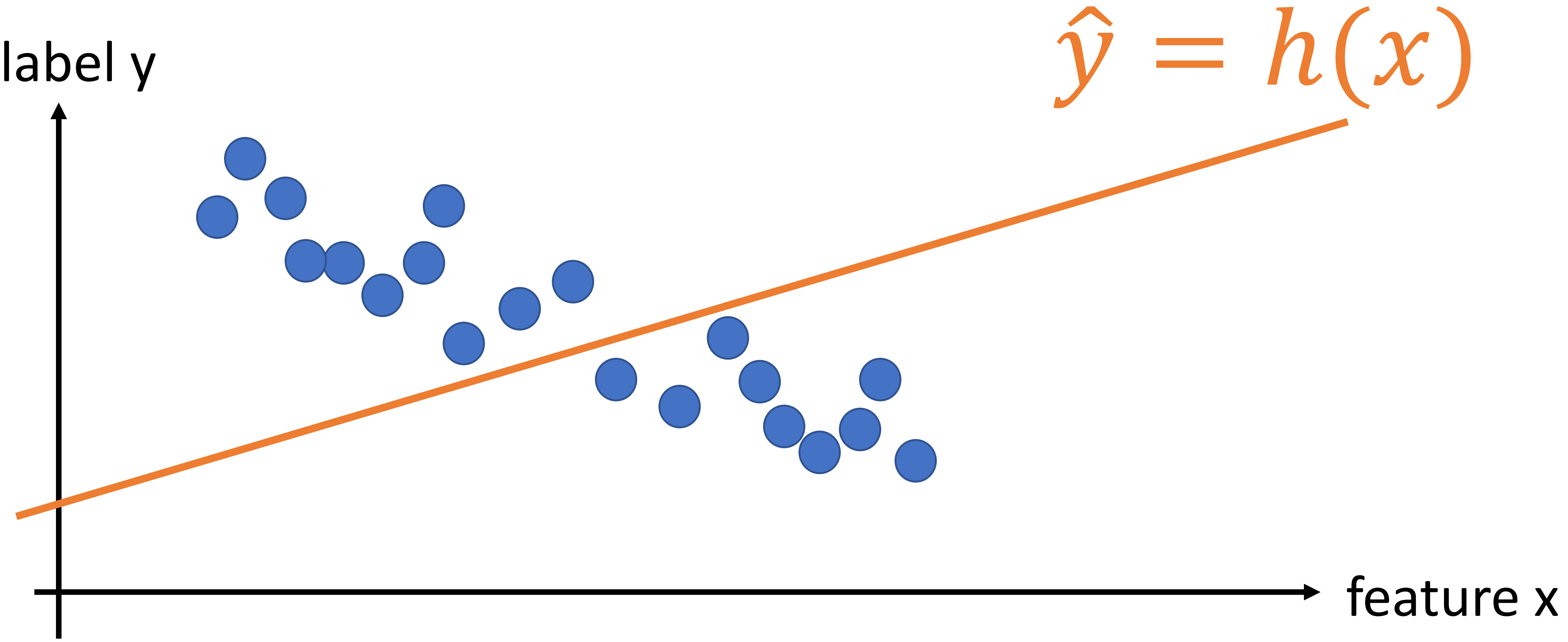


How to Predict?

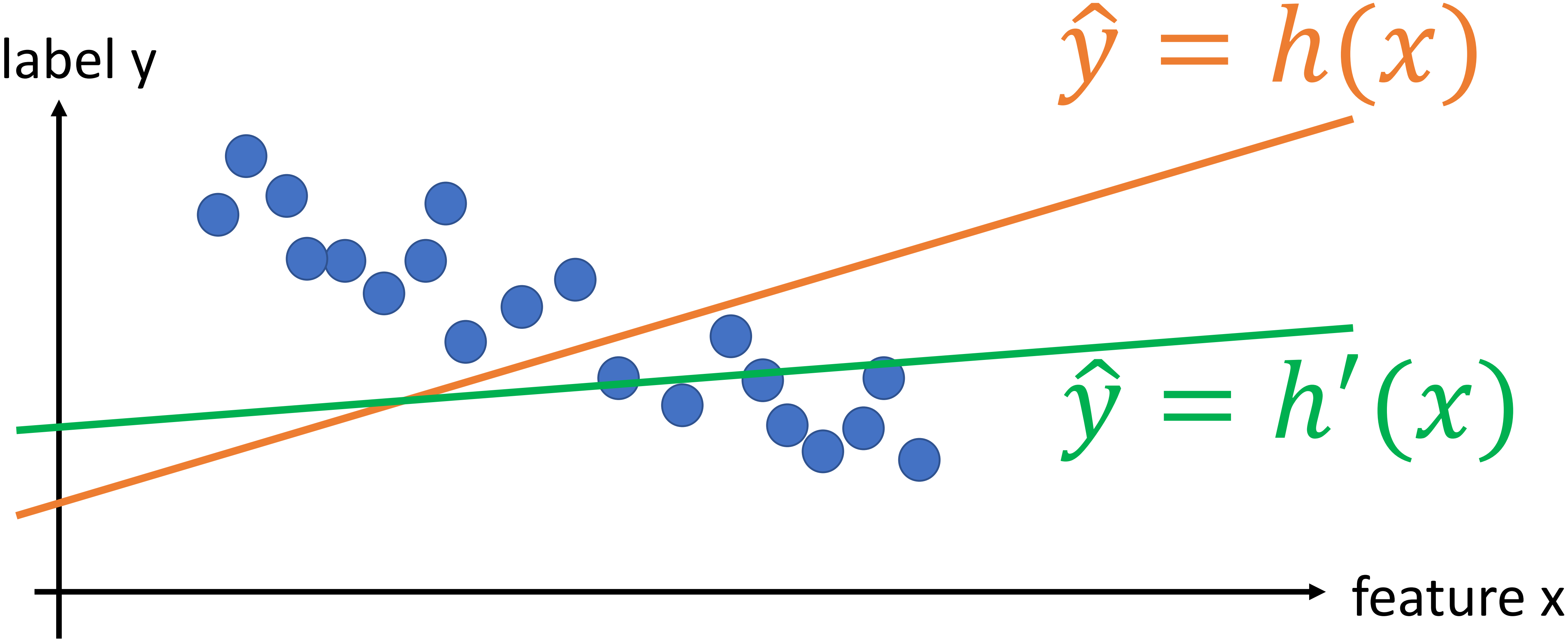
apply a hypothesis map h to features x,

$$\hat{y} = h(x)$$

A Hypothesis.

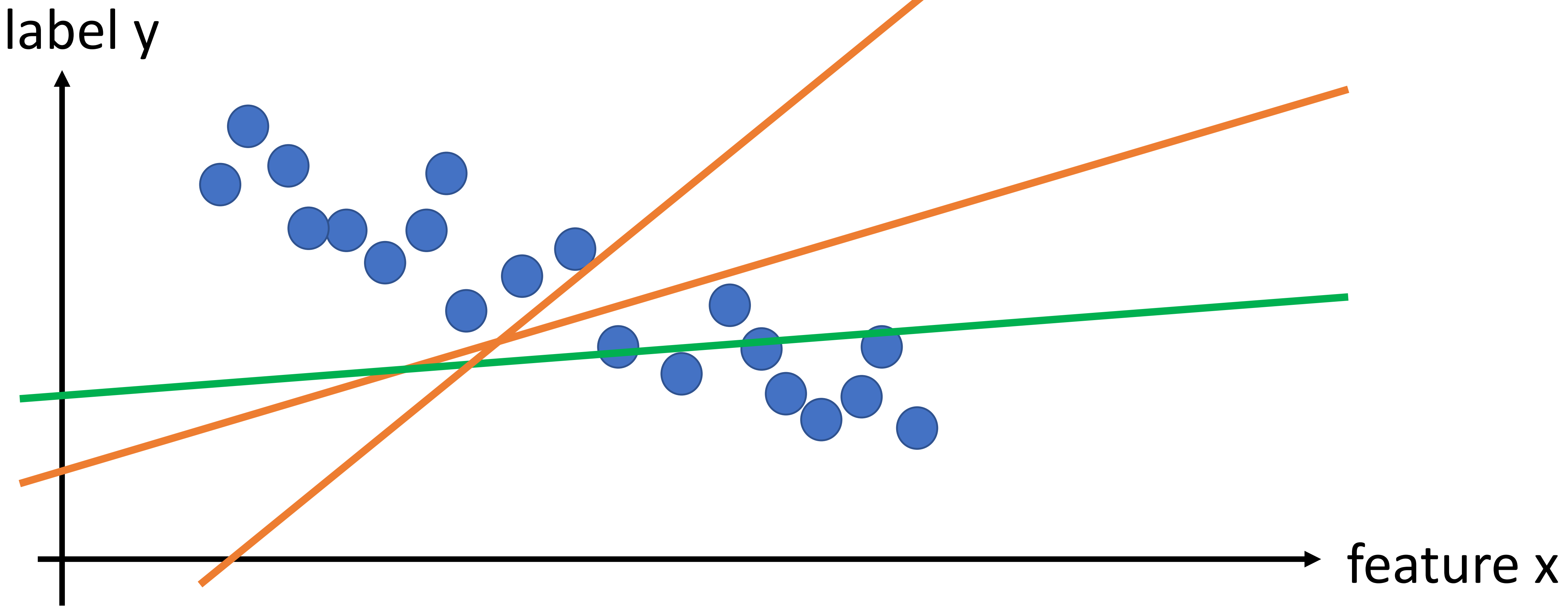


Model = Several Hypotheses.



