Methods for Artificial Intelligence

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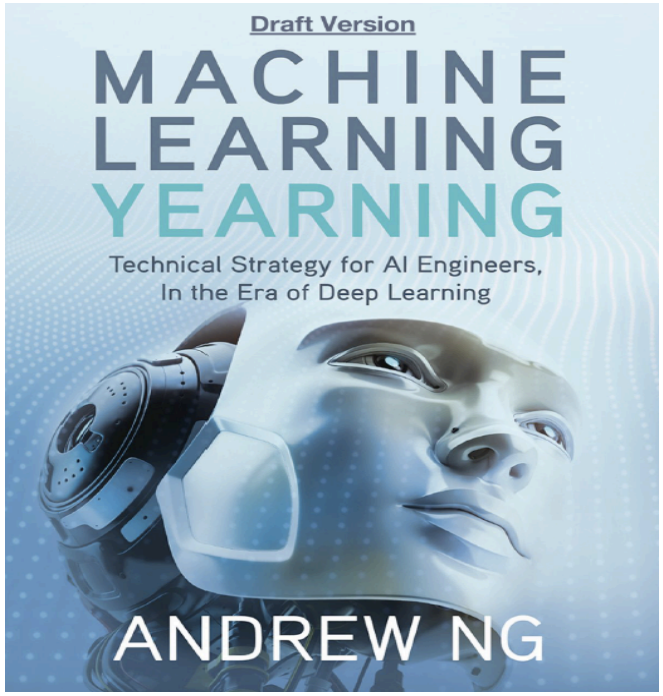
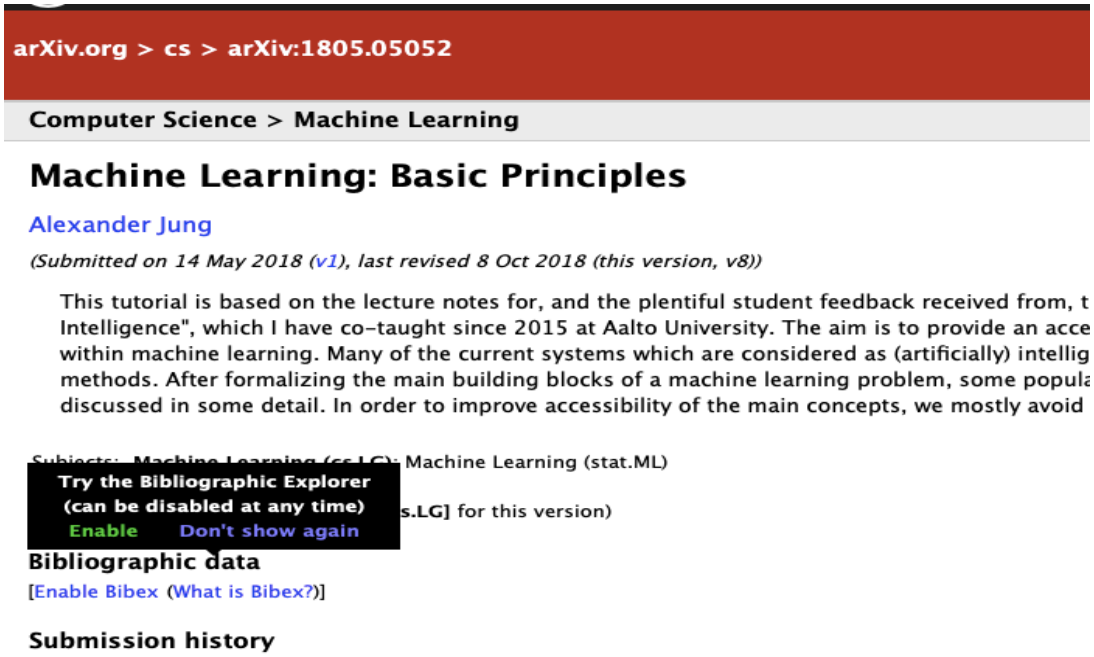
Reading Material

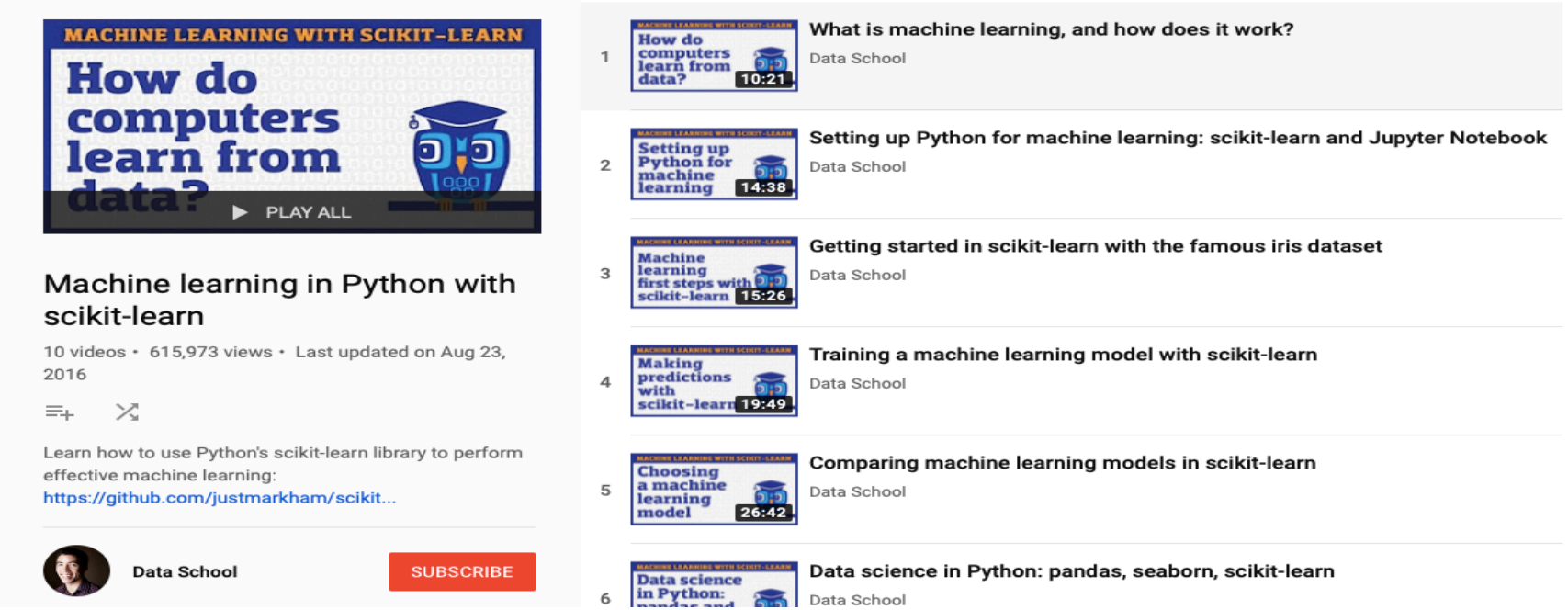
https://arxiv.org/abs/1805.05052





https://www.deeplearning.ai/machine-learning-yearning/

Some Video Material



https://www.youtube.com/playlist?list=PL5-da3qGB5ICeMbQuqbbCOQWcS6OYBr5A

(Artificial) Intelligence Involves (Machine) Learning

from Wikipedia:

“Among the traits that researchers hope machines will exhibit are

reasoning, knowledge, planning, learning,

communication, perception,….“

AI Principle (Engineer Perspective)

automatically choose (compute) optimal decisions to maximize a long-term reward

Machine Learning for AI

- optimal decisions/planning require insights
- ML extracts high-level insights from raw data
- ML is low-level AI

What is Machine Learning?

computer programs (algorithms) which use historic data to learn how to make predictions

When to Harvest?

When will my bus arrive?

Is Everything OK? Where is the Patient?

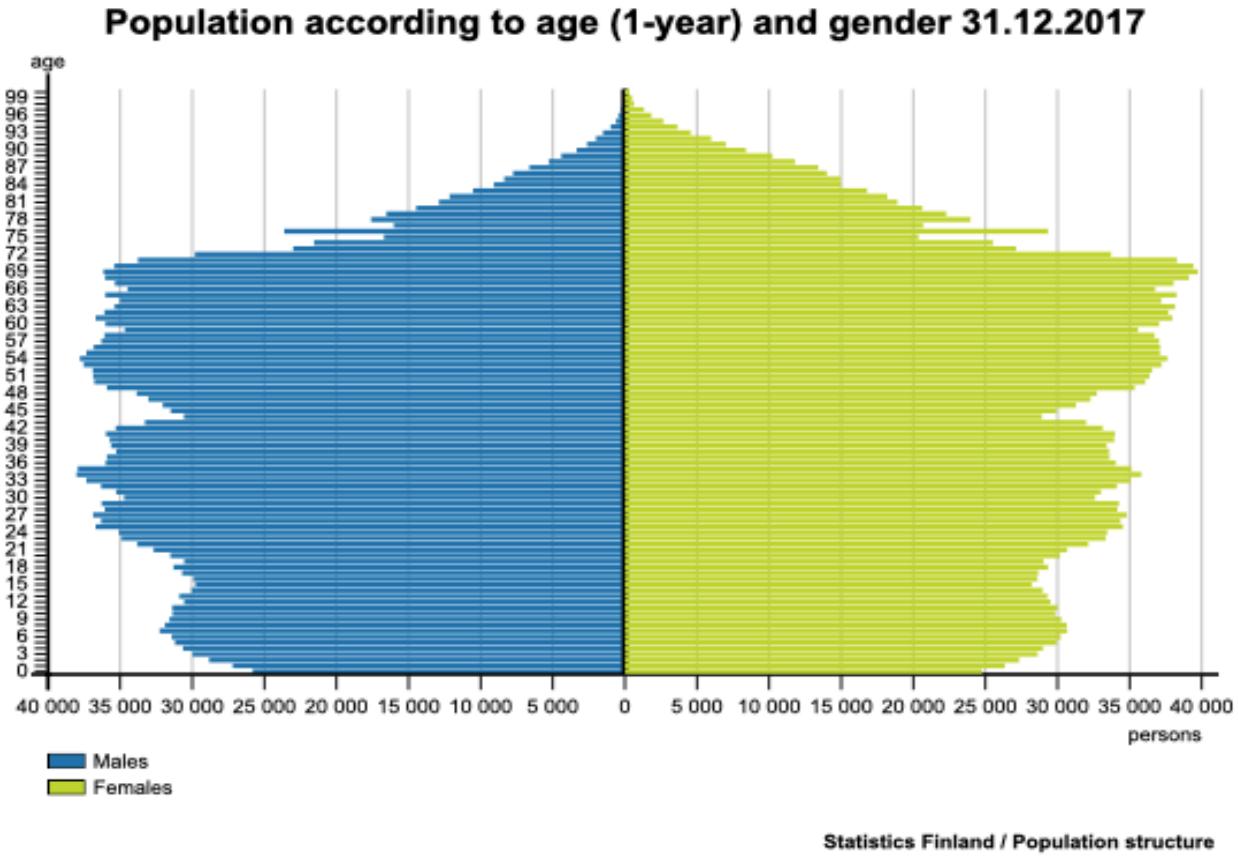
Say “OK Google…“

- https://www.youtube.com/watch?v=p5DVeDWtA5U

Age Distribution in Finland

old

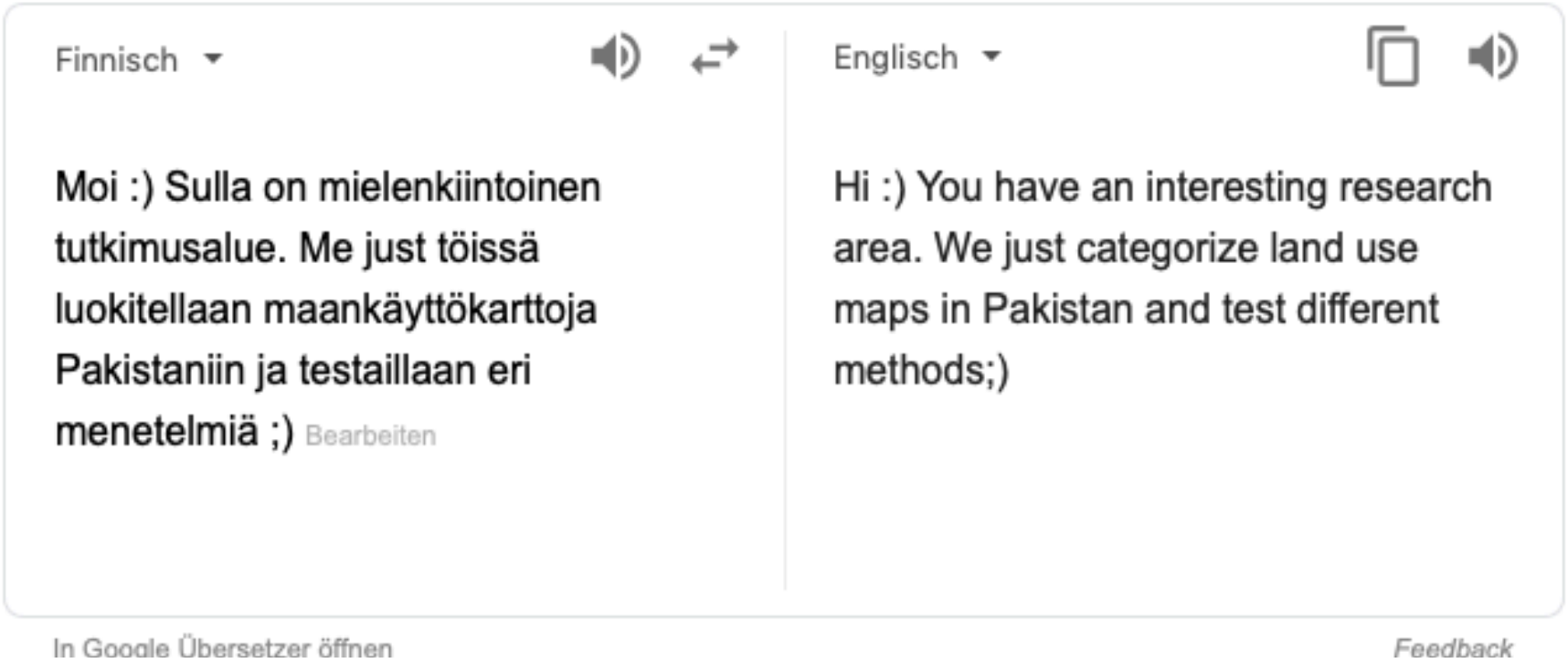
young



What are Laws of Motion?

https://users.aalto.fi/~junga1/AppleFalling.mp4

I still don’t speak Finnish ☹



Reliable AI

How much can we trust the prediction ?

Understandable AI

- why this particular prediction?
- e.g.: automated decision for KELA benefits
- decisions require detailed justification based on law

Privacy Preserving AI

- how to learn from data without revealing sensitive data?

In a Nutshell

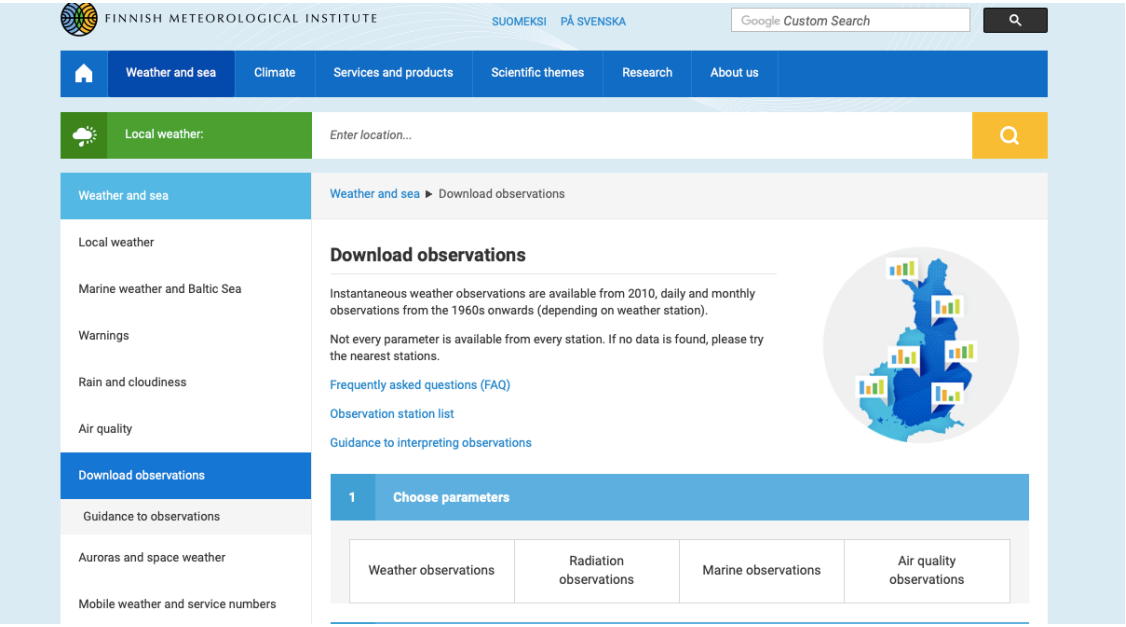
ML methods fit (complicated) models to (tons of) data

Nice Ski Day Ahead!

A ML Problem

- plan a decent ski trip
- which wax should I use?
- depends on temperature during day
- know the min temperature (its 07:00 am)
- what will be max temperature?