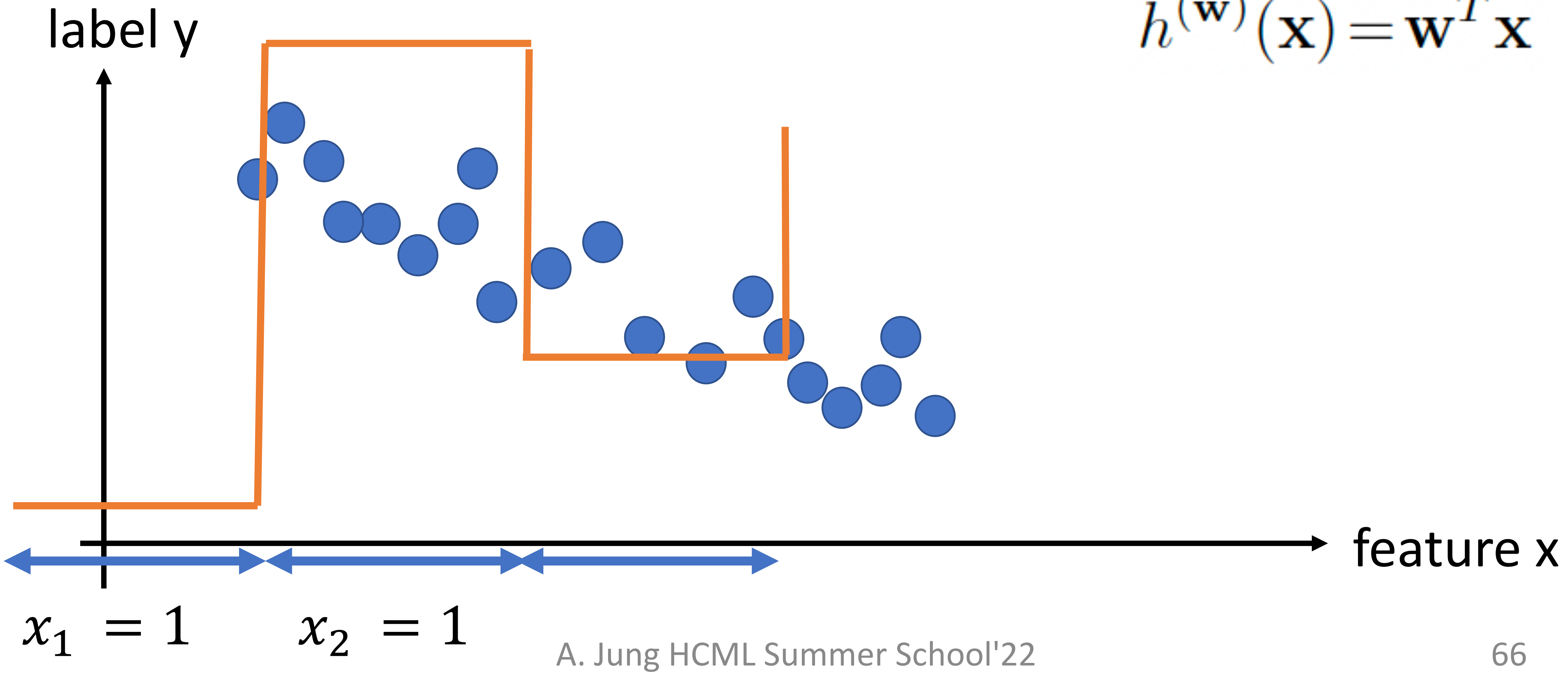
Linear Model

$$h^{(\mathbf{w})}(\mathbf{x}) = \mathbf{w}^T \mathbf{x}$$



Linear Model is Versatile!

$$h^{(\mathbf{w})}(\mathbf{x}) = \mathbf{w}^T \mathbf{x}$$



Linear + Feature Map

linear map

feature map

$\phi(\cdot)$

$$\mathbf{w}^T\mathbf{x} = \sum_{j=1}^{n} w_j x_j$$

single feature x

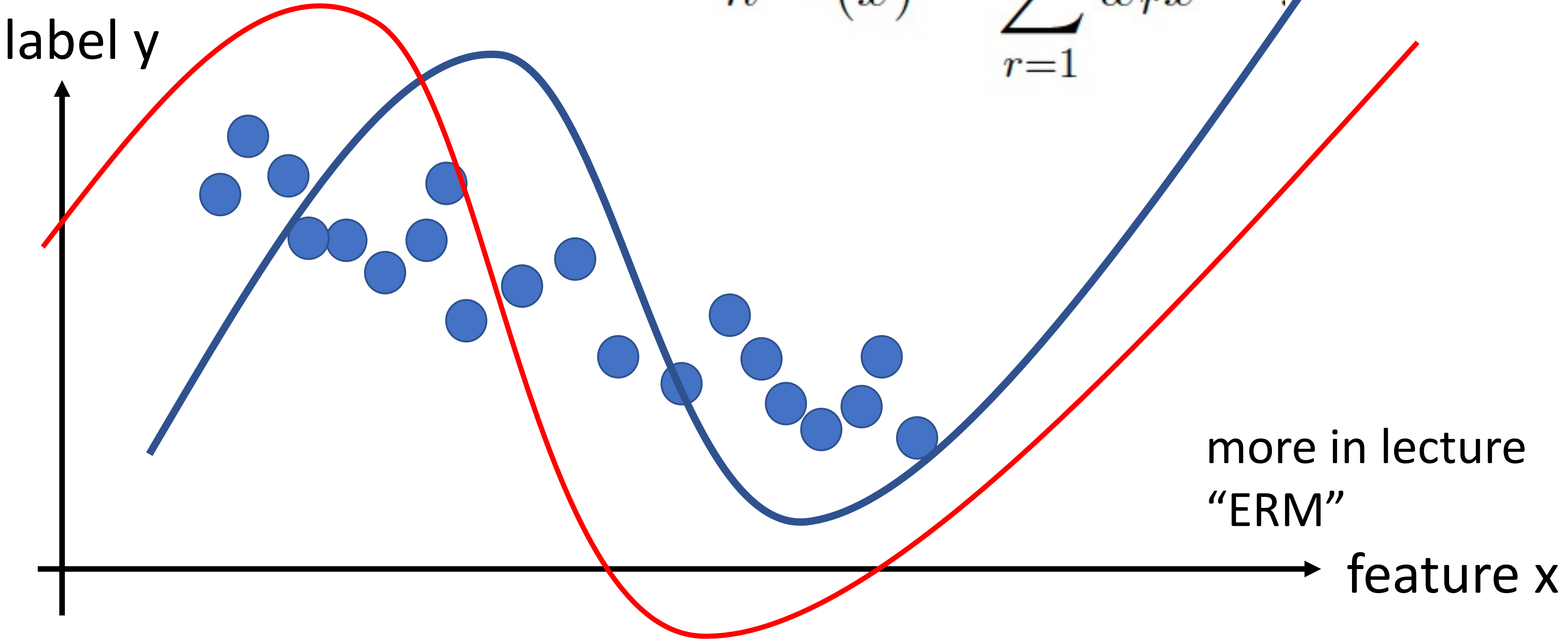
$$\begin{pmatrix} x_1 = \phi_1(x) \\ x_2 = \phi_2(x) \\ \vdots \\ x_n = \phi_n(x) \end{pmatrix}$$

h(x)

$$h(x) = \sum_{j=1}^{n} w_j \phi_j(x)$$

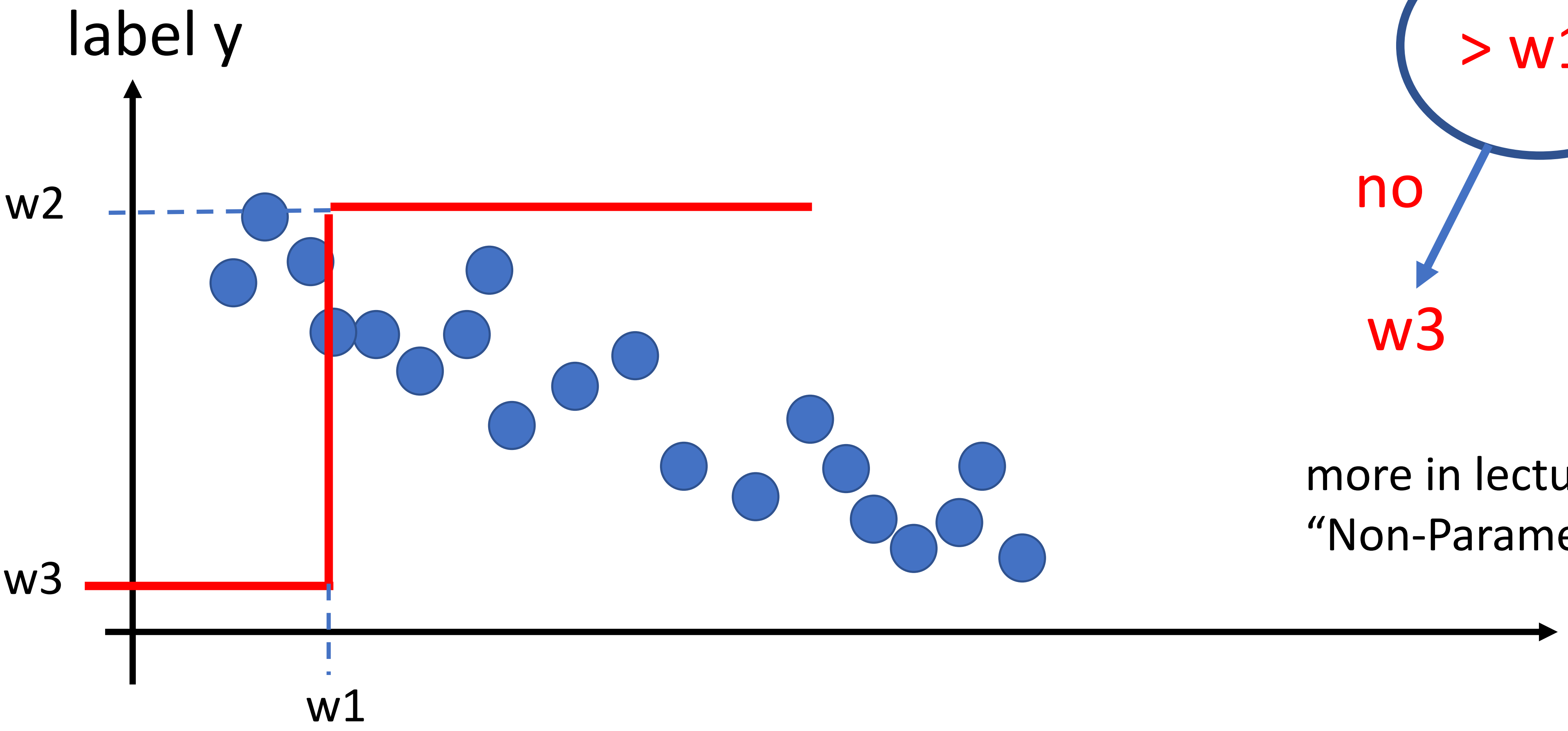
Polynomials

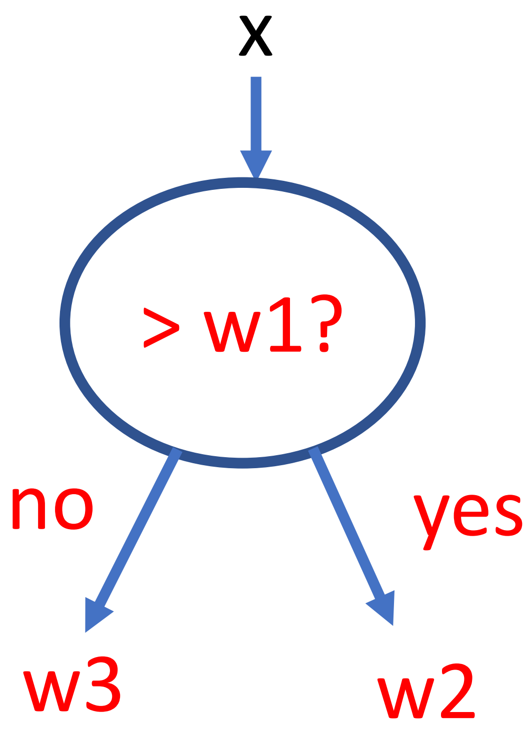
$$h^{(\mathbf{w})}(x) = \sum_{r=1}^{n} w_r x^{r-1}.$$



more in lecture
"ERM"

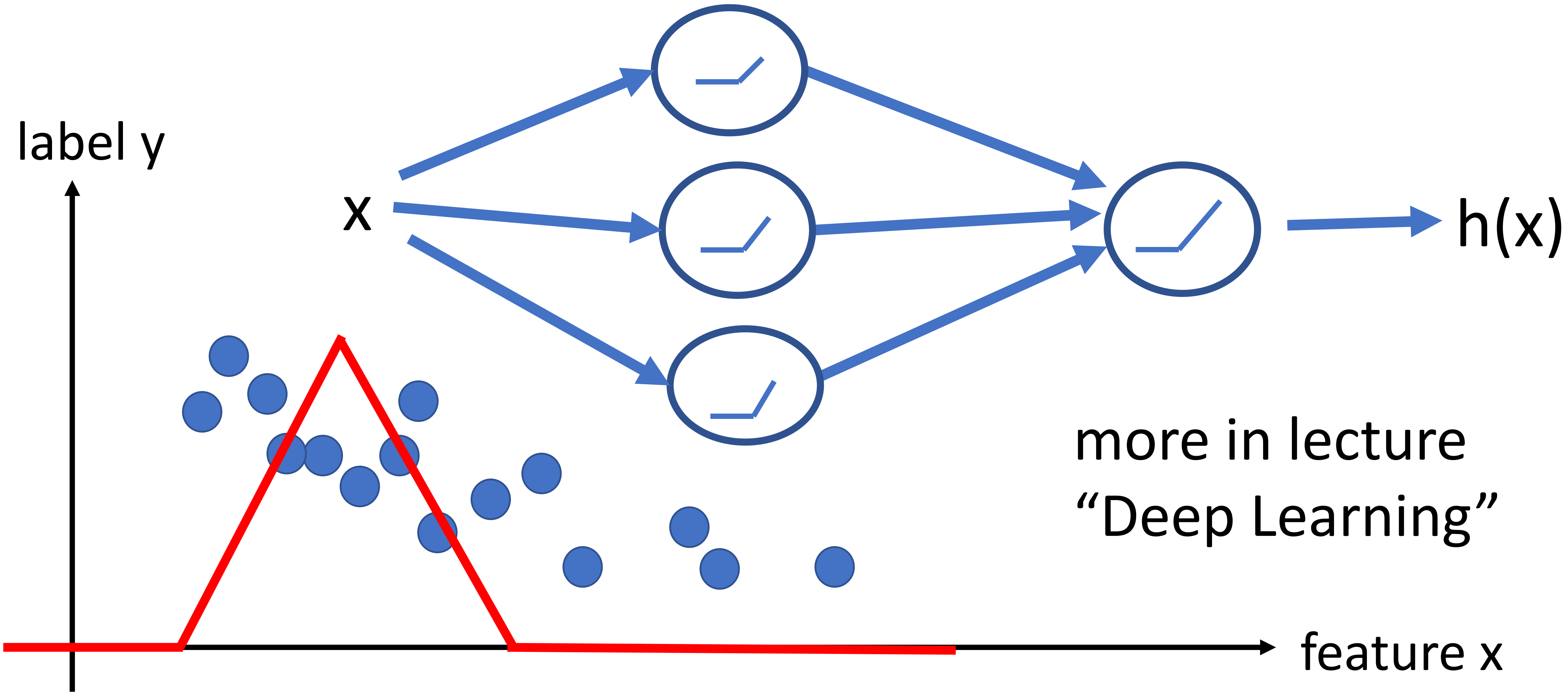
Decision Tree





more in lecture
"Non-Parametric Models"

Artificial Neural Network

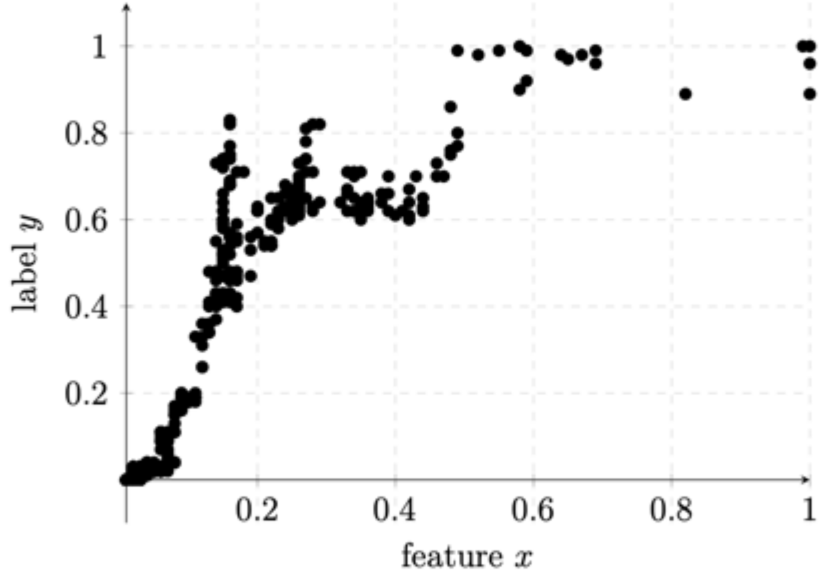


more in lecture
"Deep Learning"

Which Model To Choose?