Data



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

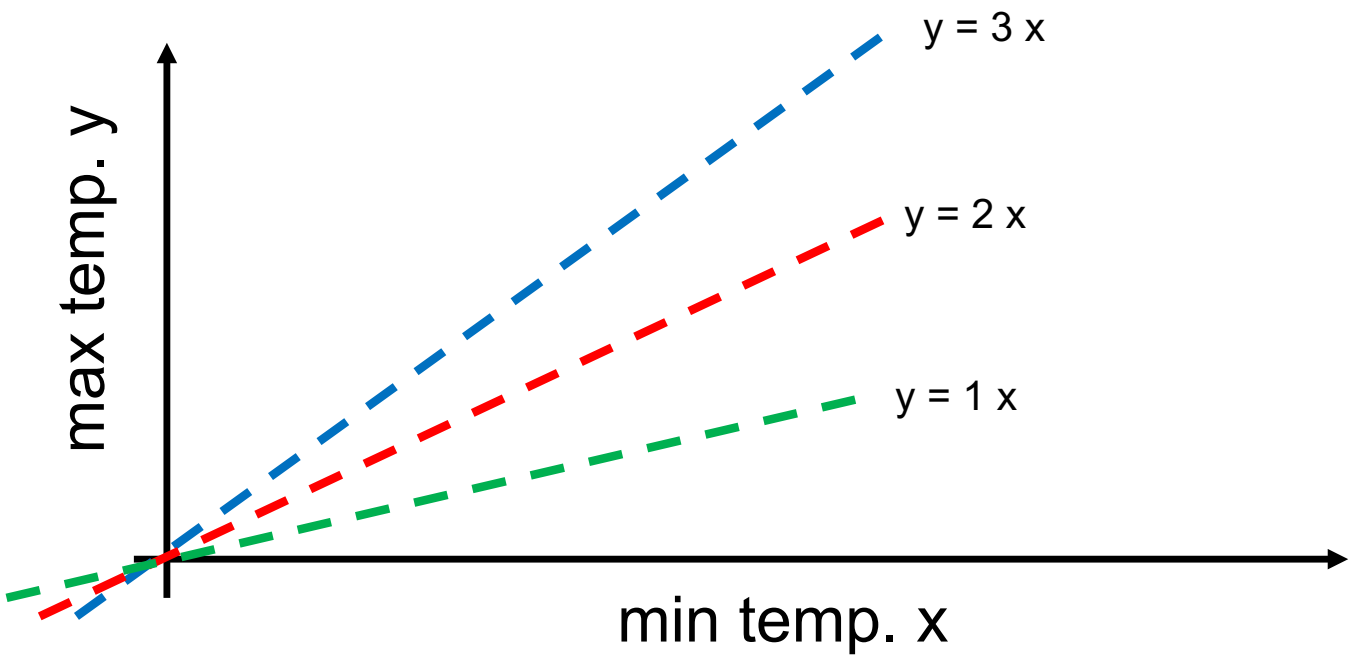
Historic Data

	Year	m	d	Time	Prec	snow	tmp	maxtemp	mintmp
0	2016	1	2	00:00	-1.0	-1.0	-7.0	-5.5	-7.8
1	2016	1	3	00:00	3.2	-1.0	-8.7	-7.2	-10.0
2	2016	1	4	00:00	-1.0	4.0	-11.2	-4.9	-13.5
3	2016	1	5	00:00	0.6	4.0	-17.6	-13.3	-19.6
4	2016	1	6	00:00	-1.0	4.0	-20.3	-16.4	-21.3

data point

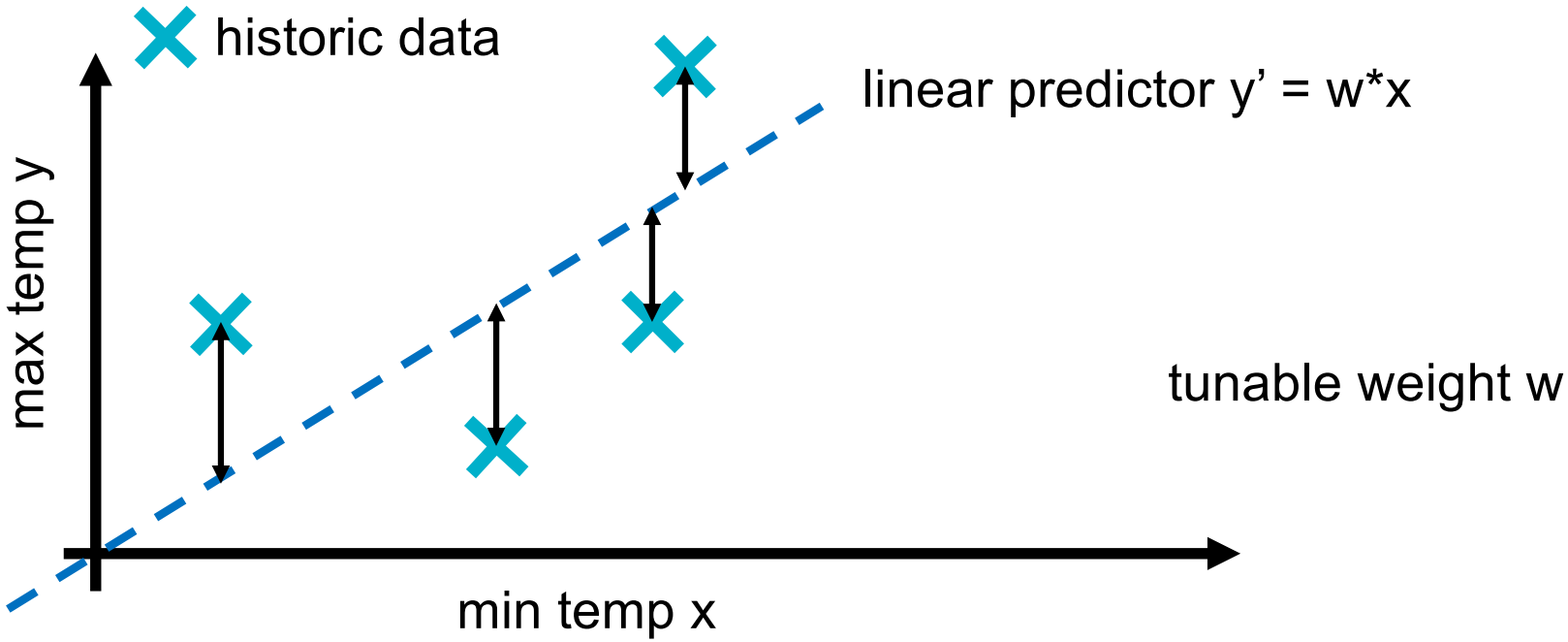
Model

- hypothesis: linear relation between min and max tmp



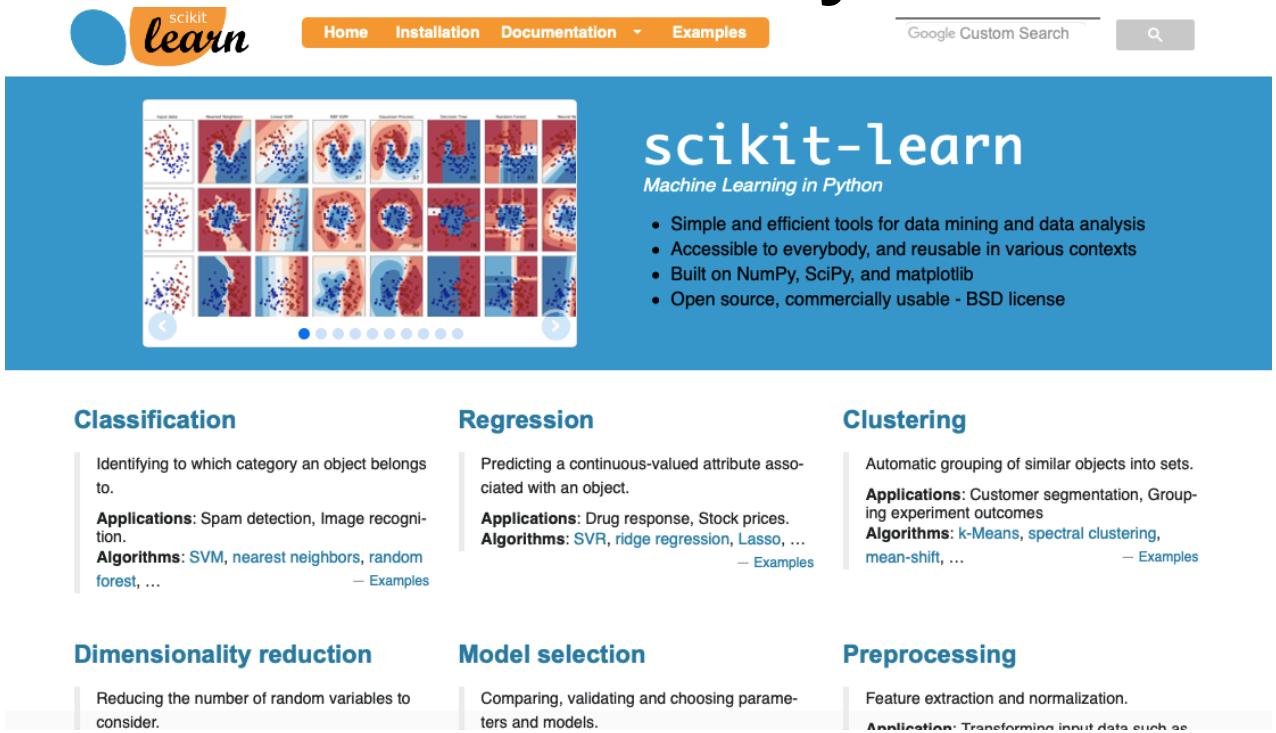
Fitting the Model to Data

- fit linear predictor y'=h(x) by minimizing mean squared error



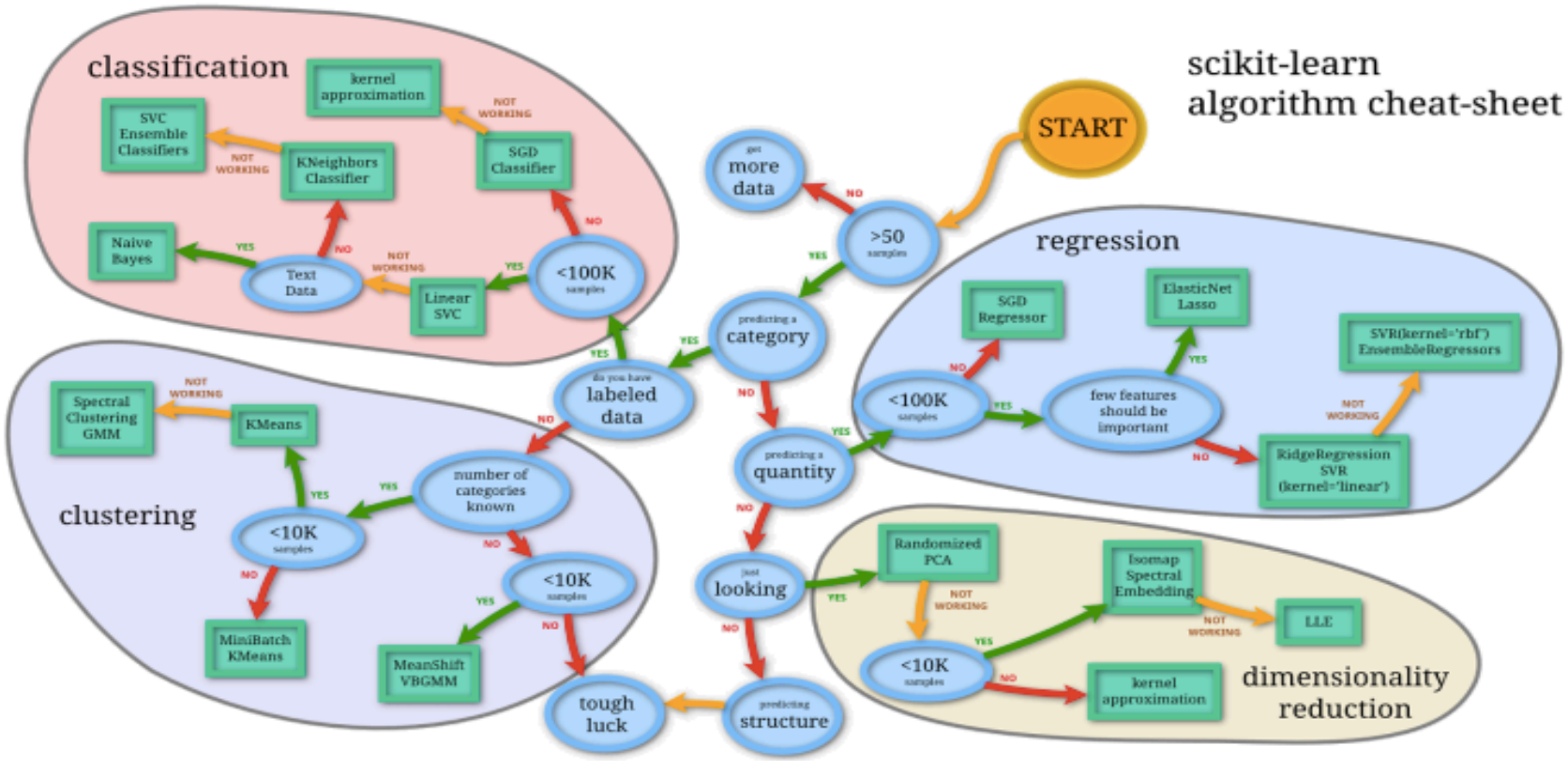
HOW TO FIT ?

ML Methods Available in Python/MATLAB/R/…



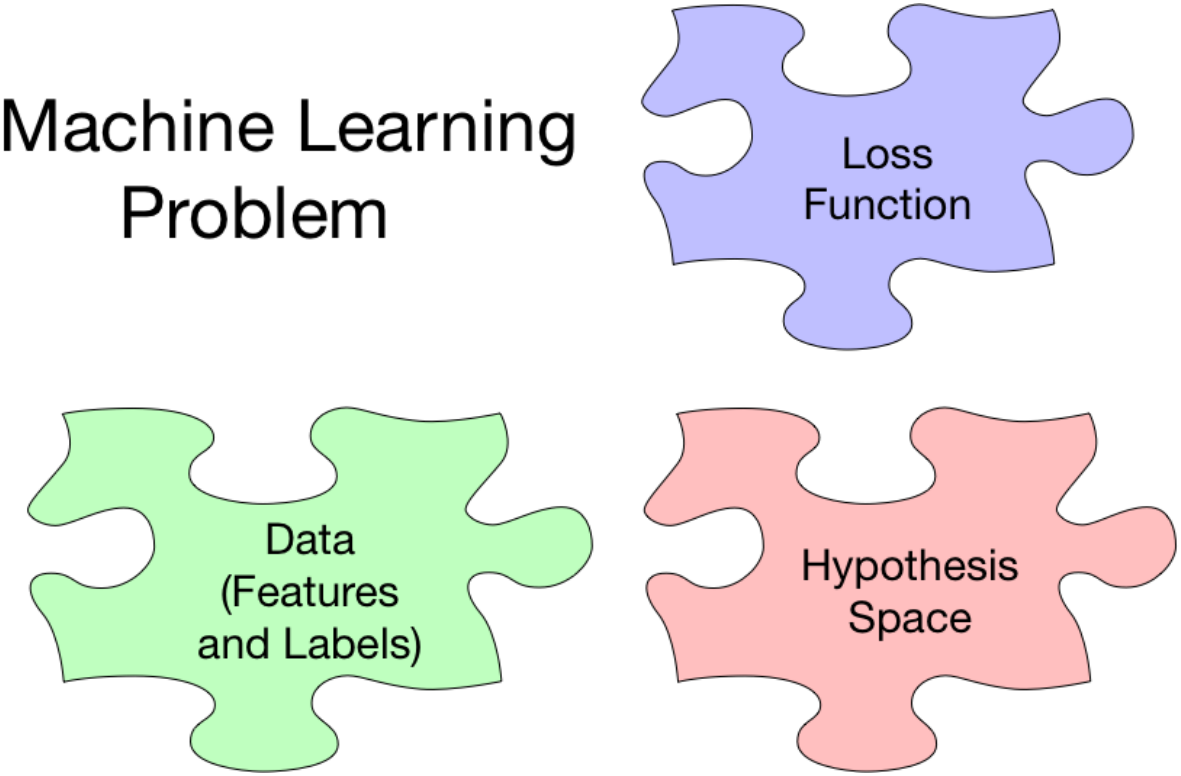
https://scikit-learn.org/stable/

Python Cheat Sheet



Elements of Machine Learning

A Machine Learning Problem



The Data

Data

Download observations

Instantaneous weather observations are available from 2010, daily and monthly observations from the 1960s onwards (depending on weather station).

Not every parameter is available from every station. If no data is found, please try the nearest stations.

Frequently asked questions (FAQ)

Observation station list

Guidance to interpreting observations

1 Choose parameters

Weather observations	Radiation observations	Marine observatior

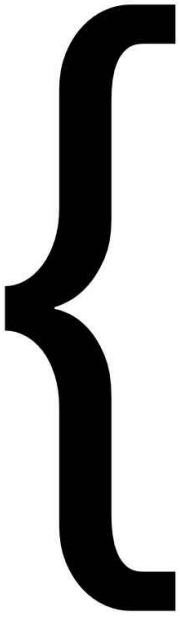
2 Choose time period

January 30, 2019 12:00 AM – January 30, 2019 11:59 PM

Data Points

break raw data into atomic pieces (chunks)
of data, e.g., individual files stored on hard disk

raw data

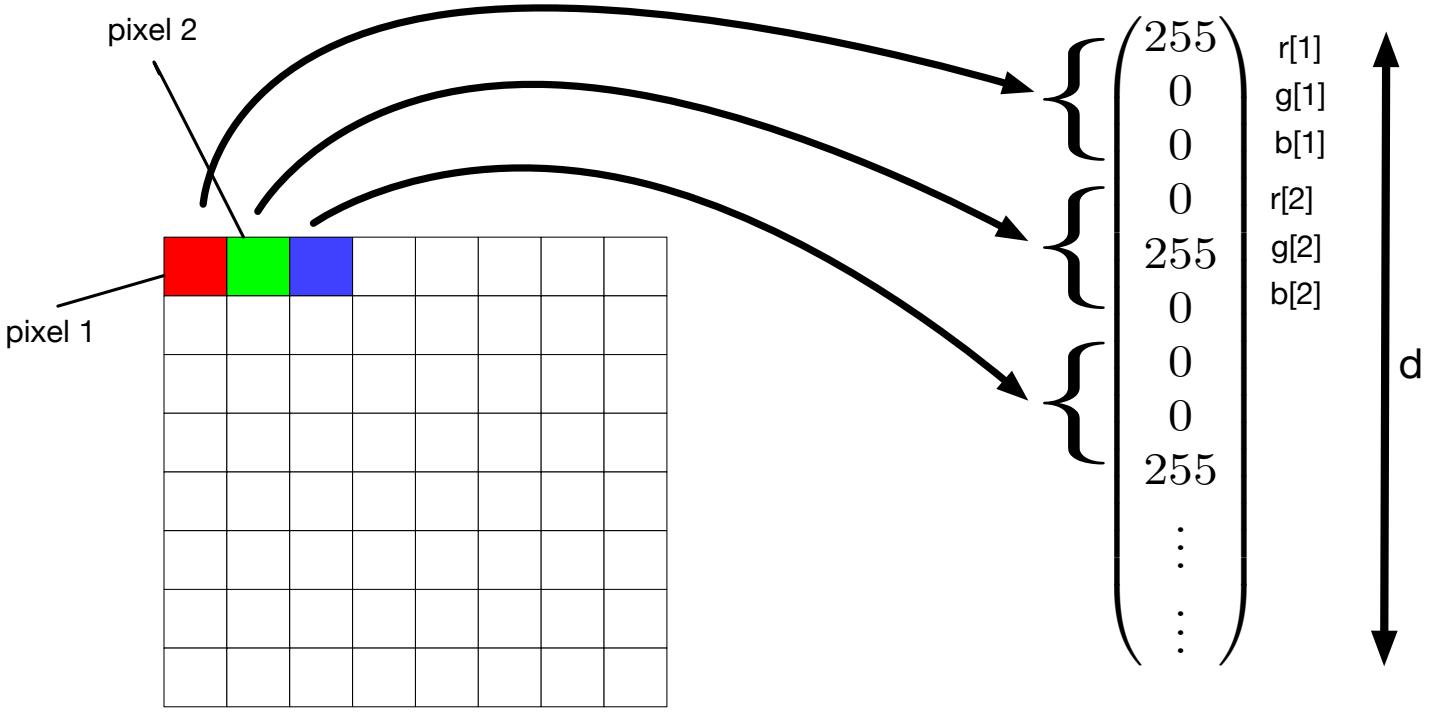


“data point”