- large to offer a good hypothesis
- small to fit computational resources
- simple or interpretable

Sufficiently Large



linear model might be to small for such data

there is no straight line that fits well the data points here

need larger models that also contain non-linear maps

more on large (non-linear) models in Lectures "Deep Learning" and "Non-Parametric Models"

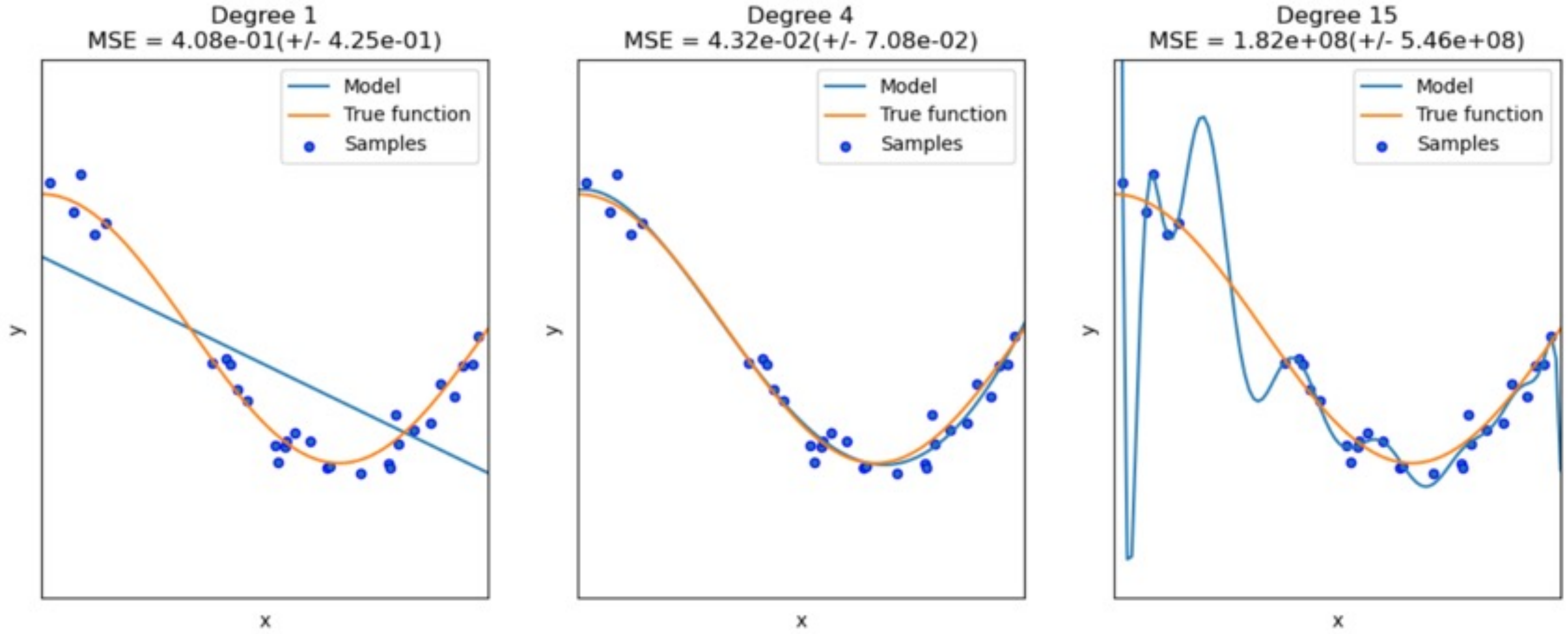
Sufficiently Small (Statistically)

- large model contains by accident a hypothesis that perfects fits training data

- model fits well training data but does a very poor job outside the training data

more on overfitting in Lectures
“Model Val/Sel” and “Diagnosing ML”

Sufficientlv Small (Statistically)



source: https://scikit-learn.org/stable/auto_examples/model_selection/plot_underfitting_overfitting.html

rule of thumb:

training set (much) larger than # model parameters

Sufficiently Small (Comput.)

- consider linear model using n features
- fit linear model on m > n datapoints
- need to invert “n by n” matrix ! [Sec. 4.3, MLBook]

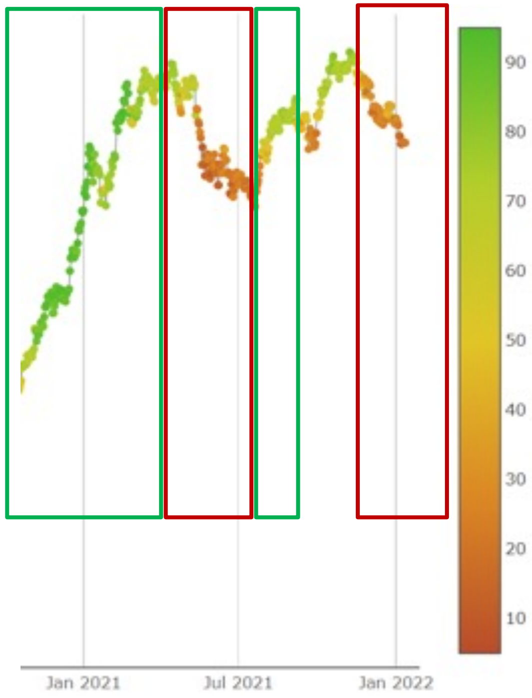
Sufficiently Simple (Comput.)

- hypothesis maps h(x) should be easy to evaluate
- recent MSc thesis on “Predicting Gas Valve Position”

need to compute h(x) in real-time (while engine is running!)

Problem: predict the price trend of a cryptocurrency other than Bitcoin (e.g., ADA)

tradingview.com



lookintobitcoin.com

- Datapoint: some day
- Features:
  - Bitcoin price
  - Fear and Greed Index
- Label: ADA's price

by Esther Gallego

Predicting future purchases

Datapoint = some customer

Features = customer attributes (age, sex, purchase history, etc.)

Label = interest in some (new) product

Marko Ikävalko

Datapoint = A Day in the Canteen

features:

label:

https://commons.wikimedia.org/wiki/File:Suzhou_High_School-canteen.jpg

by Jasu Vehtari

Datapoint = A Cow

Features:

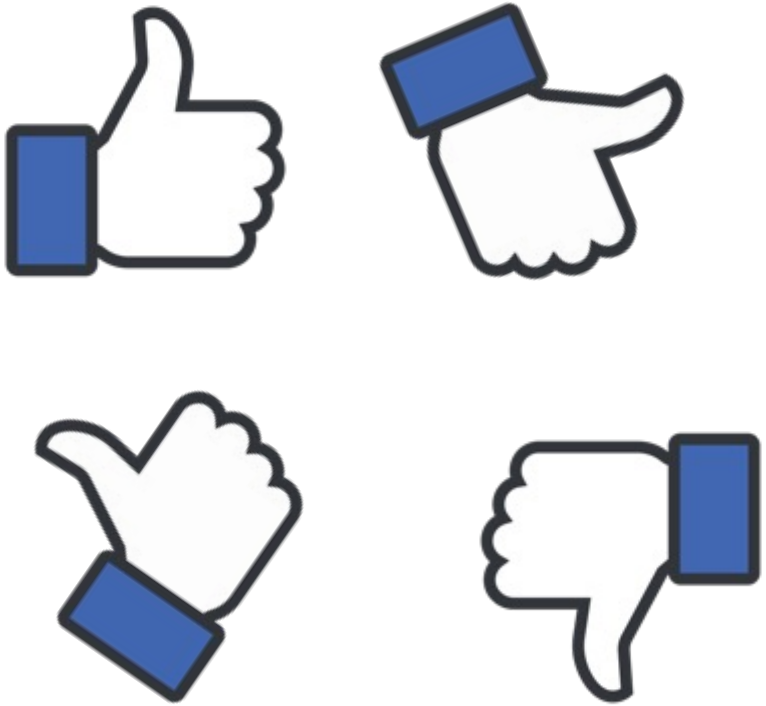
- Quantity of milk produced per day or over time
- Temperature of the milk

Labels:

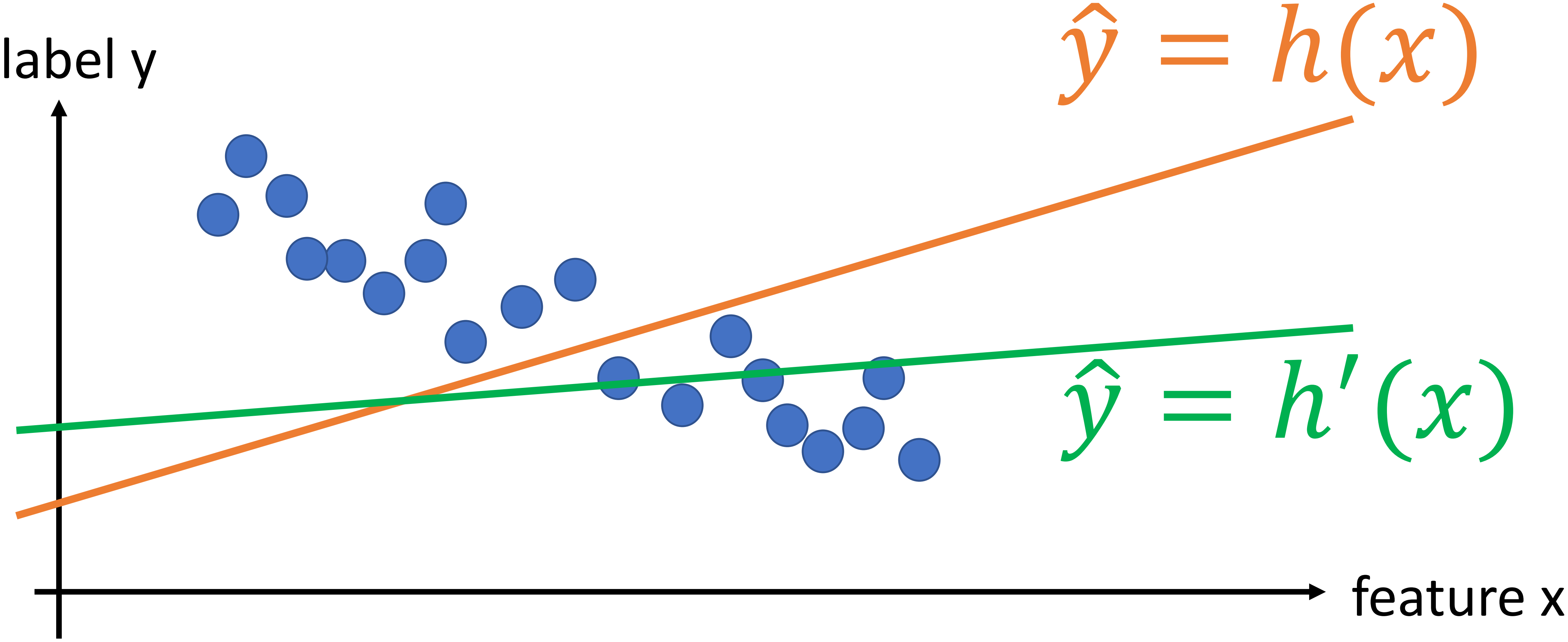
- Is the cow sick or not.
- Is it past its peak productin time or not.
- Is it of species X or Y.

by Carlos Santos

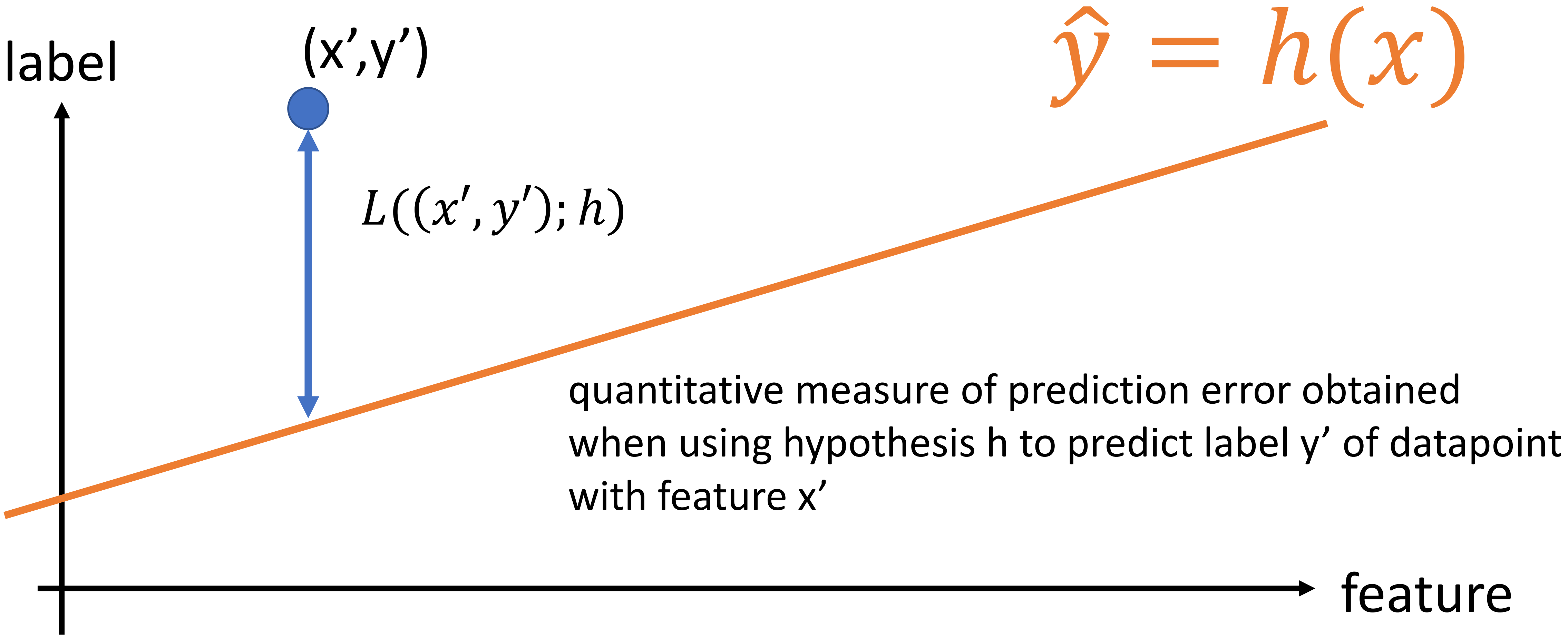

loss



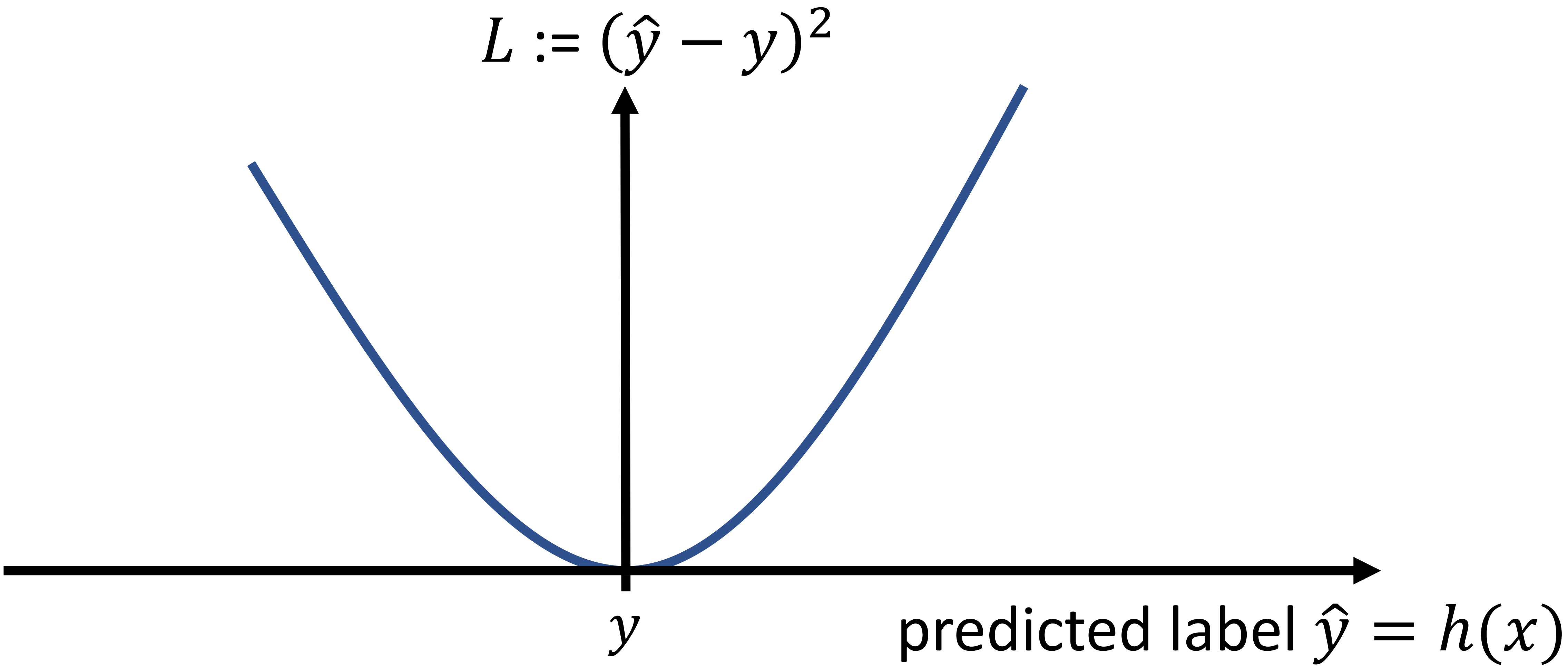
Which Hypothesis is Better?