Data Points

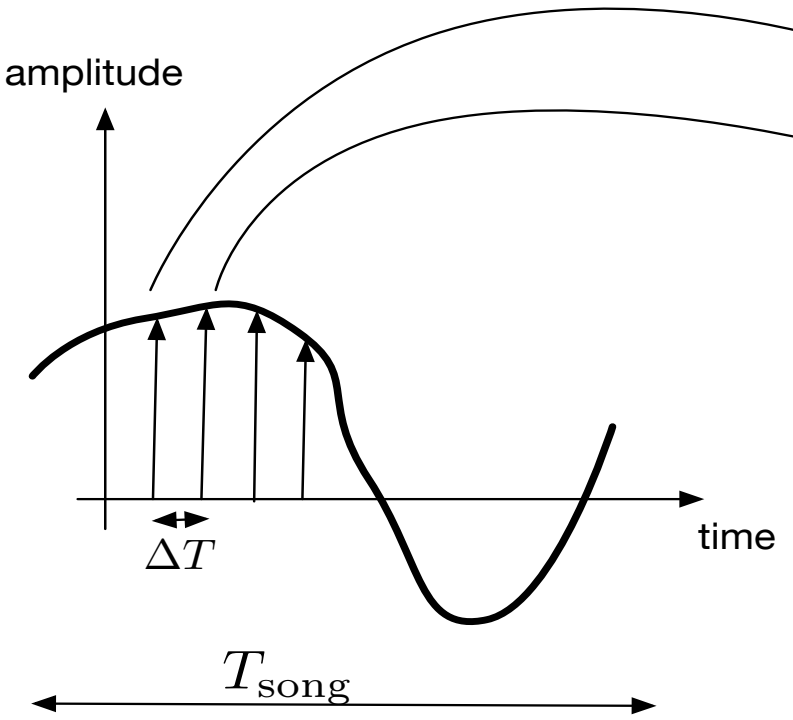
	Year	m	d	Time	Prec	snow	tmp	maxtemp	mintmp
0	2016	1	2	00:00	-1.0	-1.0	-7.0	-5.5	-7.8
1	2016	1	3	00:00	3.2	-1.0	-8.7	-7.2	-10.0
2	2016	1	4	00:00	-1.0	4.0	-11.2	-4.9	-13.5
3	2016	1	5	00:00	0.6	4.0	-17.6	-13.3	-19.6
4	2016	1	6	00:00	-1.0	4.0	-20.3	-16.4	-21.3

Features for Image Data



8 x 8 pixels (red green blue bitmap)

Features for Time Signals



$$\begin{pmatrix} 0.85 \\ 0.9 \\ 0.87 \\ 0.7 \\ \vdots \\ \vdots \end{pmatrix} \in \mathbb{R}^d$$

$$d \approx T_{\text{song}}/\Delta T$$

Features for Text

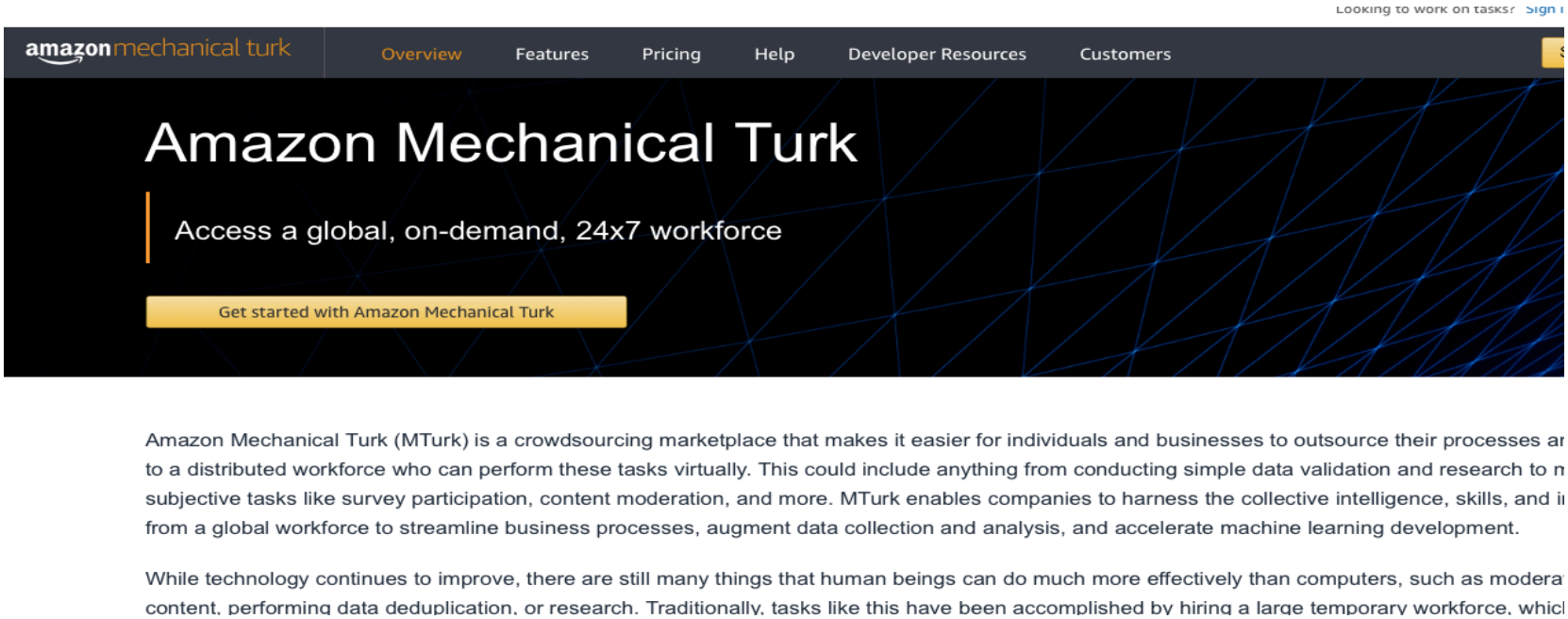
- consider simple language with vocabulary {“have”, “a”, “good”, “great”, “day”}
- represent words by ”one-hot encoding”
- “have”=(1,0,0,0,0); „a“=(0,1,0,0,0), …., „day“=(0,0,0,0,1)
- what could be feature vector of text “have have a good great day”?

Labeled Data

- labeled data consists of data points with known label
- denote labeled data point with feature x and label y as (x,y)
- n labeled data points $(x^{(1)}, y^{(1)})$,…, $(x^{(n)}, y^{(n)})$
- sample size n is important parameter of the ML problem!
- if data is new oil, then labeled data is premium fuel!

How To Get Labeled Data?

- you can buy human labelling workforce!



Labeled Data

	Year	m	d	Time	Prec	snow	tmp	maxtemp	mintmp
0	2016	1	2	00:00	-1.0	-1.0	-7.0	-5.5	-7.8
1	2016	1	3	00:00	3.2	-1.0	-8.7	-7.2	-10.0
2	2016	1	4	00:00	-1.0	4.0	-11.2	-4.9	-13.5
3	2016	1	5	00:00	0.6	4.0	-17.6	-13.3	-19.6
4	2016	1	6	00:00	-1.0	4.0	-20.3	-16.4	-21.3

label

Missing Data

	Year	m	d	Time	Prec	snow	tmp	maxtemp	mintmp
0	2016	1	2	00:00	-1.0	-1.0	-7.0	-5.5	-7.8
1	2016	1	3	00:00	3.2	-1.0	-8.7	-7.2	-10.0
2	2016	1	4	00:00	-1.0	4.0	-11.2	NaN	-13.5
3	2016	1	5	00:00	0.6	4.0	-17.6	-13.3	-19.6
4	2016	1	6	00:00	-1.0	4.0	-20.3	-16.4	-21.3

there are ML “autofill” tools known as “data imputation”

Labeled Data

raw data

“no cat”

”cat”

”cat”

“no cat”

Classification Problem

	Year	m	d	Time	Prec	snow	tmp	maxtemp	mintmp
0	2016	1	2	00:00	-1.0	-1.0	-7.0	-5.5	-7.8
1	2016	1	3	00:00	3.2	-1.0	-8.7	-7.2	-10.0
2	2016	1	4	00:00	-1.0	4.0	-11.2	-4.9	-13.5
3	2016	1	5	00:00	0.6	4.0	-17.6	-13.3	-19.6
4	2016	1	6	00:00	-1.0	4.0	-20.3	-16.4	-21.3

will max temp today be more than 0 or not ?

Classification Problem

does image on the left show “cat” or “no cat” ?

we can encode this by defining label of an image as y=1 if it shows cat and y=-1 if not

how can we get the true label y for an image?

Regression Problem

	Year	m	d	Time	Prec	snow	tmp	maxtemp	mintmp
0	2016	1	2	00:00	-1.0	-1.0	-7.0	-5.5	-7.8
1	2016	1	3	00:00	3.2	-1.0	-8.7	-7.2	-10.0
2	2016	1	4	00:00	-1.0	4.0	-11.2	-4.9	-13.5
3	2016	1	5	00:00	0.6	4.0	-17.6	-13.3	-19.6
4	2016	1	6	00:00	-1.0	4.0	-20.3	-16.4	-21.3

what will maxtemp be today (mintmp was -5)?

Regression vs. Classification

- AI engineer defines what the label is !
- numeric label (e.g., max temp) yield regression problems
- discrete label (e.g., “cat” vs. “dog”) yields classification
- distinction between regression and classification is blurry!
- “cat” vs. “dog” classification can be modeled as regression problem with numeric label y=“confidence that image shows rather cat than dog”

The Data – Wrap Up

- collection of atomic data units “data points”
- data point characterized by features and labels
- **features** are quantities that can be **determined easily**
- **labels** are difficult to determine (requires **human labor**)
- ML methods **guess label based on features**

Hypothesis Space (“Model”)

Hypothesis Space

- need hypothesis (model) relating features (input) and label (output)
- represent hypothesis as map or function h(x)
- input features x and output predicted label h(x)
- other names for hypothesis map are
  - “predictor” for numeric labels (e.g., temperature next day)
  - “classifier” discrete labels (e.g., image shows ”cat” or “dog”)

“Hypothesis”/”Predictor”/”Classifier” = Map from Features to Labels

map h(.)

features x  **predicted label y’=h(x)**

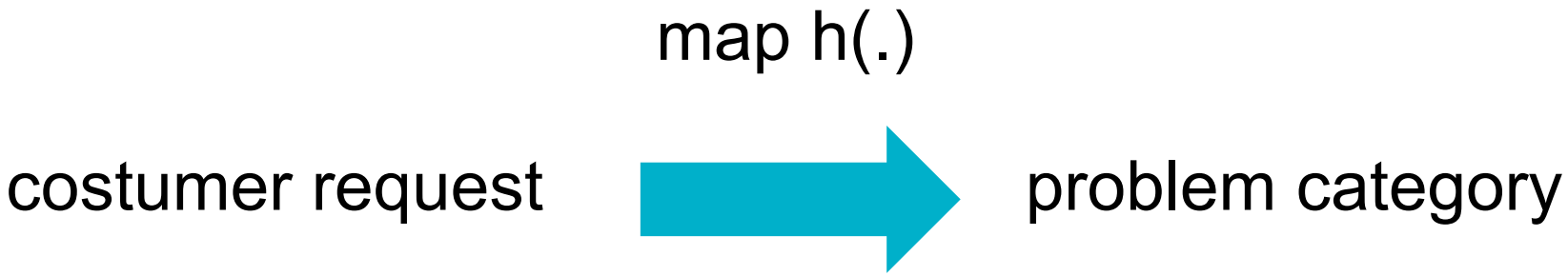
choose h(.) s.t. “predicted label ≈ true label”

Example of a Predictor

map h(.)

optimal candidate
“Kalle Koivunen”

Example of a Predictor



Example of a Predictor

current operational data of cruise ship

from Wikimedia Commons

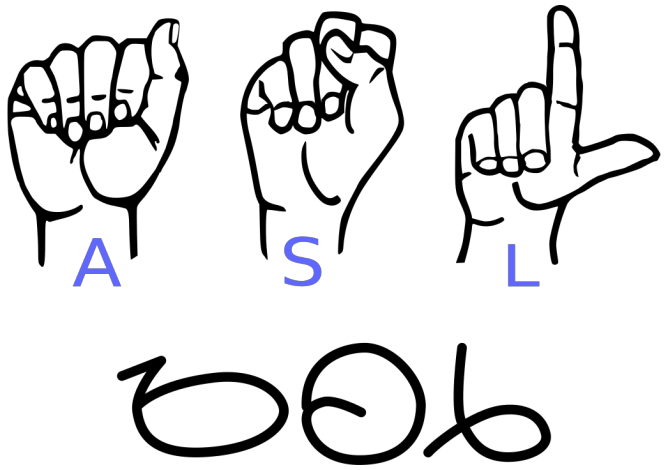
map h(.)

Schnitzel demand at next dinner?

from Wikimedia Commons

Example of a Predictor

sequence of gestures



from Wikimedia Commons

map h(.)

sentence

“Please google …“

Example of a Predictor

Transaction

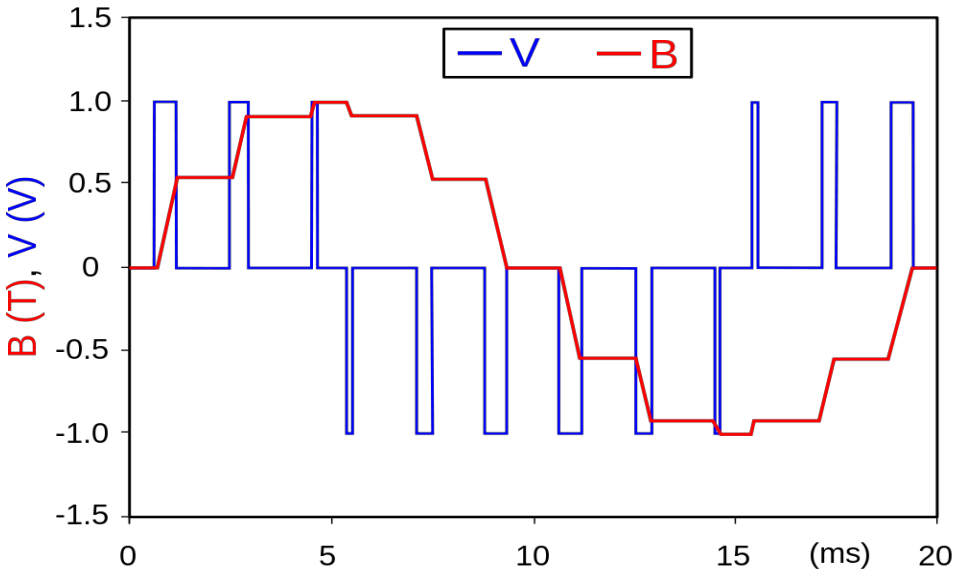
6.7.18	-62,20	**PKORTTIMAKSU** RISTORANTE AI DUE L AQUILEIA Viesti: 000432277******6607 OSTOPVM 180704 MF NRO 74935008186868663596579 VARMENTAJA 400	844431	201807065	EL2148652 J
6.7.18	-218,00	**PKORTTIMAKSU** ERLEBNIS HOTEL PIRK LATSCHACH Viesti: 000432277******6607 OSTOPVM 180704 MF NRO 74548188186110001211713 VARMENTAJA 400	52100	201807065	EL2284885 J

map h(.)

“No Money Laundry”

Example of a Predictor

measurements

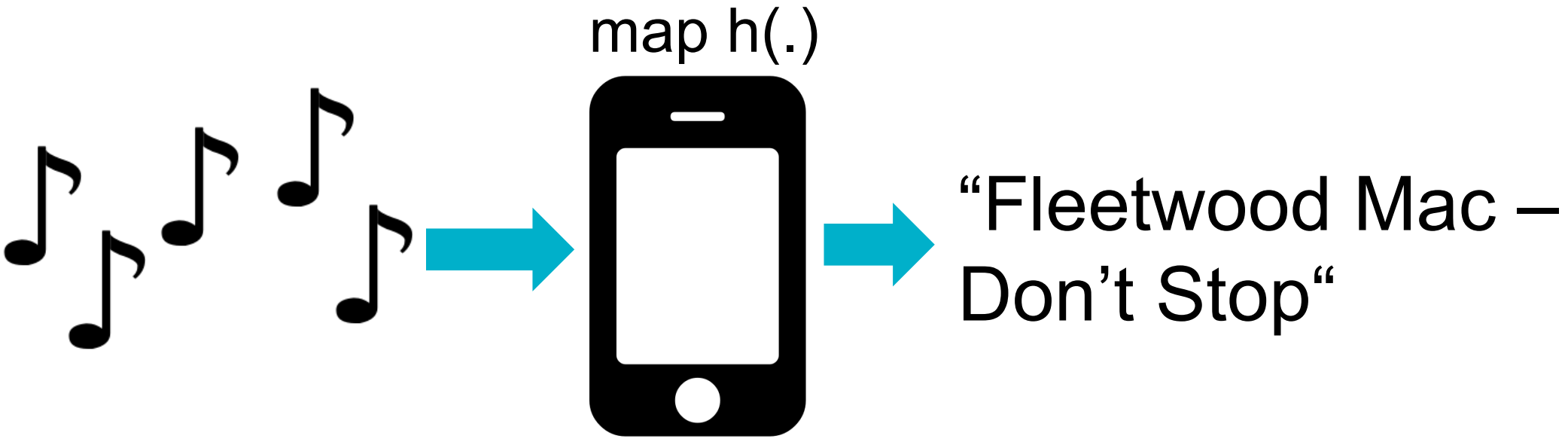


map h(.)

risk of fault within next week

60 %

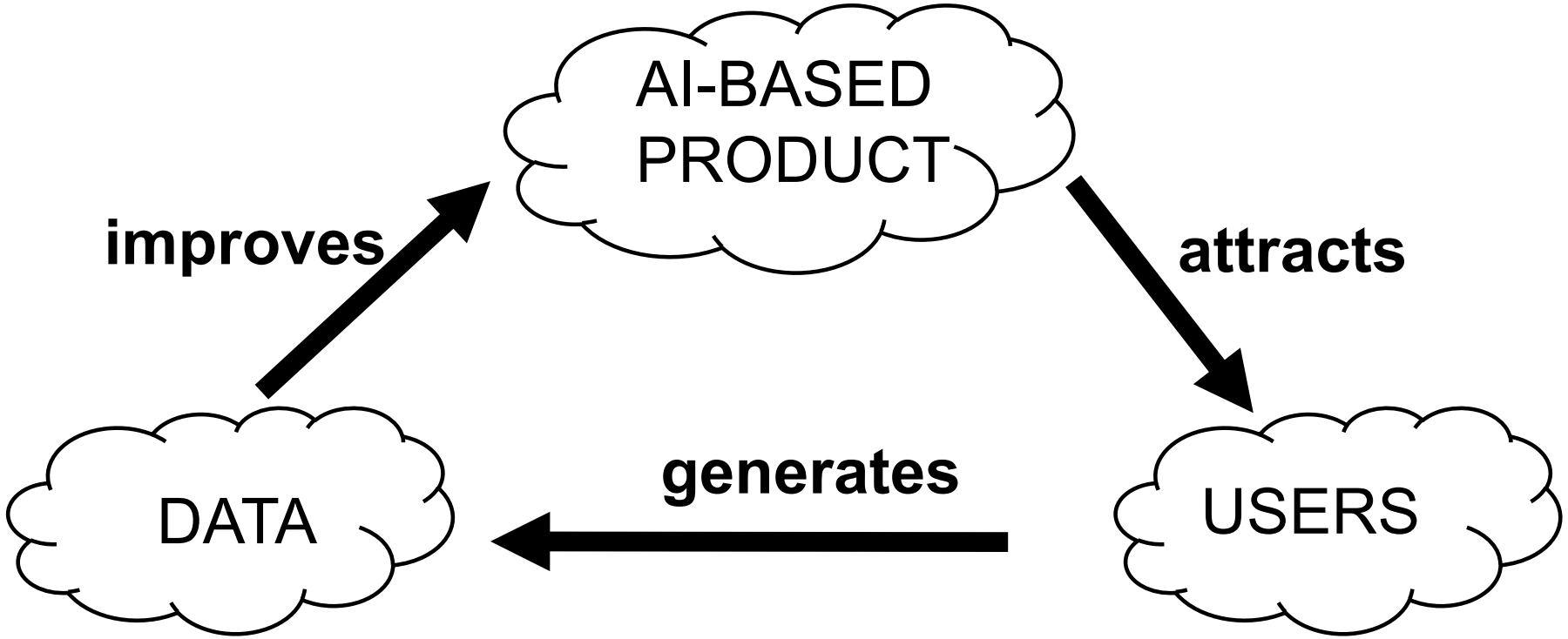
Example of a Predictor



From Predictions to Actions

- this module focuses on ML methods that deliver predictions
- predictions are further used e.g. to inform actions/decisions
- actions then result in new data (produced by costumers)
- results in a feedback loop “The Virtuous AI Cycle”

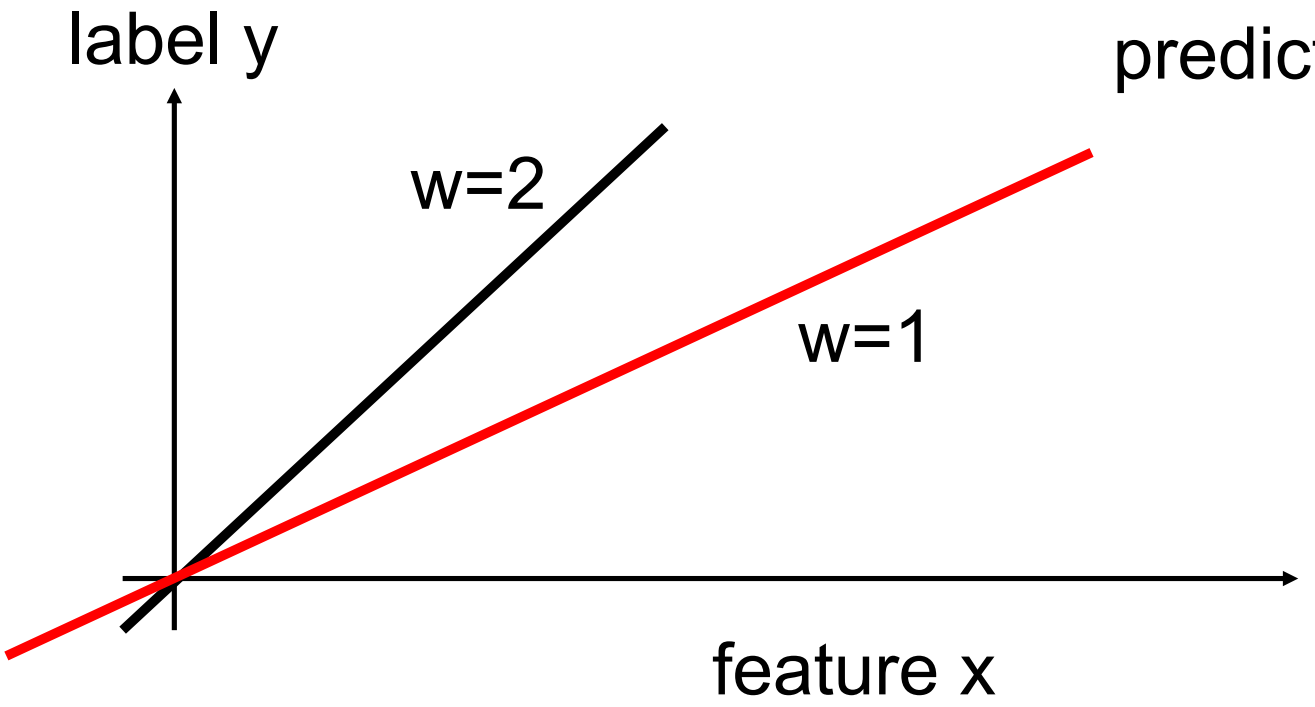
The Virtuous AI Cycle



How to Implement Predictors?

- predictor is a map h(x)
- maps feature x to a predicted label y’
- computing a prediction amounts to evaluation the map
- sounds trivial but can be challenging
- how can we efficiently represent a map h(x) ?

Linear Predictors (Linear Regression)



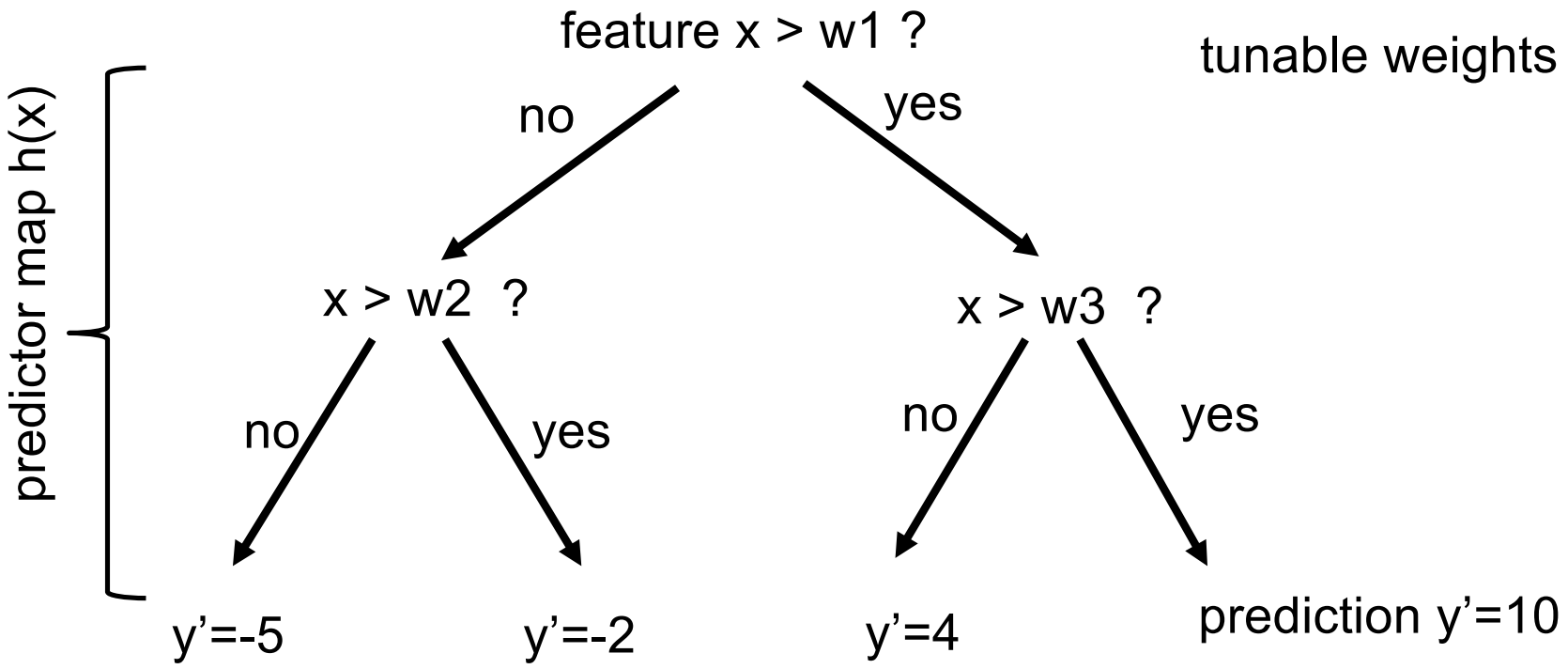
predictor h(x) = w * x

tunable weight w

Linear Predictors

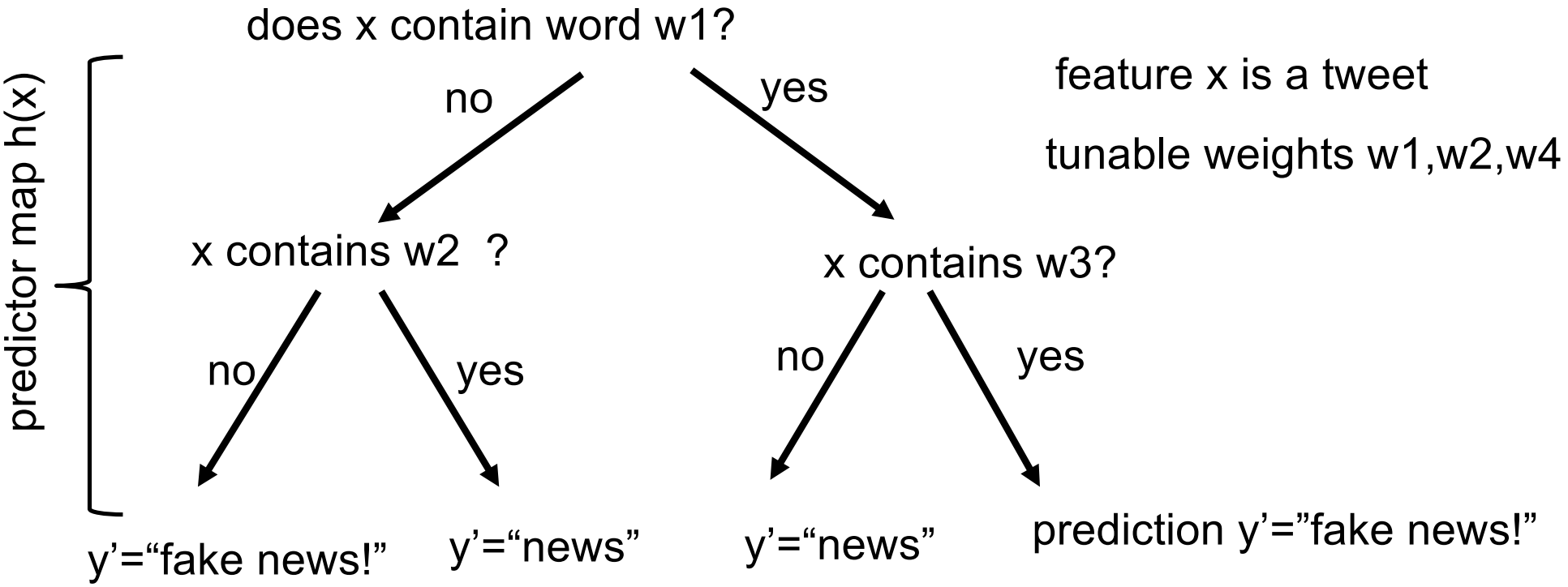
- widely used
- lot of engineering effort to make ML methods efficient
- hardware (GPUs) is tailored to linear methods
- linear ML methods are a mature technology
- can be used directly only with numeric features (vectors)
- how to apply it to text ?

Decision Trees



tunable weights w1,w2,w4

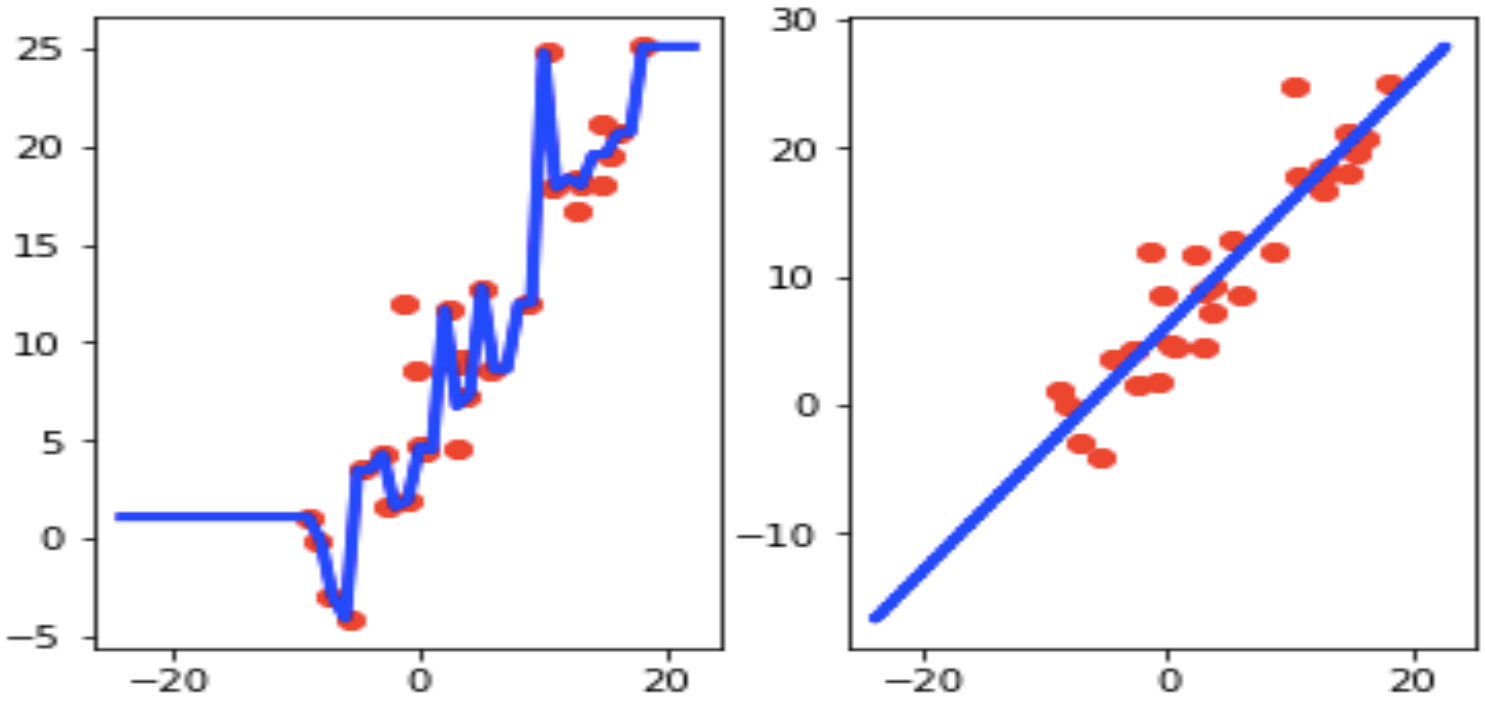
Decision Trees for Text



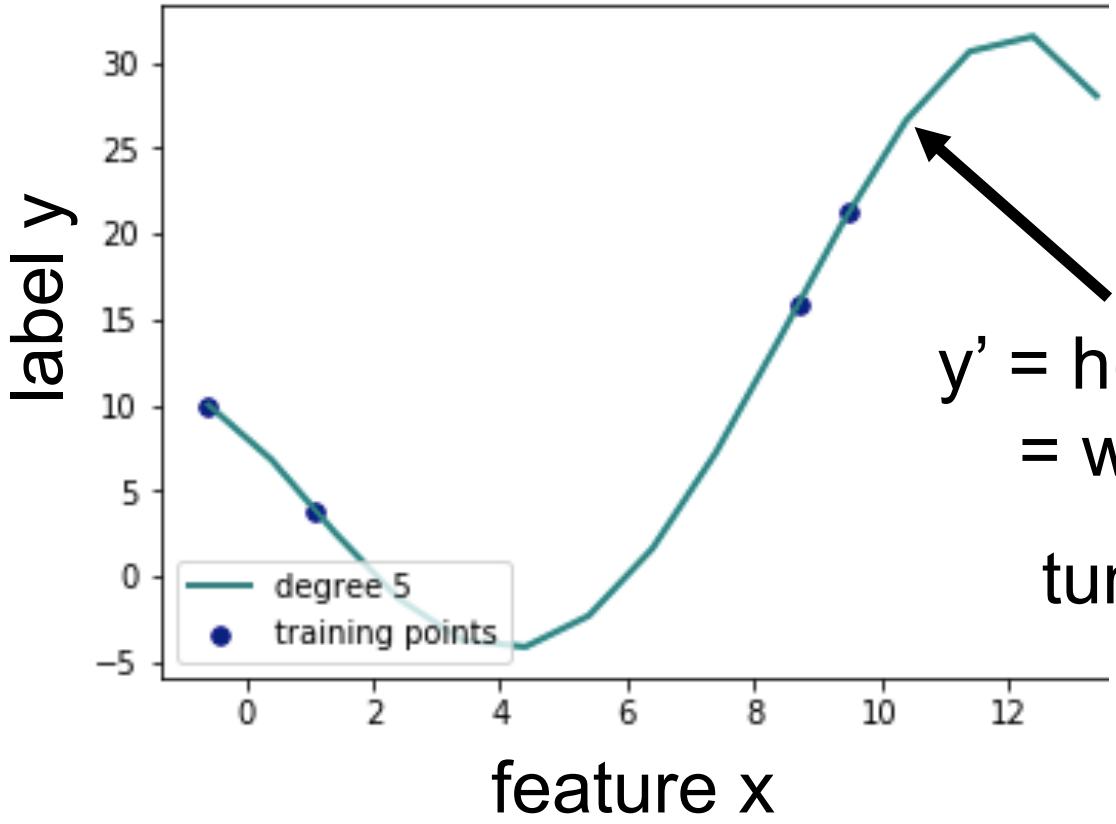
Decision Trees

- predictions arise from sequence of elementary tests
- tests (e.g. x>5?) provide explanation for prediction
- predict “tmp=10” because of x>5 and x<20 ….
- predict “benefit granted“ due to Fact 1 and Law 1 …