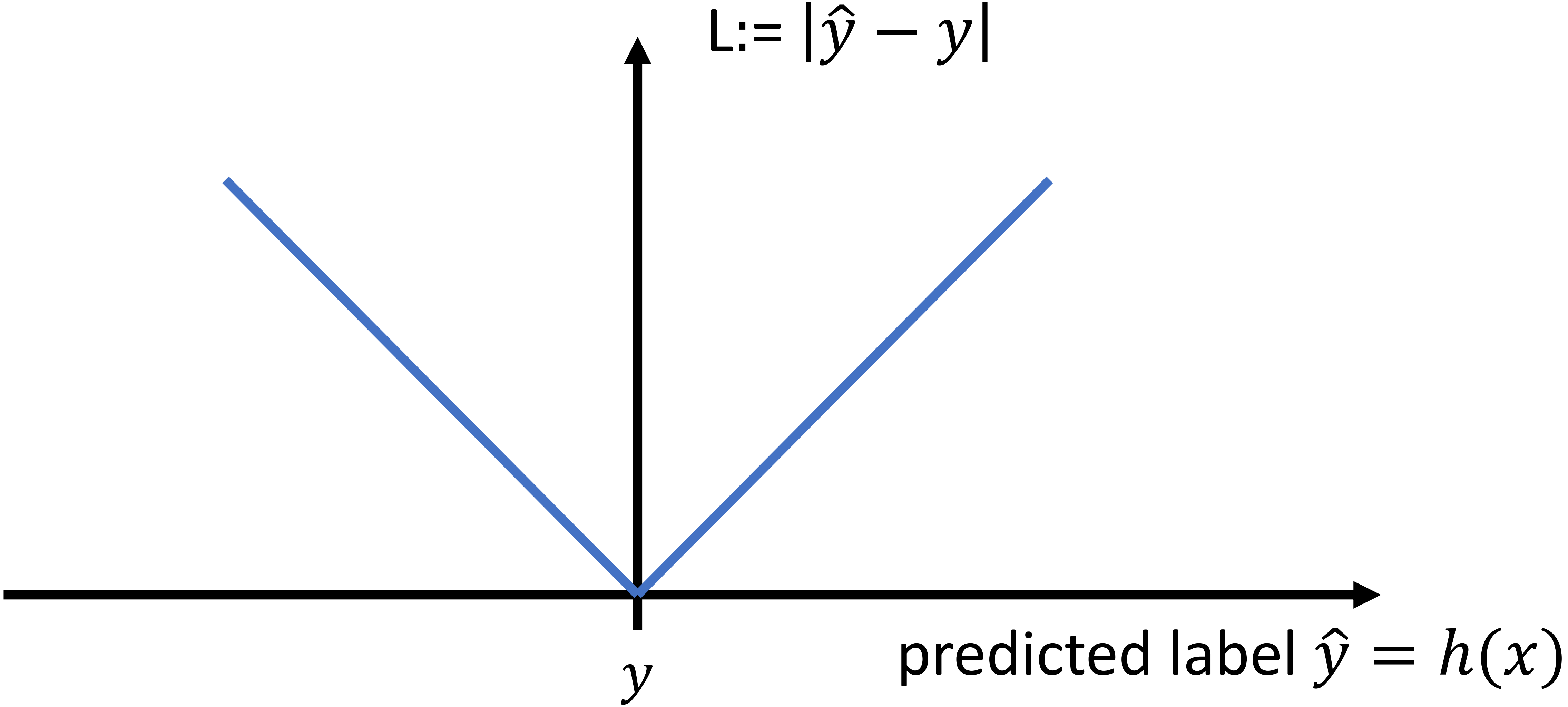
A Loss Function



The Squared Error Loss

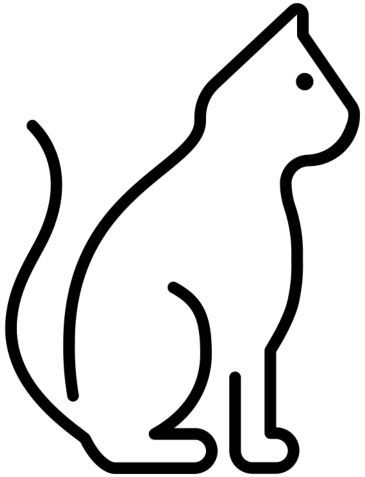


The Absolute Error Loss



Loss Functions for Binary Classification

label y = “cat”



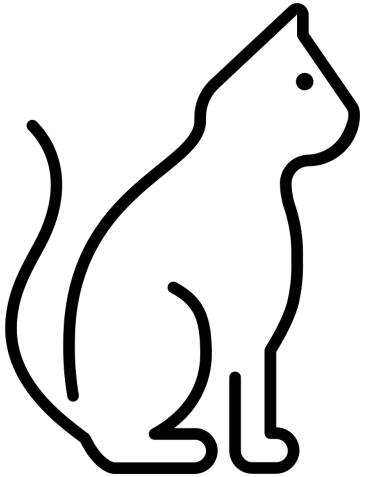
h(x) = “dog”

features x = pixels

Loss = 100

Loss Functions for Binary Classification

label y = “cat”



h(x) = “cat”

features x = pixels

Loss = 0

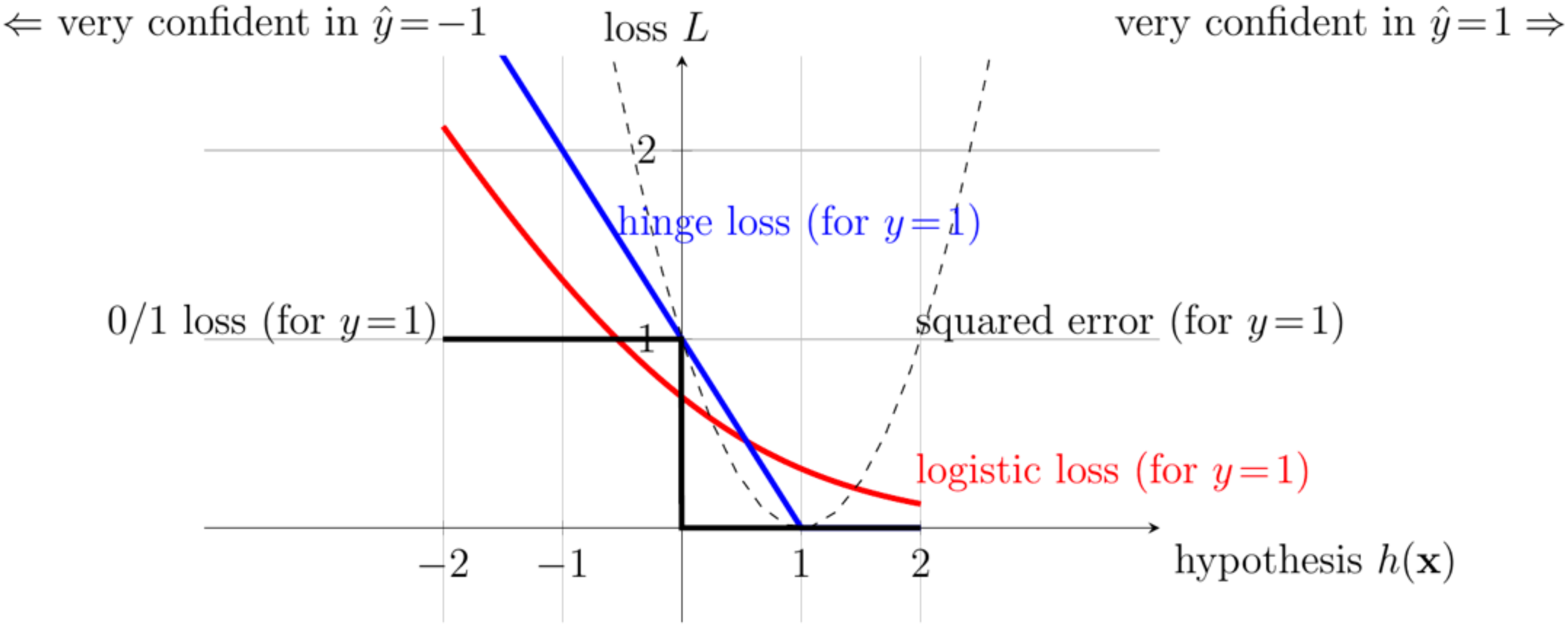
Classifiers

- consider label values either "cat" or "dog"

- features vector x = pixels values
- can we use linear hypothesis maps h(x)?

- YES!
- use sign h(x) to classify: h(x) > 0 → "dog"
- use |h(x)| as confidence measure

Loss Functions for Binary Classification



more on this in lecture "Classification"

Which Loss Function ?

- statistical aspects (should favour “reasonable” hypothesis)
- computational aspects (must be able to minimize them)
- interpretation (what does log-loss = -3 mean ?)

…..choosing a suitable loss function is often non-trivial !

Recent Paper about Constructing Loss Function

Algorithm 1 Generalized ground truth matching method for typical object detector performance evaluation.