Decision Tree vs. Linear Predictor



Polynomial Predictor

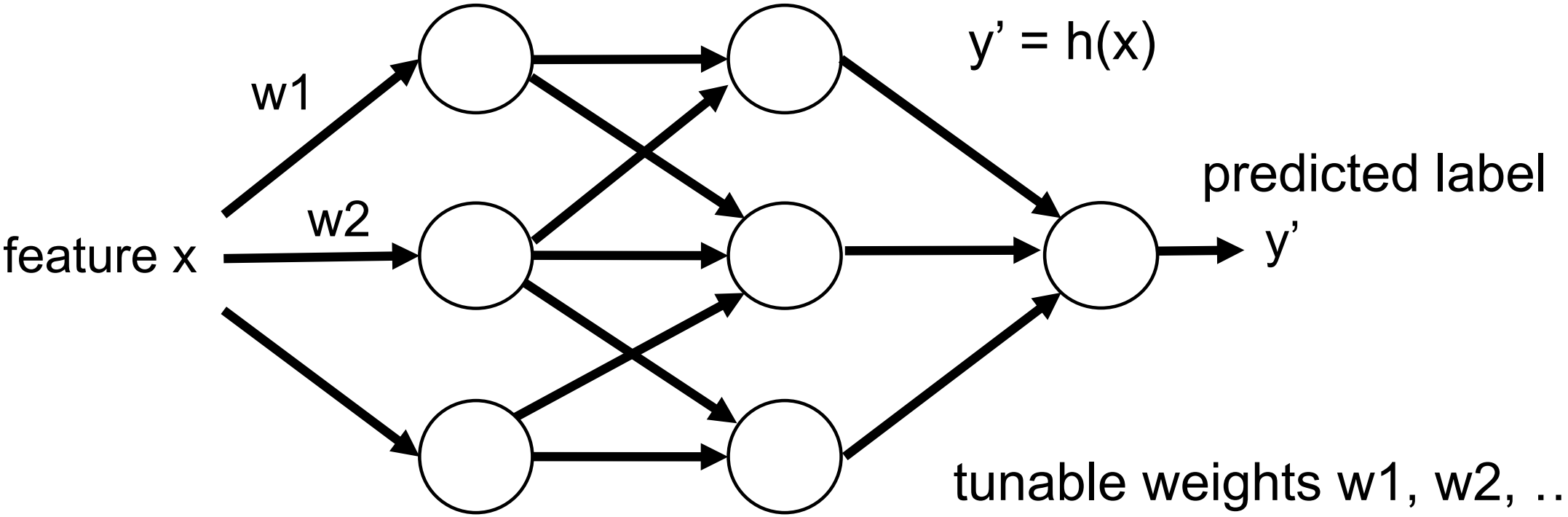


y’ = h(x)

= w1 + w2*x + w3*x^2+w4*x^3

tunable weights w1,w2,w3,w4

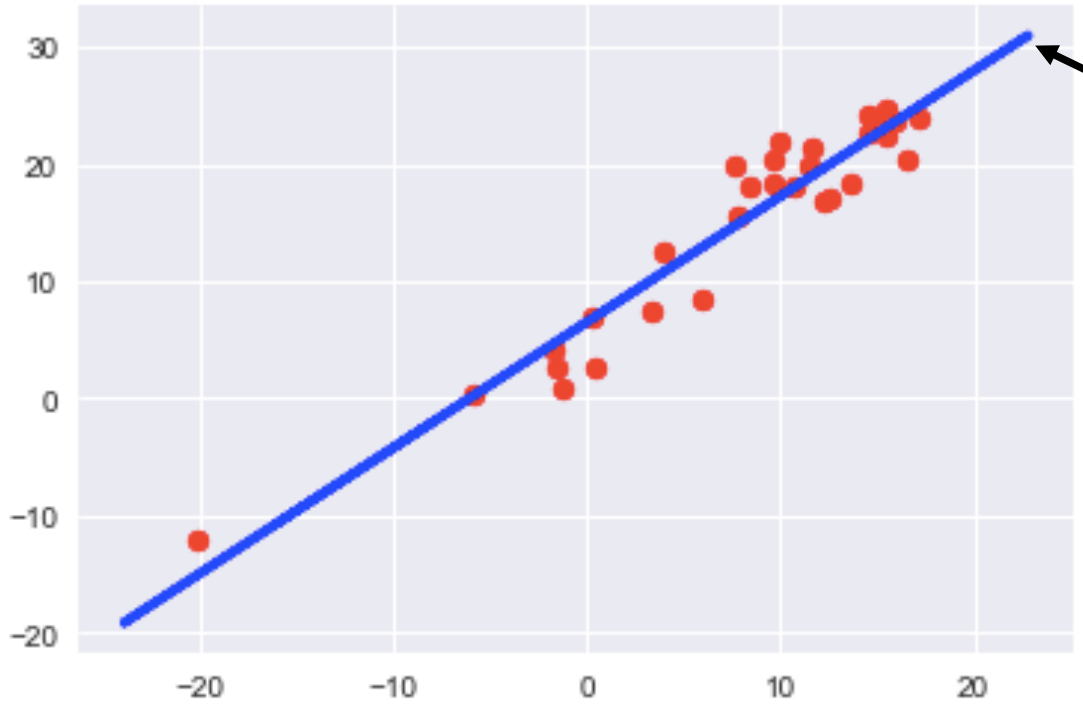
Artificial Neural Networks



The Loss Function

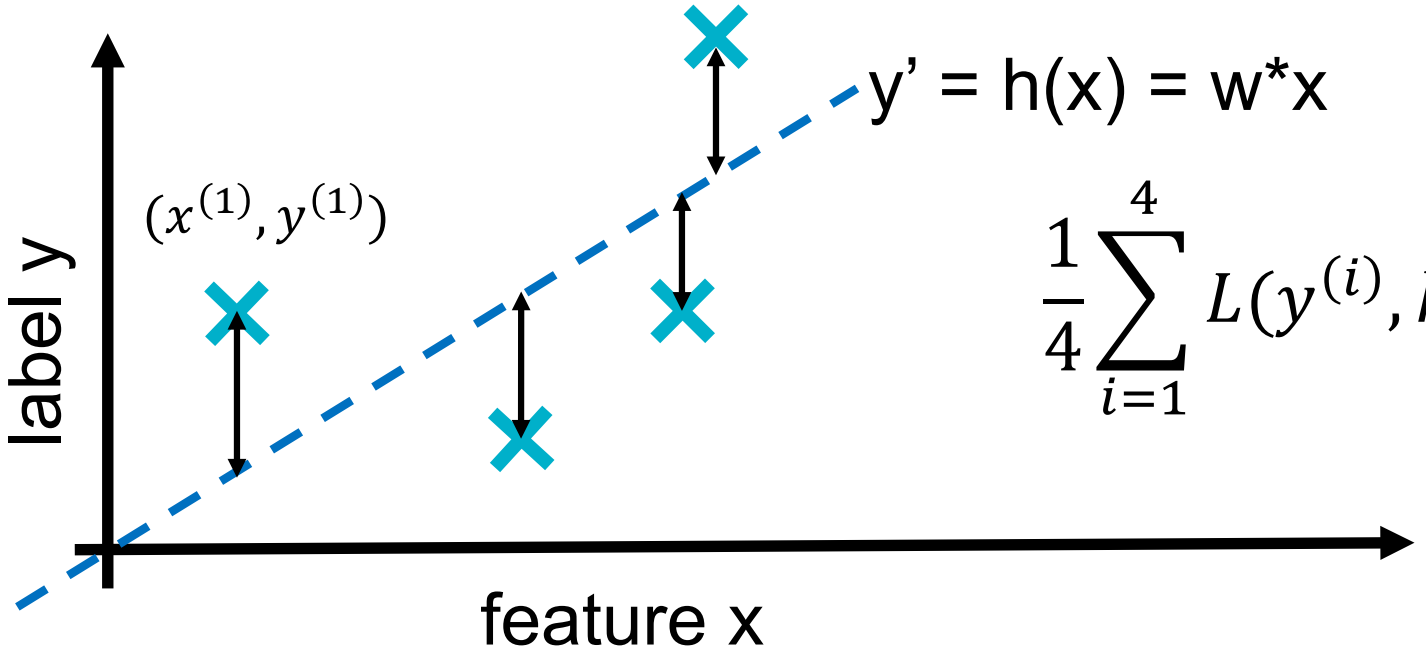
How Good is a Predictor?

- define loss L(y,h(x)) of predicting true label y by y'=h(x)



y' = h(x) = w *x

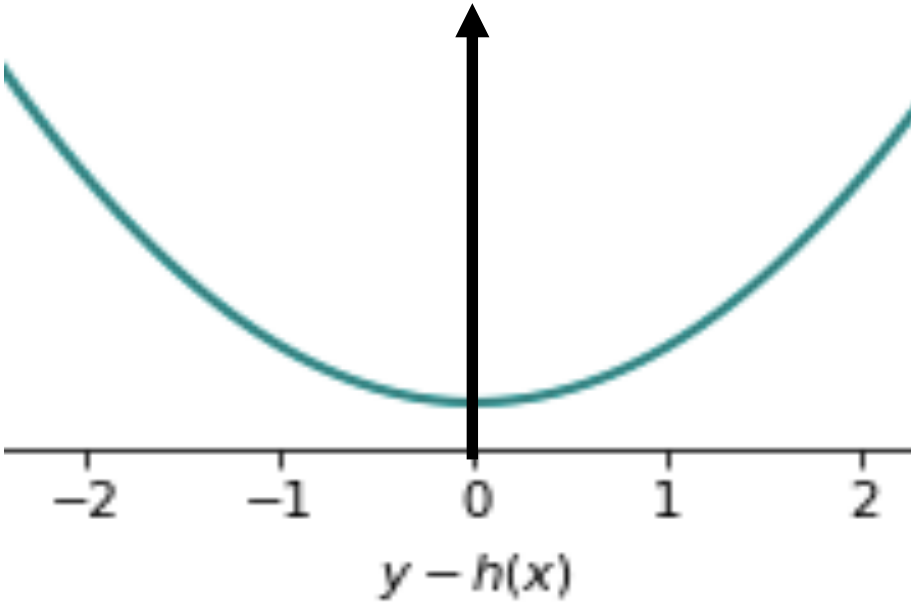
Average Loss (Empirical Risk)



$$\frac{1}{4}\sum_{i=1}^{4} L(y^{(i)}, h(x^{(i)}))$$

Squared Error Loss

L(y,h(x)) = (y-h(x))^2



Training Data = Bunch of Labeled Data

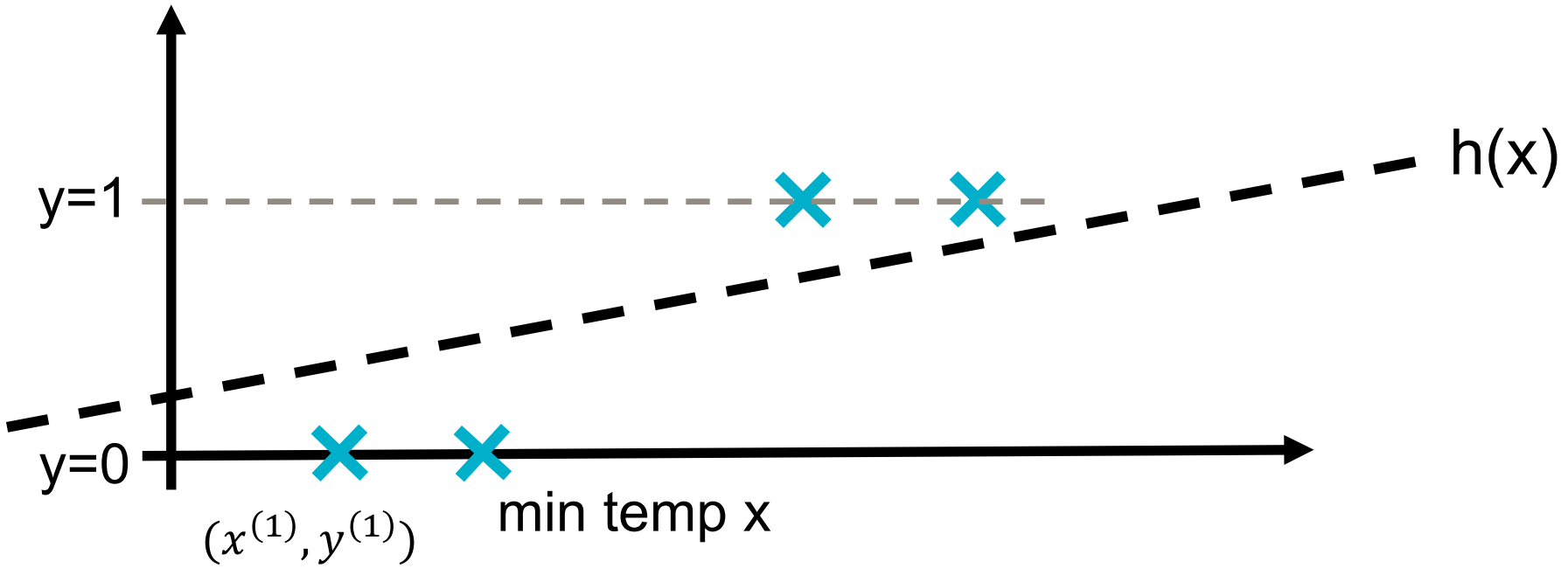
- evaluating loss L(y,h(x)) requires label y of data point !
- need labeled data points $\left(x^{(1)}, y^{(1)}\right), \cdots$ (“training data”)
- assess predictor h(x) by average loss (or empirical risk)

$$\frac{1}{n}\sum_{i=1}^{n} L(y^{(i)}, h\left(x^{(i)}\right))$$

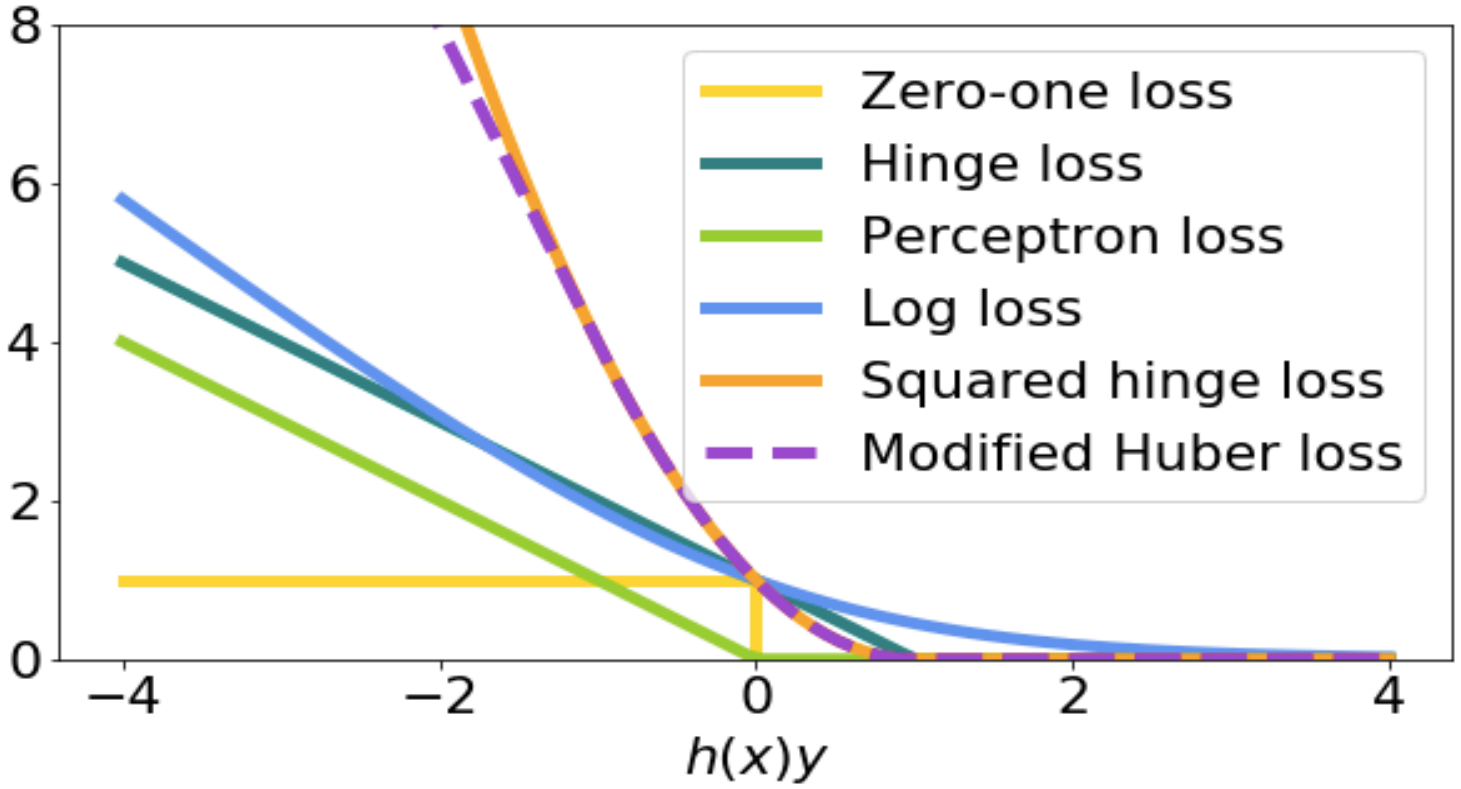
Choosing Loss Function

- loss function is design choice (specified by AI engineer)
- for numeric labels, squared error loss is widely used
- sq. error has nice statistical and computational properties
- for discrete labels, squared error loss is not well suited

Squared Error Loss Bad for Binary Labels



Loss Function for Binary Labels y=-1 or y=1



Loss Function for Binary Labels (y=-1 or y=1)

- consider AI for harvester
- camera snapshot is labeled **y=1 (-1) if person present (absent)**
- loss L(y=1,y'=-1) should be very large since **y=1, y'=-1 means there is person but AI misses her**
- loss L(y=-1,y'=1) can be small **(AI sees person which is not there)**

Loss Function Selection

sklearn.tree.DecisionTreeRegressor

class `sklearn.tree.` **`DecisionTreeRegressor`** (*criterion='mse', splitter='best', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features=None, random_state=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, presort=False*) [source]

A decision tree regressor.

Read more in the User Guide.

Parameters: **criterion : *string, optional (default="mse")***

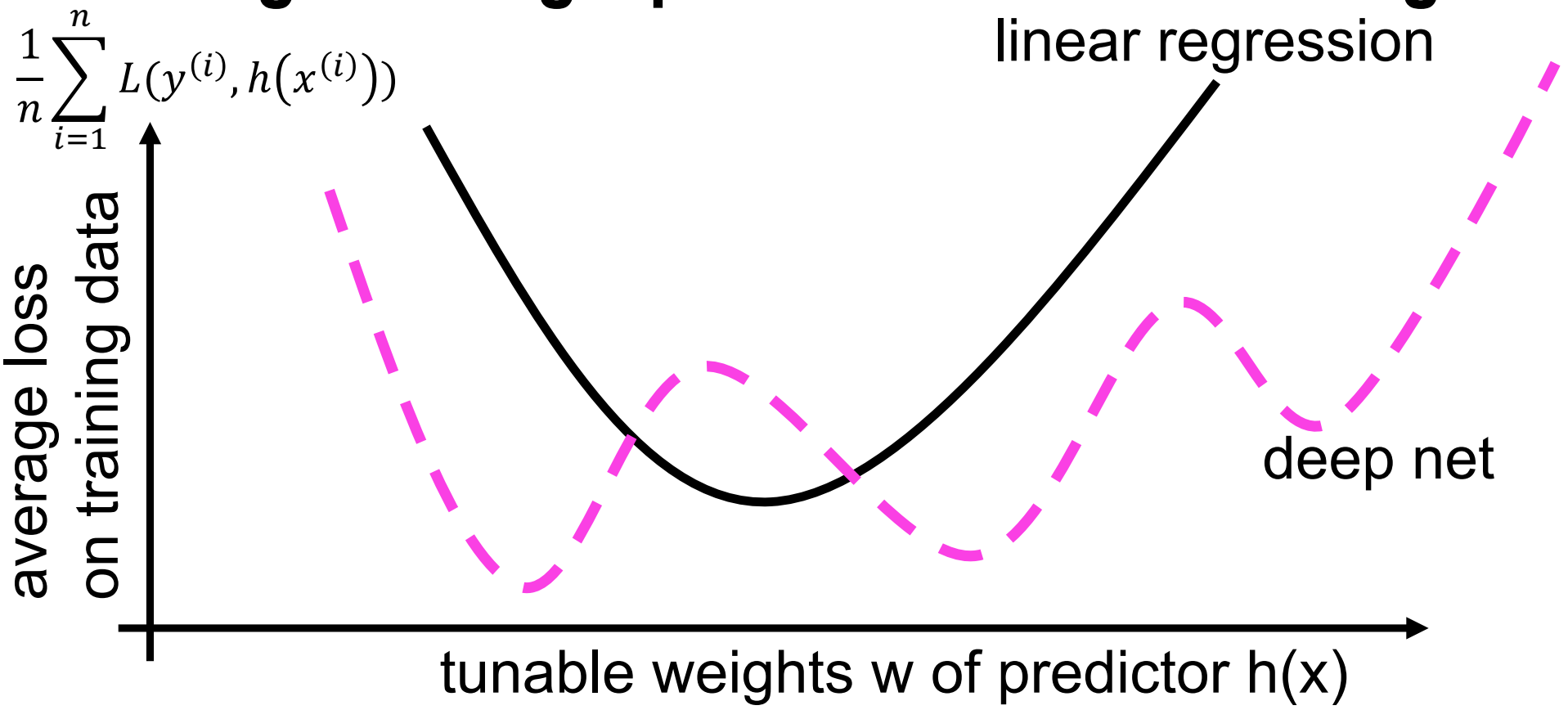
The function to measure the quality of a split. Supported criteria are "mse" for the mean squared error, which is equal to variance reduction as feature selection criterion and minimizes the L2 loss using the mean of each terminal node, "friedman_mse", which uses mean squared error with Friedman's improvement score for potential splits, and "mae" for the mean absolute error, which minimizes the L1 loss using the median of each terminal node.

New in version 0.18: Mean Absolute Error (MAE) criterion.

Putting Together the Pieces

- collect/measure/compute labeled data points
- choose predictor (linear, tree, artificial neural net, …)
- choose loss function
- tune weights of predictor to minimize the average loss

Learning/Training/Optimization/Model Fitting



Model Selection

Model = Choice for Hypothesis Space

- ML method/model = family of predictors with same structure
- linear regression uses h(x) = w*x with tunable w
- family of predictors constitutes the hypothesis space

Example: Linear Regression

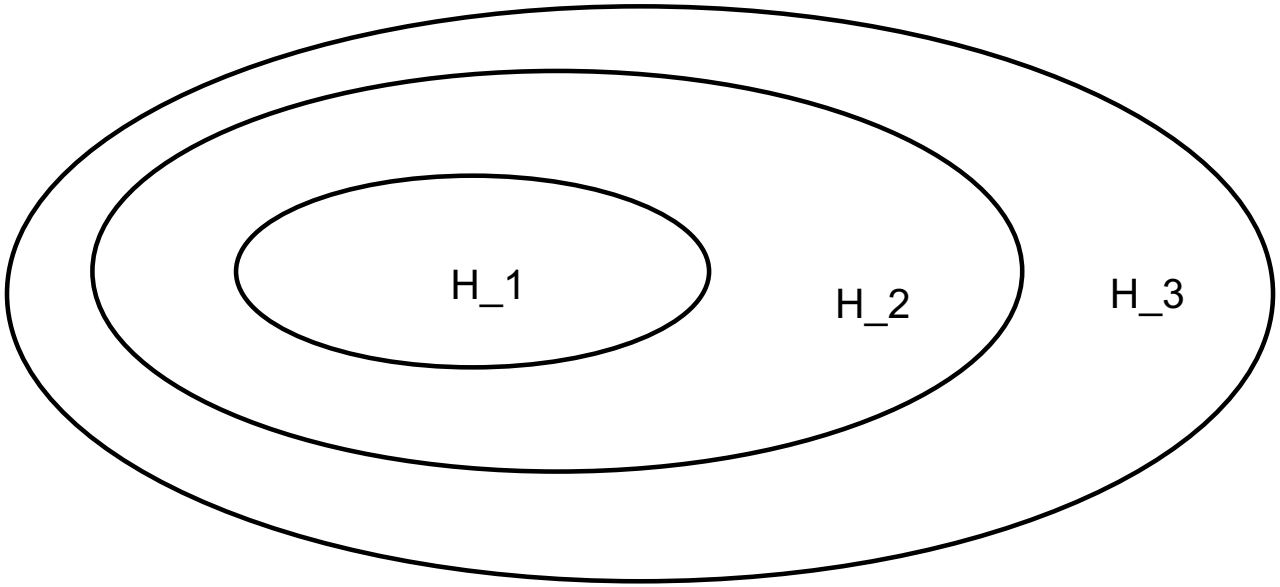
- consider data point having four features x1,…,x4
- want to predict some numeric label y of data point
- linear regression relates features and label via y' = h(x) = w1*x1+w2*x2+w3*x3+w4*x4
- different tuning weights w1,…,w4 yield different predictors !

Which Model Shall We Use?

- decision trees
- (deep) artificial neural nets
- linear predictors
- polynomial predictors
- ….

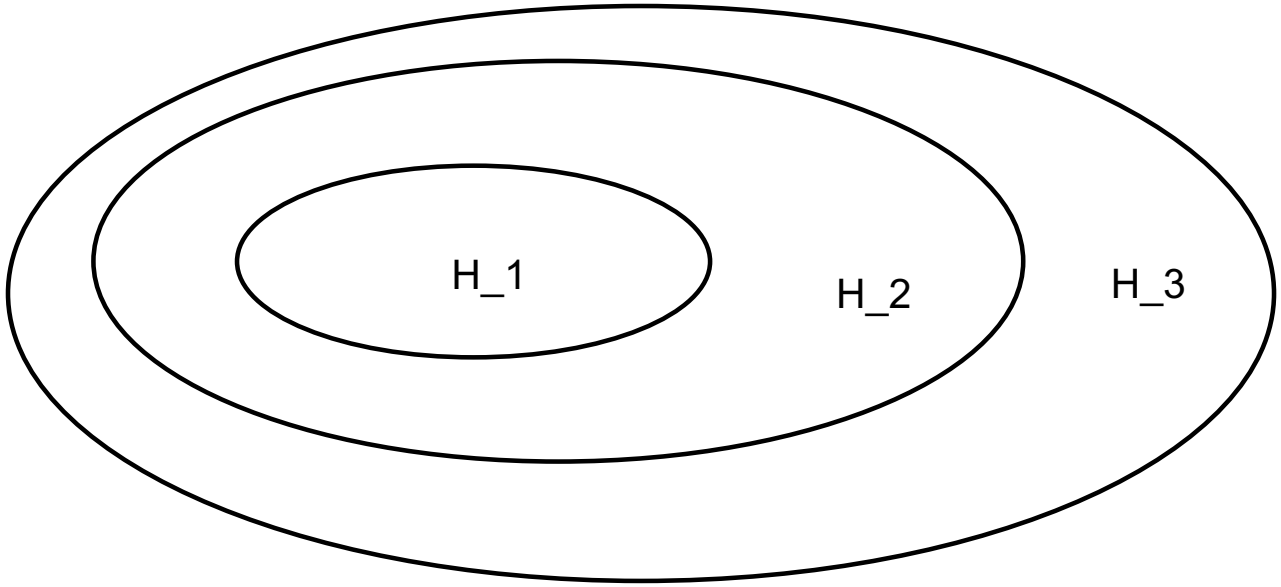
Nested Models

- H_d = set of linear predictors which use first d features



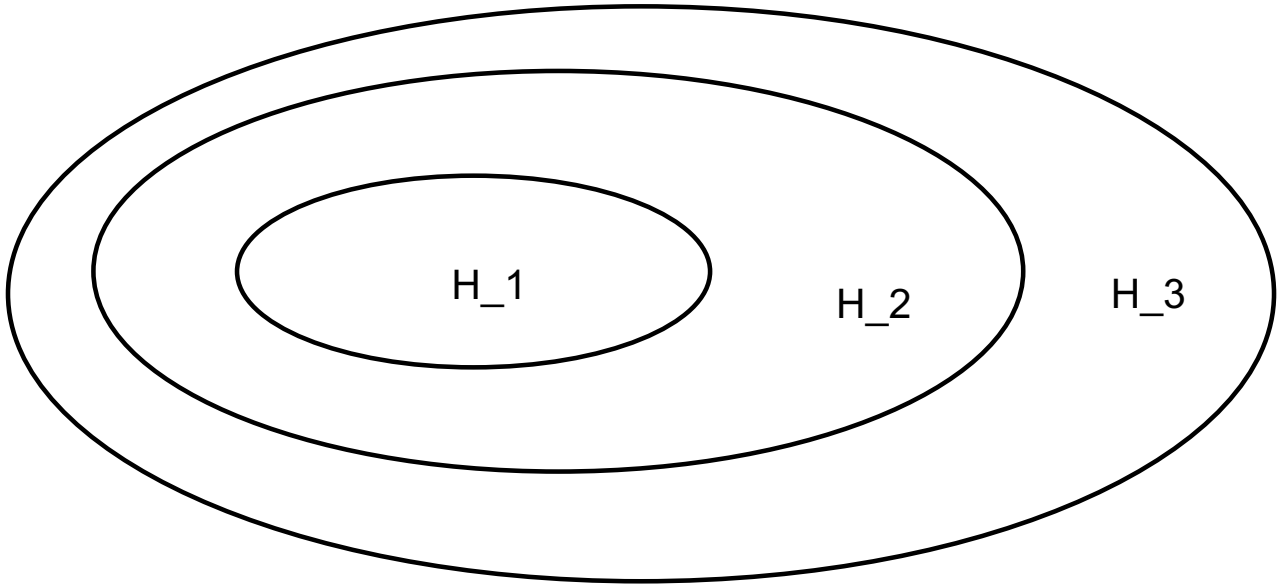
Nested Models

- define model H_d by set of polynomials with max. degree d
- H_d included in H_e if d>=e



Nested Models

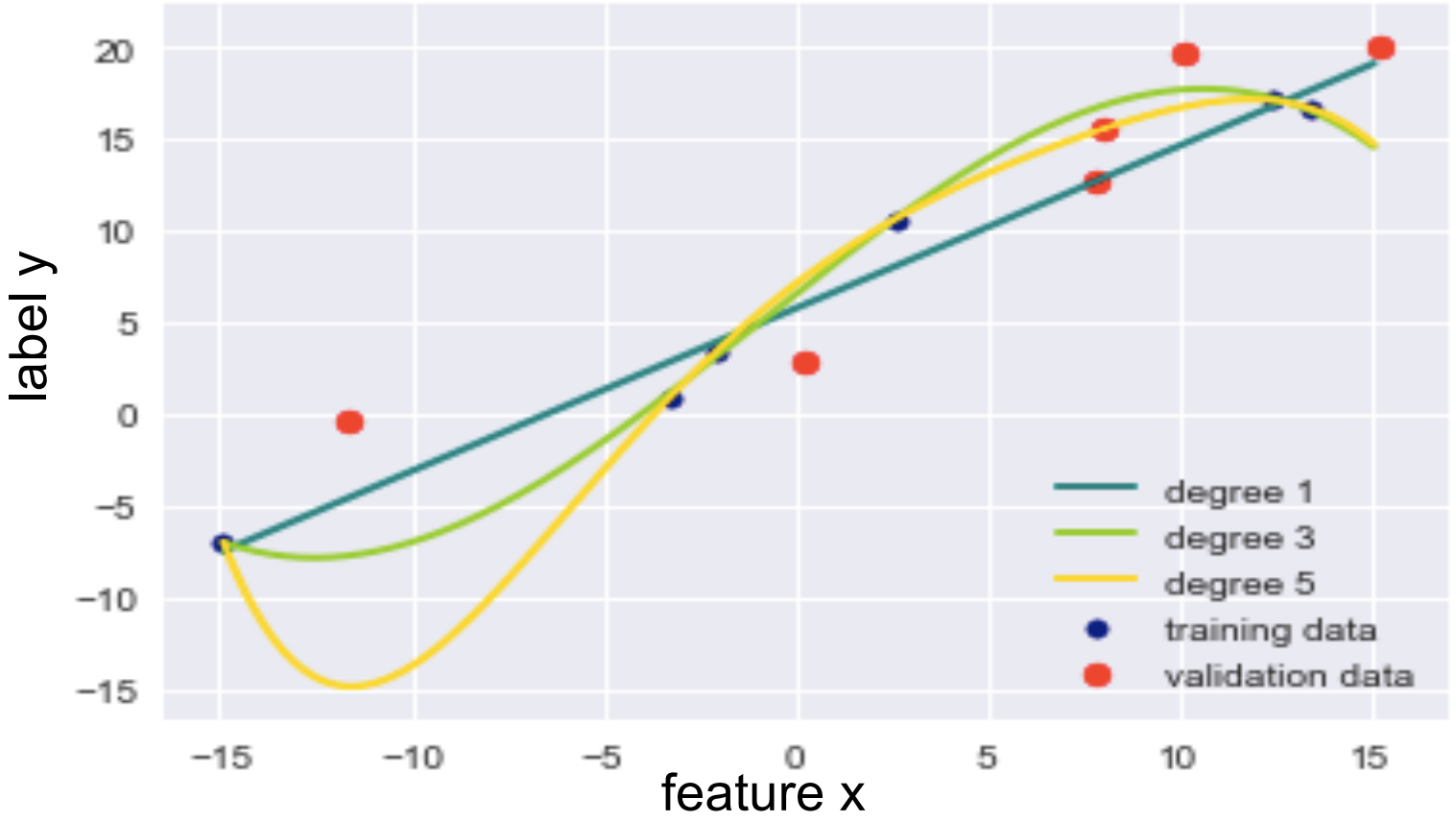
- model H_d given by ANN with d hidden units



Training Error

- consider particular model (e.g., polynomial predictor with max. degree d)
- model constituted by maps with different choices for tuning weights w
- choose weights by minimizing average loss (training error) over training set
- if we use larger model, we can only reduce training error !
- degree 5 polyn. can fit training data at least as good as degree 3 polyn.
- why not simply using the largest possible model (polyn. with large degree)?

Overfitting



Validate!

- average loss E_train on training set can be misleading!
- indeed, we optimize the predictor based on training set
- after training, try out on different (validation) data!
- compare training error E_train with validation error E_val
- when E_train << E_val, ML model is overfitting !!!

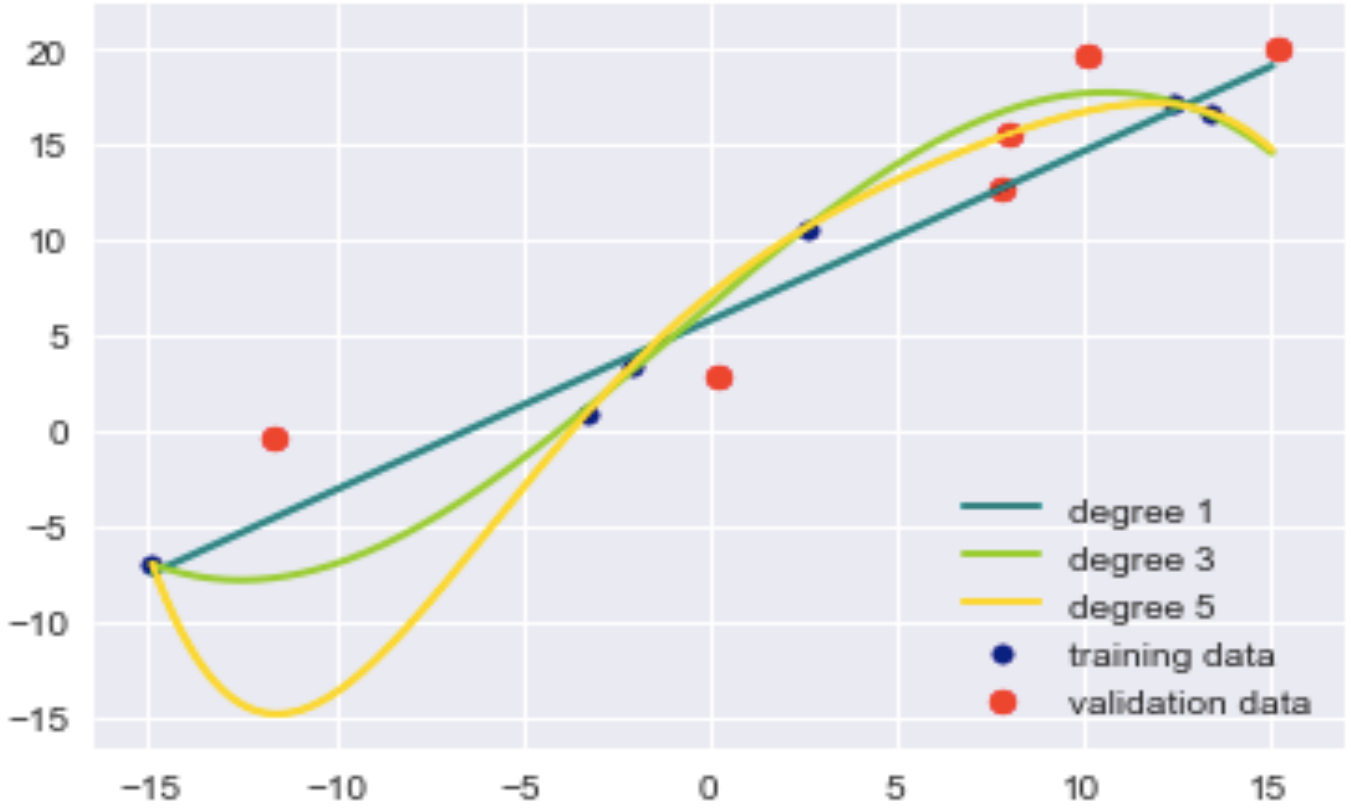
Labeled Data

	Year	m	d	Time	Prec	snow	tmp	maxtemp	mintmp
0	2016	1	2	00:00	-1.0	-1.0	-7.0	-5.5	-7.8
1	2016	1	3	00:00	3.2	-1.0	-8.7	-7.2	-10.0
2	2016	1	4	00:00	-1.0	4.0	-11.2	-4.9	-13.5
3	2016	1	5	00:00	0.6	4.0	-17.6	-13.3	-19.6
4	2016	1	6	00:00	-1.0	4.0	-20.3	-16.4	-21.3

training

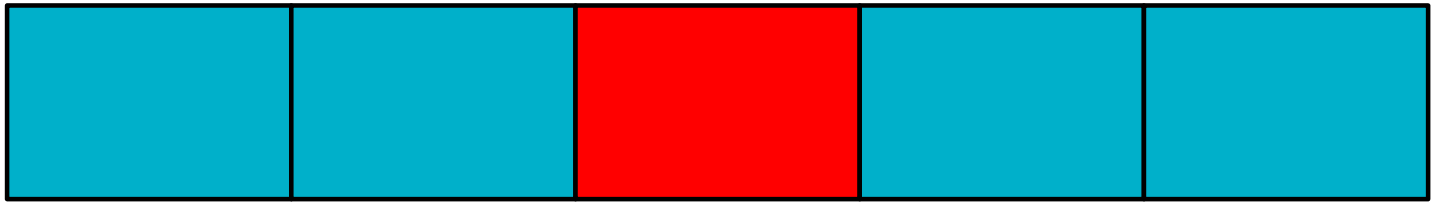
validation

Training and Validation Error



K-Fold Cross Validation

n labeled data points (assume n is integer multiple of K)