Input:	$\mathcal{B}^p = \{(b_i^p, s_i)\}_{i=1}^D$	| D bounding box predictions sorted | by decreasing confidence score s_i | for class c from input image $\mathbf{I}$.
	$\mathcal{B}^g = \{b_k^g\}_{k=1}^N$	| N ground truth bounding box labels | for class c from input image $\mathbf{I}$.
	$\varepsilon \in [0,1] \subset \mathbb{R}$	| Box IoU threshold for matching.
	$g_{\max} \in \mathbb{N}$	| Maximum number of GT boxes b_k^g | to match with a single prediction b_i^p.
	$a_{\min} \in [0,1] \subset \mathbb{R}$	| Minimum value for $A(b_k^p)/A(b_k^g)$, | which limits TP prediction box size.
Output:	$\mathcal{Y} \in \{0,1\}^X$	| A binary sequence of variable length | $X \in \mathbb{N}_0$ indicating true and false | positives, if $g_{\max} = 1 \Rightarrow X = D$.

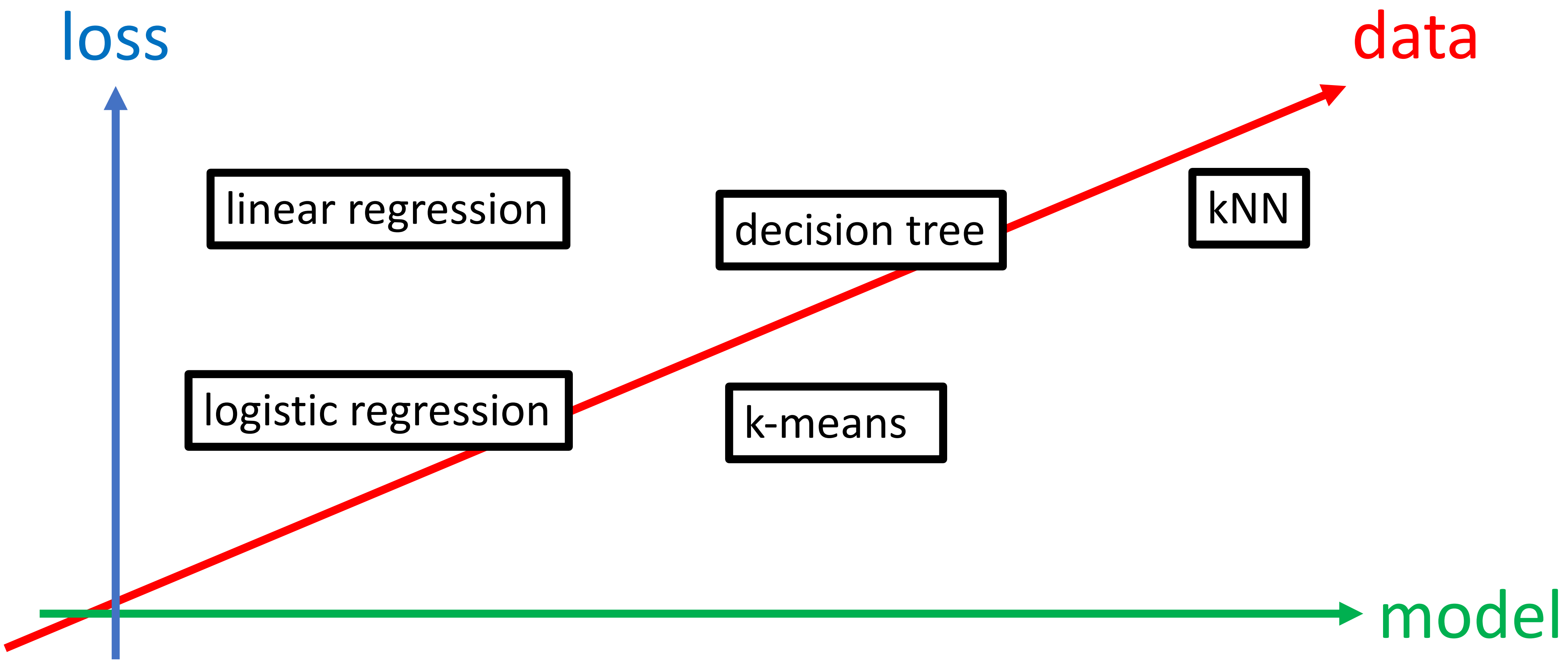
1 **function** MATCHBOXESGENERIC($\mathcal{B}^p, \mathcal{B}^g, \varepsilon, g_{\max}, a_{\min}$)
2 $\quad \mathcal{Y} \leftarrow \emptyset$

https://arxiv.org/pdf/2111.09406.pdf

Main Components of ML

- data
- model
- loss

Landscape of ML Methods



ML Method: Linear Regression

```
>>> import numpy as np
>>> from sklearn.linear_model import LinearRegression
>>> X = np.array([[1, 1], [1, 2], [2, 2], [2, 3]])
>>> # y = 1 * x_0 + 2 * x_1 + 3
>>> y = np.dot(X, np.array([1, 2])) + 3
>>> reg = LinearRegression().fit(X, y)
>>> reg.score(X, y)
1.0
>>> reg.coef_
array([1., 2.])
>>> reg.intercept_
3.0...
>>> reg.predict(np.array([[3, 5]]))
array([16.])
```

data

model, loss

ML Method: Decision Tree Classifier

```
[11]: from sklearn.datasets import load_iris
      from sklearn.tree import DecisionTreeClassifier

      iris = load_iris()

      X = iris.data
      y = iris.target

      # Train
      clf = DecisionTreeClassifier(criterion='entropy',max_depth=4).fit(X, y)
```

data

model

loss

ML Method: Deep Learning

```
# -*- coding: utf-8 -*-
import torch
import math


# Create Tensors to hold input and outputs.
x = torch.linspace(-math.pi, math.pi, 2000)
y = torch.sin(x)

# Prepare the input tensor (x, x^2, x^3).
p = torch.tensor([1, 2, 3])
xx = x.unsqueeze(-1).pow(p)

# Use the nn package to define our model and loss function.
model = torch.nn.Sequential(
    torch.nn.Linear(3, 1),
    torch.nn.Flatten(0, 1)
)
loss_fn = torch.nn.MSELoss(reduction='sum')
```