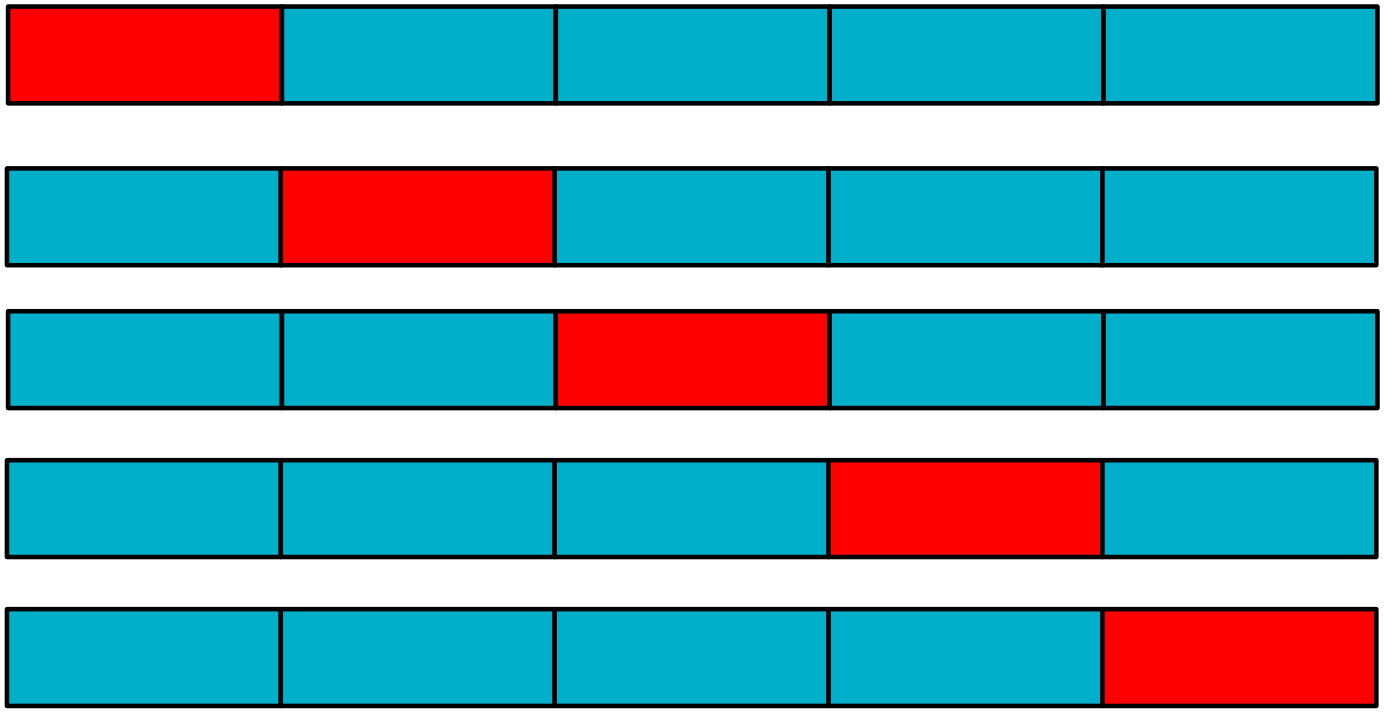


fold 1 … fold K

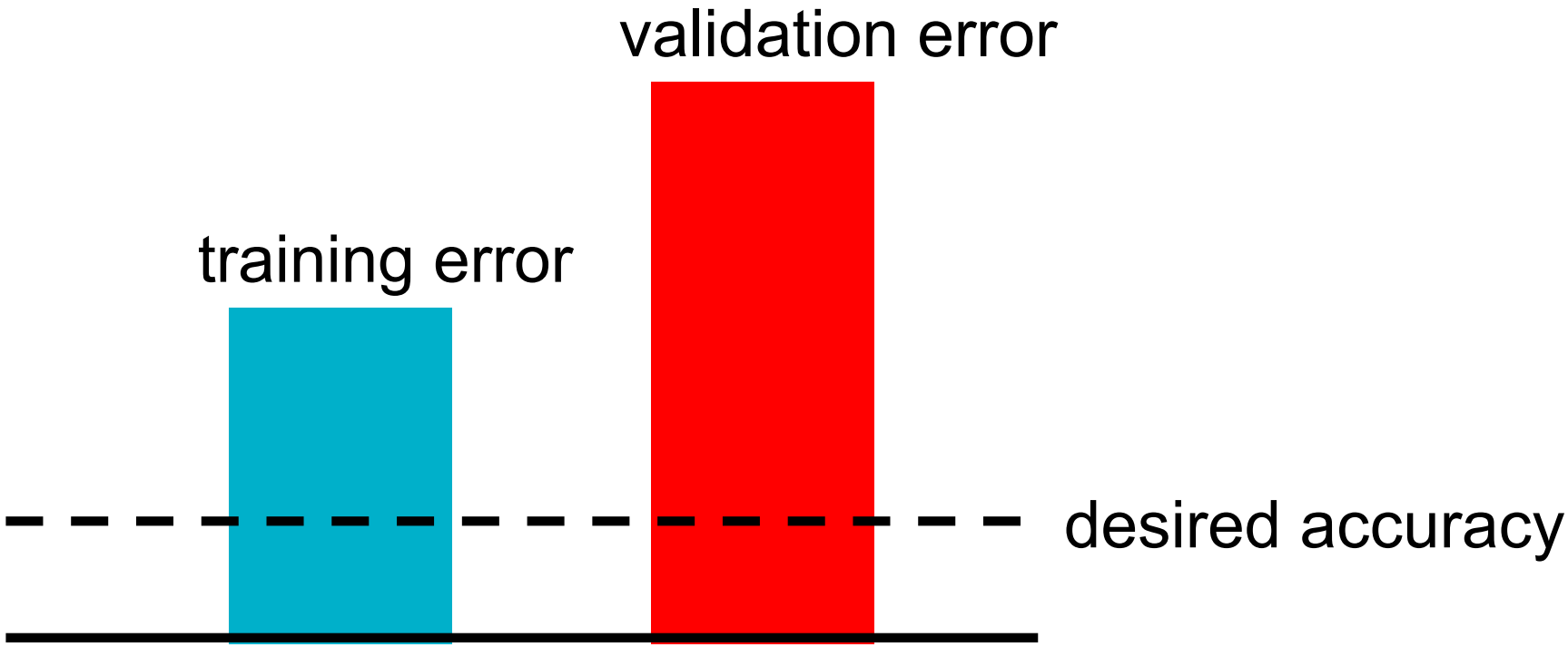
K-fold CV involves K iterations: in each iteration choose one fold as validation set; rest as training set

average the K validation errors

K-Fold CV with K=5



Diagnosing ML Methods

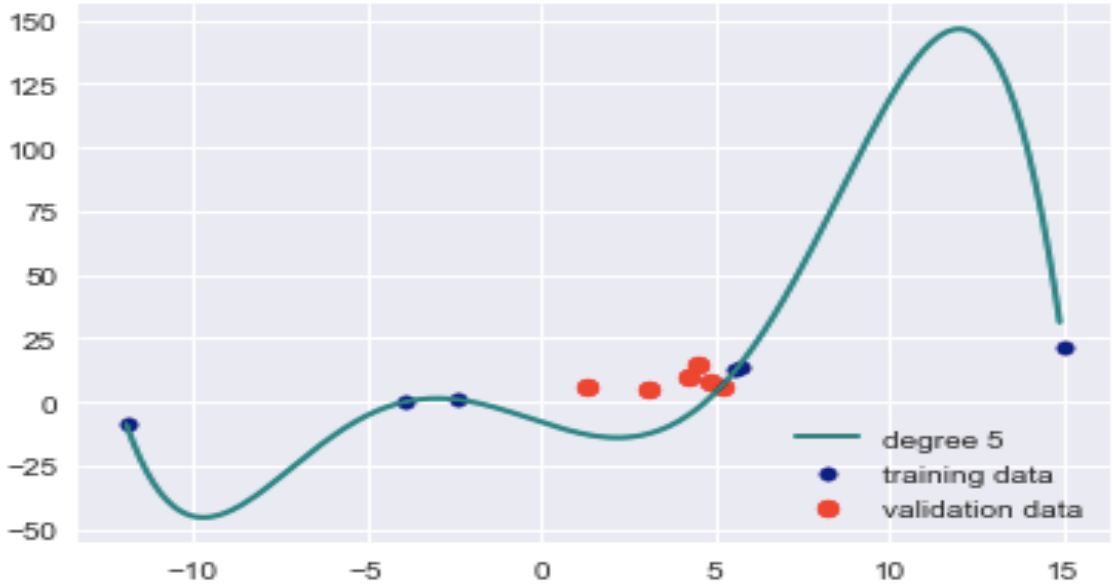


Diagnosis

- training error larger than desired accuracy:
  - use larger model (larger ANN, higher degree polyn…)
  - use more features
- training error at desired level, but validation error too large:
  - use smaller model (smaller ANN, smaller poly degree.
  - use larger training set (get more data)
  - use **regularization** techniques
- training error ≈ validation error ≈ desired accuracy: DONE!

Regularization

consider polynomial predictor with max. degree 5
h(x) = w0 + w1 *x + w2*x^2 + …. w5*x^5



The Basic Idea of Regularization

- choose weights w0,…,w5 **not only** by minimizing training error
- choose weights by min. sum of training error and regularization term
- regularization term represents anticipated increase of error on new data
- one widely used choice for reg. term is sum of squares of weights
- choose weights by minimizing

$$\frac{1}{m}\sum_{i=1}^{m} L(y^{(i)}, h(x^{(i)})) + \rho(w_0^2 + \cdots + w_5^2)$$

- tuning parameter ρ (large ρ anticipates large increase of error)

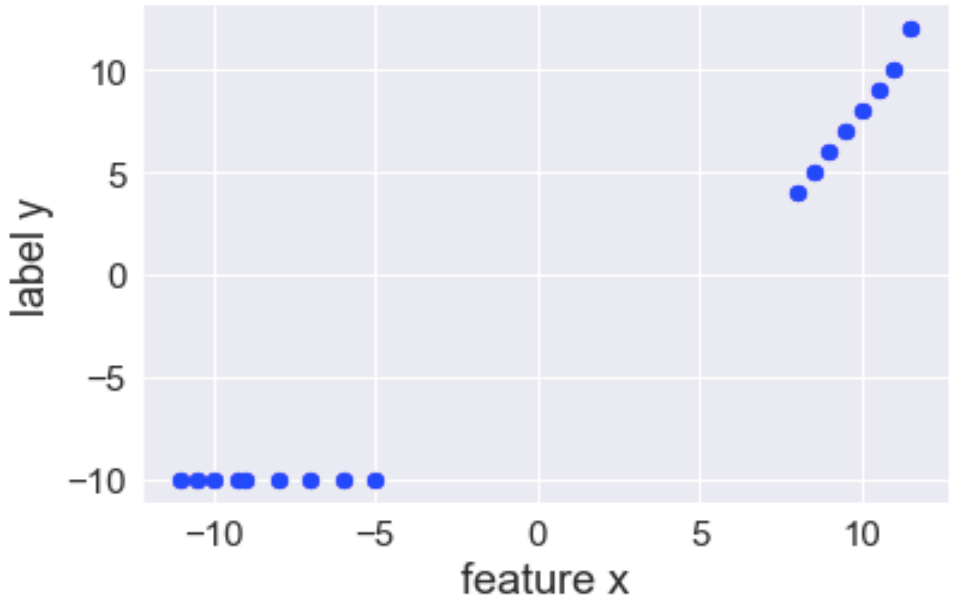
Lets get Hands Dirty!

- get some data and define features and labels
- choose ML model: linear, polynomial, ANN, decision tree
- compute training and validation error
- compare training, validation error with desired accuracy)
- change model (enlarge/reduce model) and/or get more data
- repeat

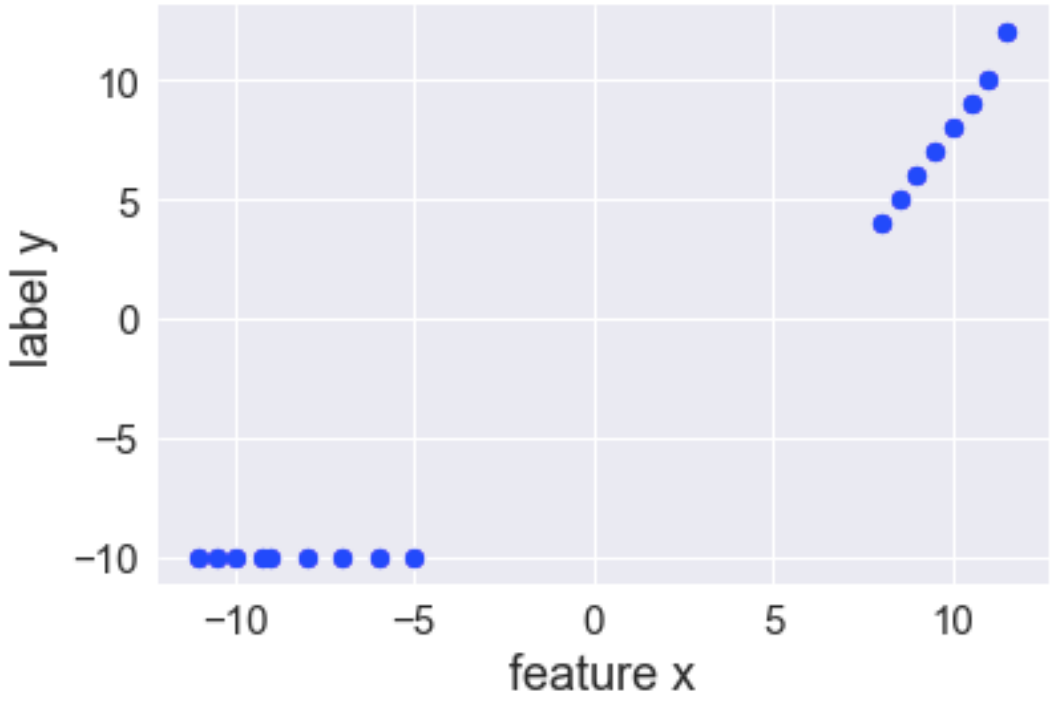
Clustering

A Linear Prediction Problem

- consider data points (x,y) with features x and label y
- assume you want to use linear predictors to predict y from x



Clustering = Grouping Similar Data Points

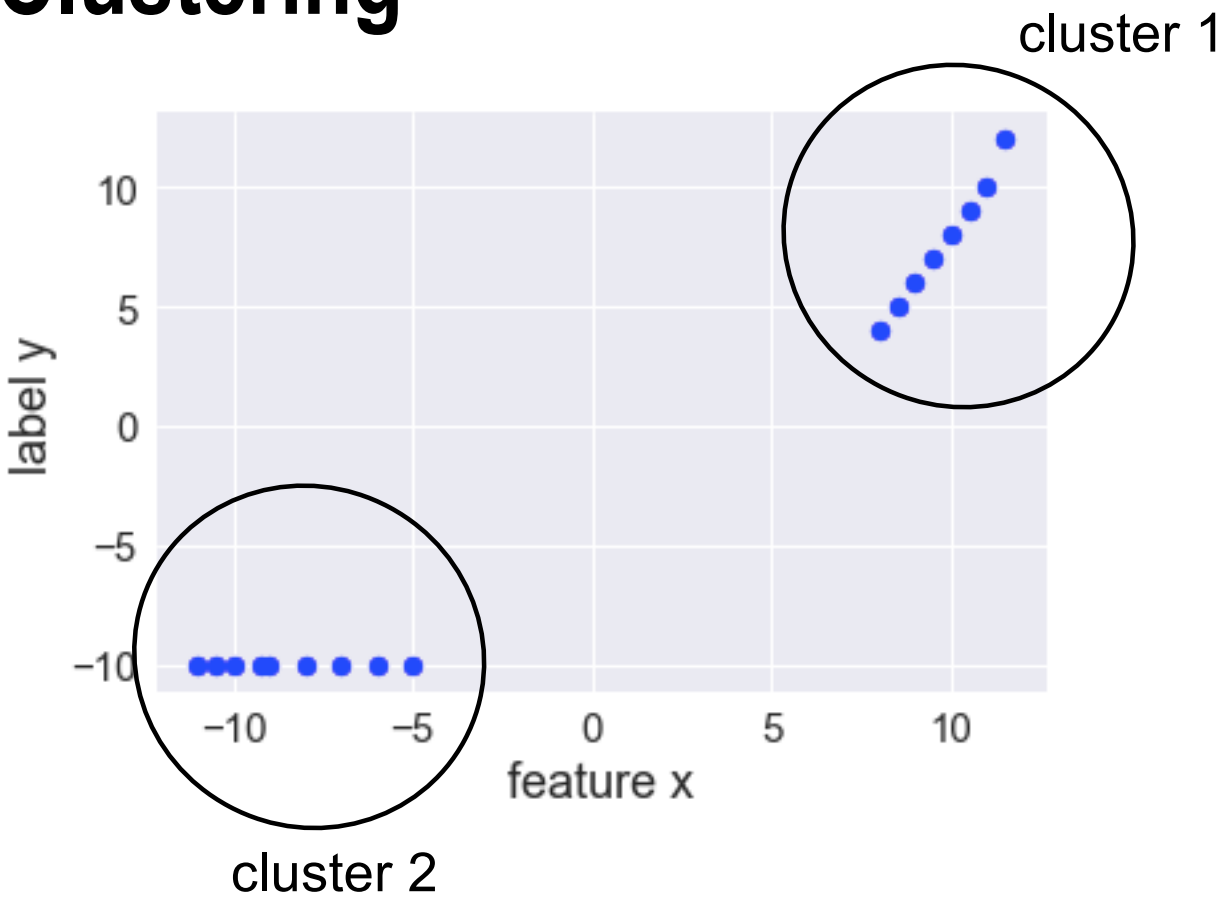


how many cluster (groups) do you see?

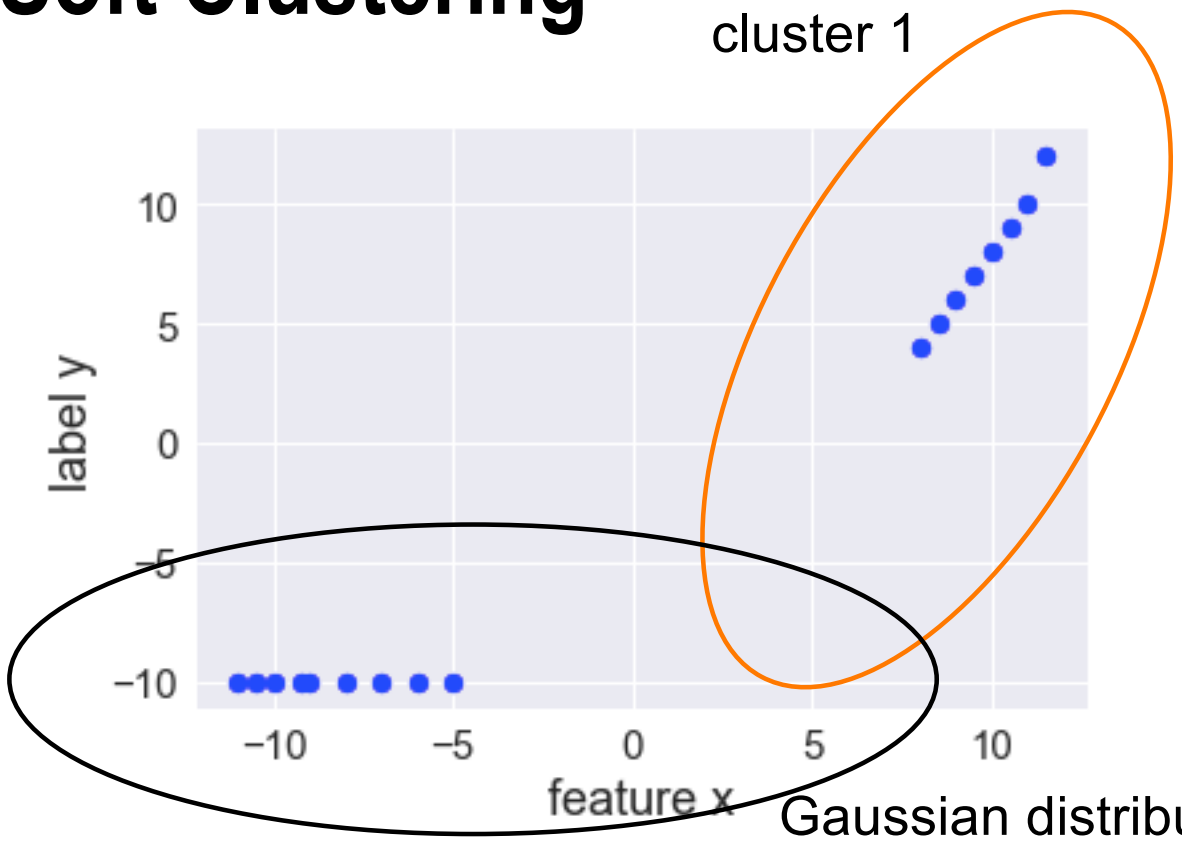
Two Main Flavors of Clustering

- hard clustering:
  - each data point belongs to exactly one cluster
  - popular method: **k-means**
- soft clustering:
  - data points belong to many clusters
  - data points have degree of belonging to particular cluster
  - popular method: **Gaussian mixture models**

Hard Clustering



Soft Clustering



Feature Learning

Long Vectors

- consider data point represented as vector **z** of length D
- what is D for a 1000 by 1000 greyscale image
- what is D for a 5 sec recording of a song ?
- what is D for a dictionary containing all English words?
- what is D for a dictionary of English 5-grams ?

What is Bad About Long Feature Vectors?

- computing with long vectors is time consuming
- risk of overfitting
- consider data points represented by vectors of length D
- linear predictors overfit training data set smaller than D

Basic Idea

raw data vector z

feature learning
method h(z)

features
x_1,x_2,…,x_n

reconstruct

reconstruction z’

map h(z) involves tunable weights w

choose weights w to ensure small reconstruction error z-z’

The Creation (Finnish)

raw data = 254820 pixels

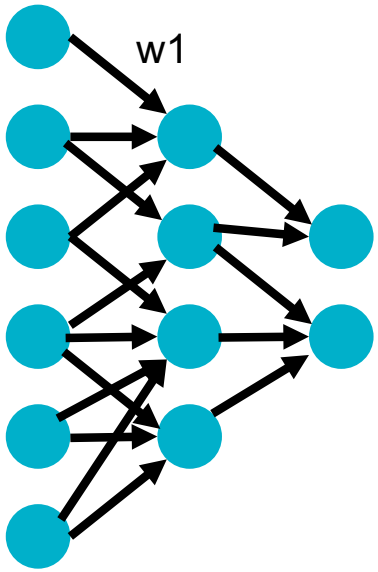
reconstruction obtained from
17837 features

Linear Feature Learning

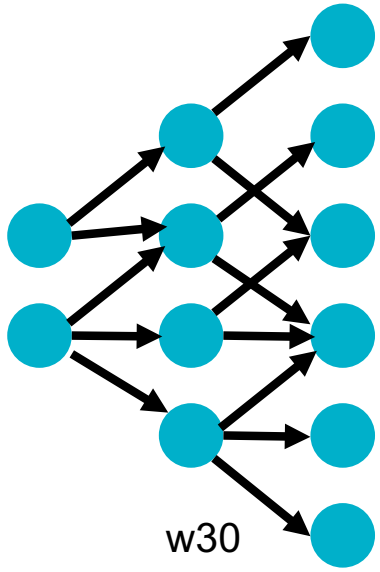
what is best choice for matrix W such that z' close to z ?

Non-linear Feature Learning – “Autoencoder”

raw data z



features x



reconstruction z’

tunable weights w1,w2,….

Transfer Learning

Basic Idea

- train ML method on different data
- massive amounts of unlabeled data to pre-train ANN
- small amount of high quality labeled data to fine-tune ANN
- allows to compress raw data into pre-trained models

Model Based ML Methods

Model Based Machine Learning

- consider data points with features x and labels y
- interpret them as realizations of random variables
- sequence of data points is a random process
- data characterized by probability distribution

Condition on Data

- specify joint distribution p(…) of all quantities in the model
- quantities include: features, labels of data points and parameters
- compute posterior distribution of variables given observed data
- https://docs.pymc.io/notebooks/GLM-linear.html

Probabilistic Machine Learning

	Year	m	d	Time	Prec	snow	tmp	maxtemp	mintmp
0	2016	1	2	00:00	-1.0	-1.0	-7.0	-5.5	-7.8
1	2016	1	3	00:00	3.2	-1.0	-8.7	-7.2	-10.0
2	2016	1	4	00:00	-1.0	4.0	-11.2	NaN	-13.5
3	2016	1	5	00:00	0.6	4.0	-17.6	-13.3	-19.6
4	2016	1	6	00:00	-1.0	4.0	-20.3	-16.4	-21.3

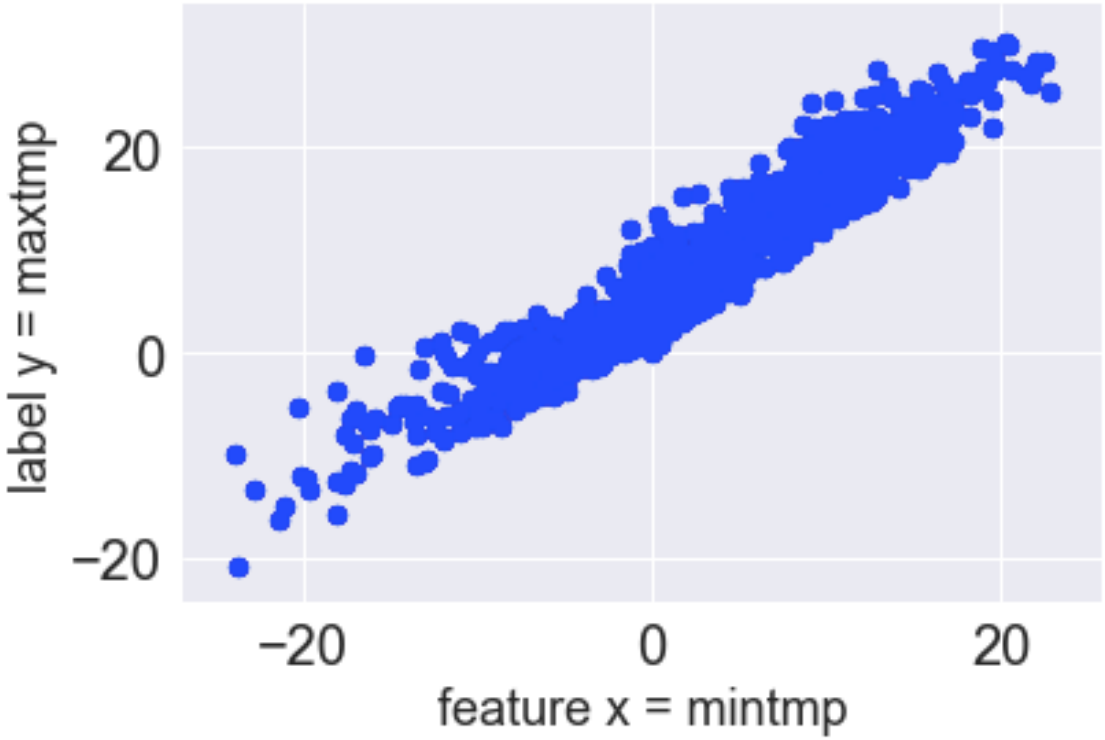
today at 07:00 am: mintmp=-10 maxtmp =?

compute posterior probability distribution p(hidden variables | data)

Two Challenges

- Challenge1: how to get joint probability distribution p(data, hidden variables) ?
- Challenge2: how to compute posterior distribution p(hidden variables | data) for extremely high-dim. distribution?

Learning Probability Distribution



what could be a good choice for p(x,y) ?

Ready Made Tools

- efficient methods for learning prob. distributions available
- efficient methods for computing posterior p(hidden variables | data) available

Reinforcement Learning

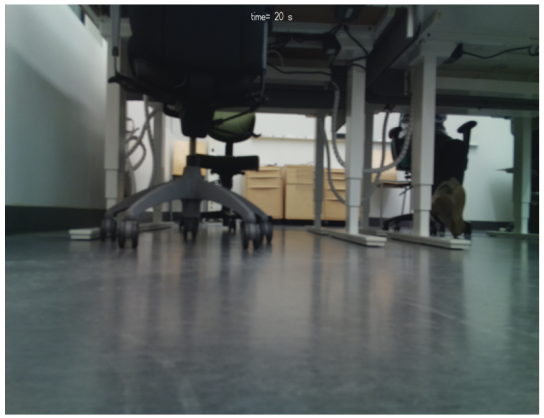
Machine Learning vs. Reinf. Learning

- ”ordinary” machine learning methods consider data given
- methods are passive; read in data → output prediction
- reinforcement learning takes effect of predictions into account
- predictions incur decisions/actions
- decisions/actions influence the data which is observed next

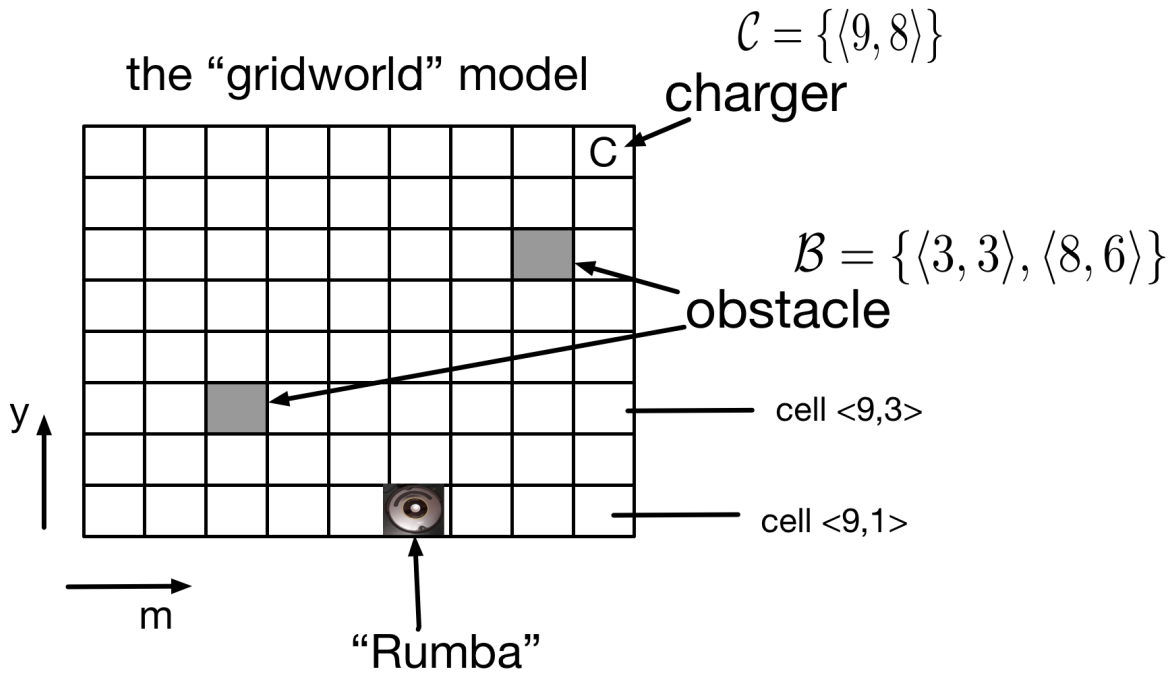
Cleaning Robot

Office Room

office room “B329”

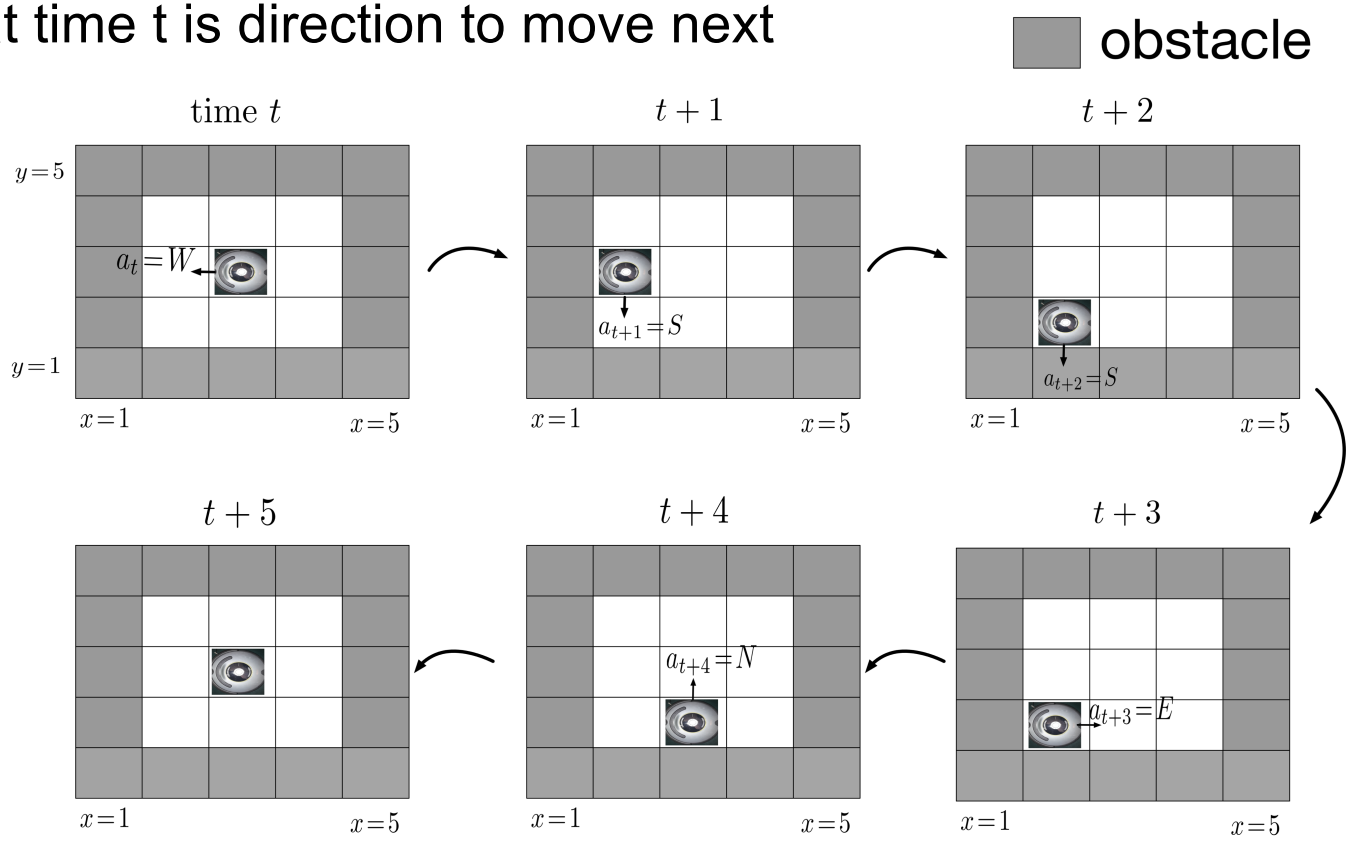


the “gridworld” model



Actions

action y_t at time t is direction to move next



Reinforcement Learning Problem

given snapshot of onboard camera,
what is best direction to move next

features x = pixels of snapshot
label y = optimal direction to move next

We do not know the true label here!
We can only observe the effect of choosing some direction!

Markov Decision Process

- interaction between AI (cleaning robot) and environment (office room)
- at time t, observe snapshot x_t
- based on snapshot decide for next direction y_t
- measure amount r_t of dust collected at time t
- sequence x_1,y_1,r_1,x_2,y_2,r_2 modelled as a Markov decision process
- MDP is a special type of random process

Optimal Policy

- AI cleaning robot implements a policy h(x)
- policy takes input x (snapshot) and outputs y (direction of next move)
- policy map h(x) depends on tunable weights (like predictors !)
- RL amounts to tuning h(x) such that reward is maximized
- AI engineer defines what the “reward” is (e.g., amount of dust collected)

THAT’S IT FOLKS!