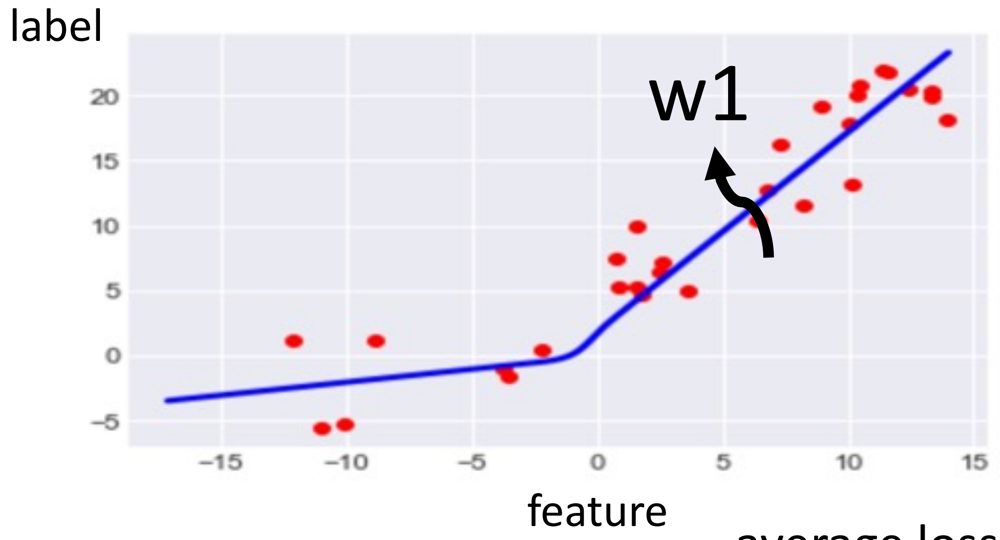
data

model

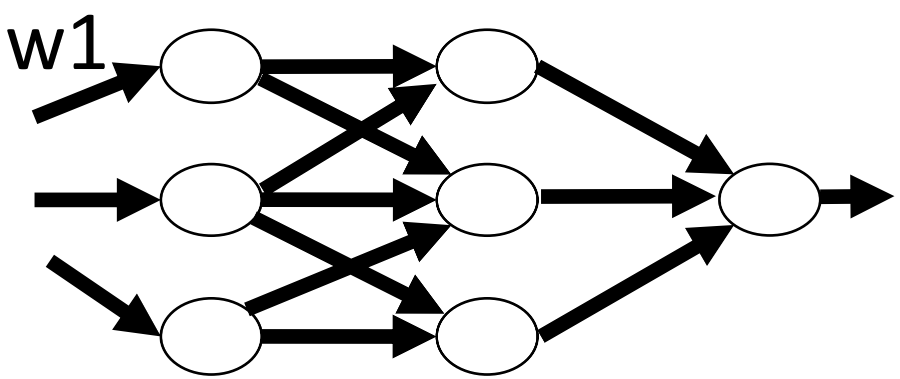
loss

Three Views on Machine Learning

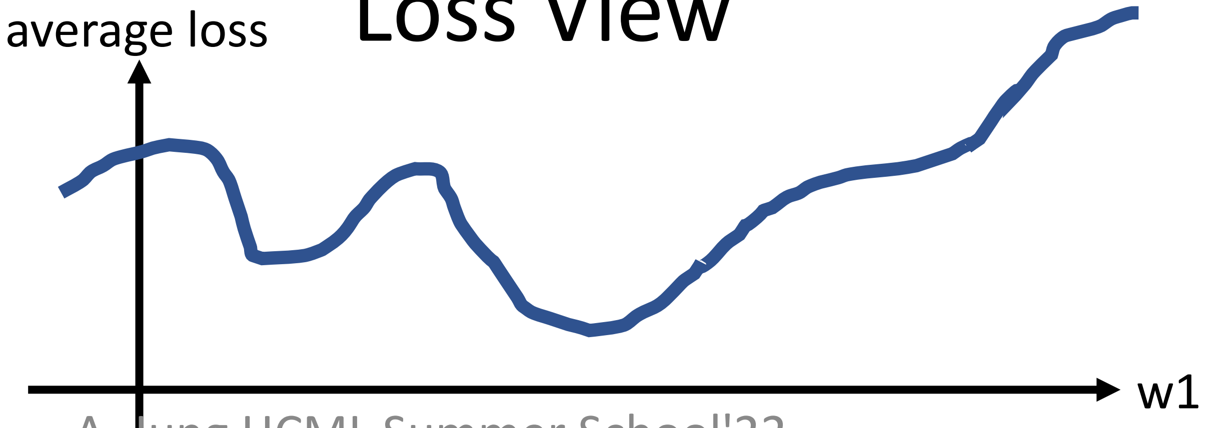
“Data View”



“Model View”



“Loss View”

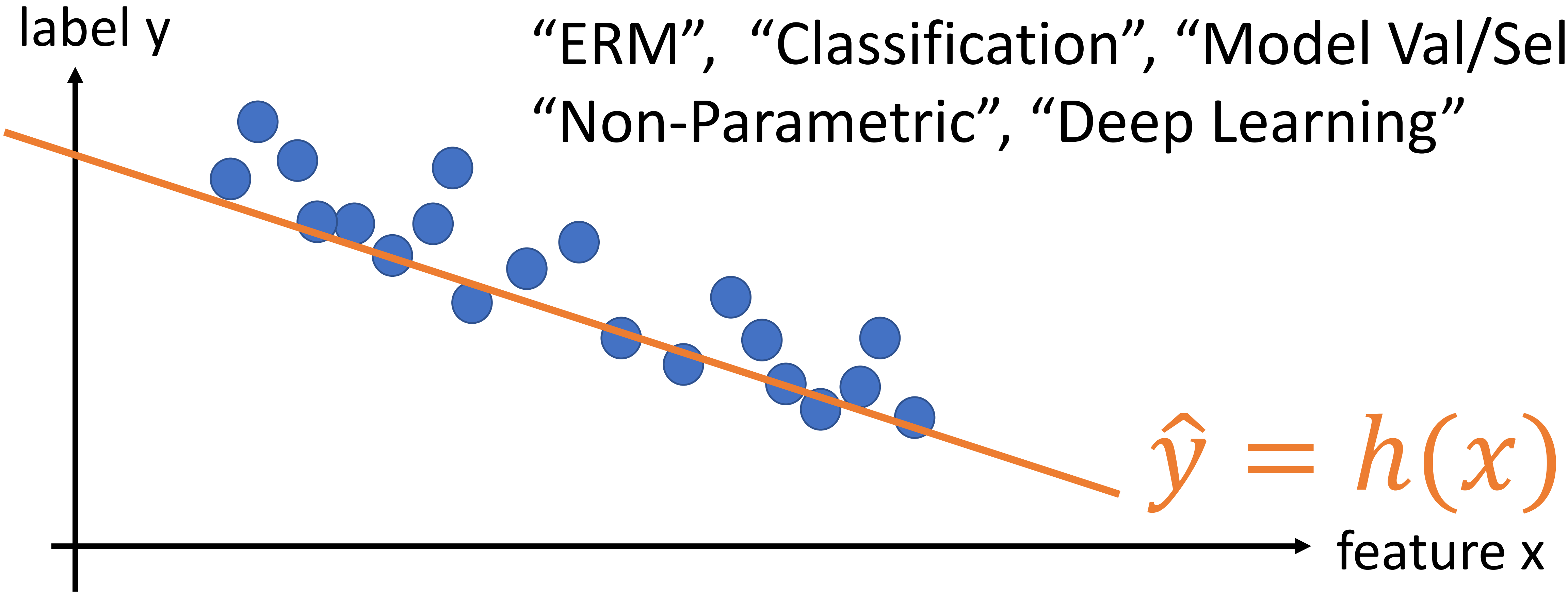


Three Main Flavours of ML

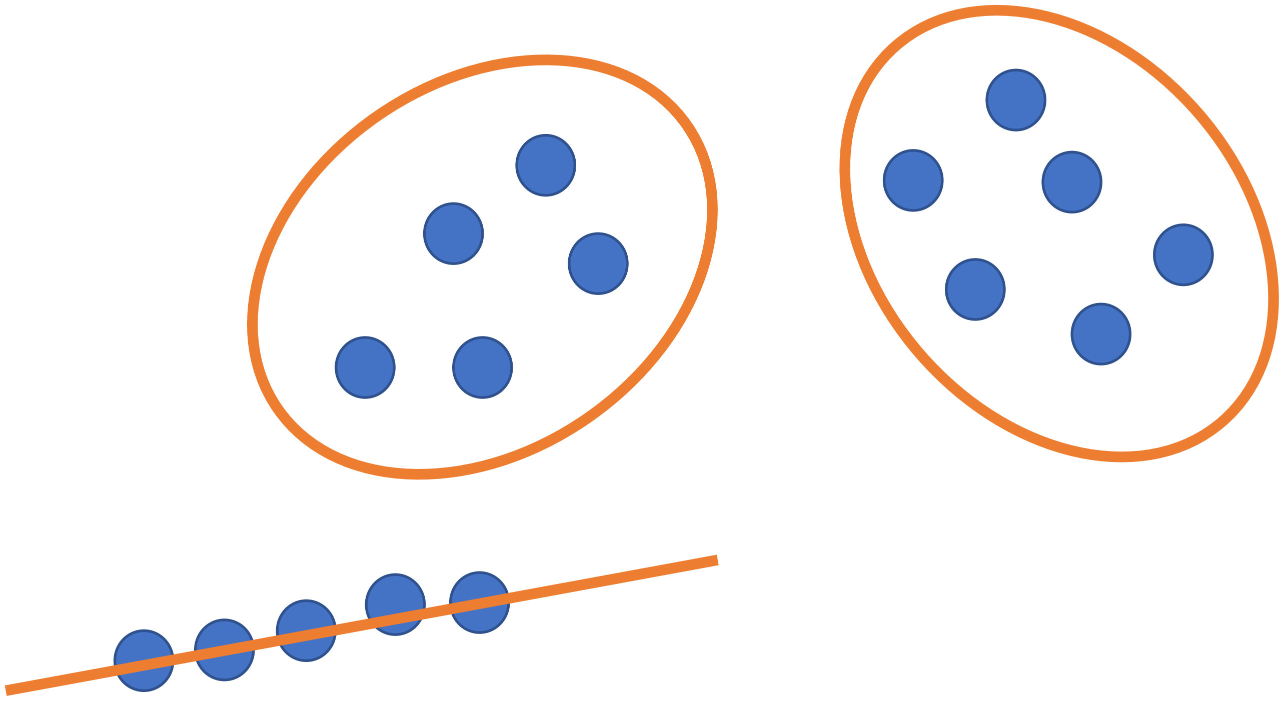
- supervised ML (use labeled data to imitate teacher)
- unsupervised ML (no labeled data needed)
- reinforcement learning (learn while collecting data)

Supervised Learning

more on this in lecture:
"ERM", "Classification", "Model Val/Sel",
"Non-Parametric", "Deep Learning"



Unsupervised Learning



more on this in Lecture
“Clustering”,
“Feature Learning”

label of datapoint = cluster assignment or
nearby subspace

Reinforcement Learning

features = on-board camera video

label = “optimal steering direction”

not covered in this school !

Wrap Up

- data points characterized by features and label
- features ≈ low-level properties
- labels ≈ high-level properties (quantity of interest)
- GOAL of ML: learn a hypothesis map h(.) such that h(x) ≈ y
- ML model = comp. tractable subset of possible maps h(.)
- ML quantifies prediction error y-h(x) with a loss function

Next Lecture: Regression

GOAL of ML: Learn hypothesis h(.) such that y $\approx$ h(x) for any data point (x,y).

what exactly is “any data point” ?