A Short Tour of Machine Learning

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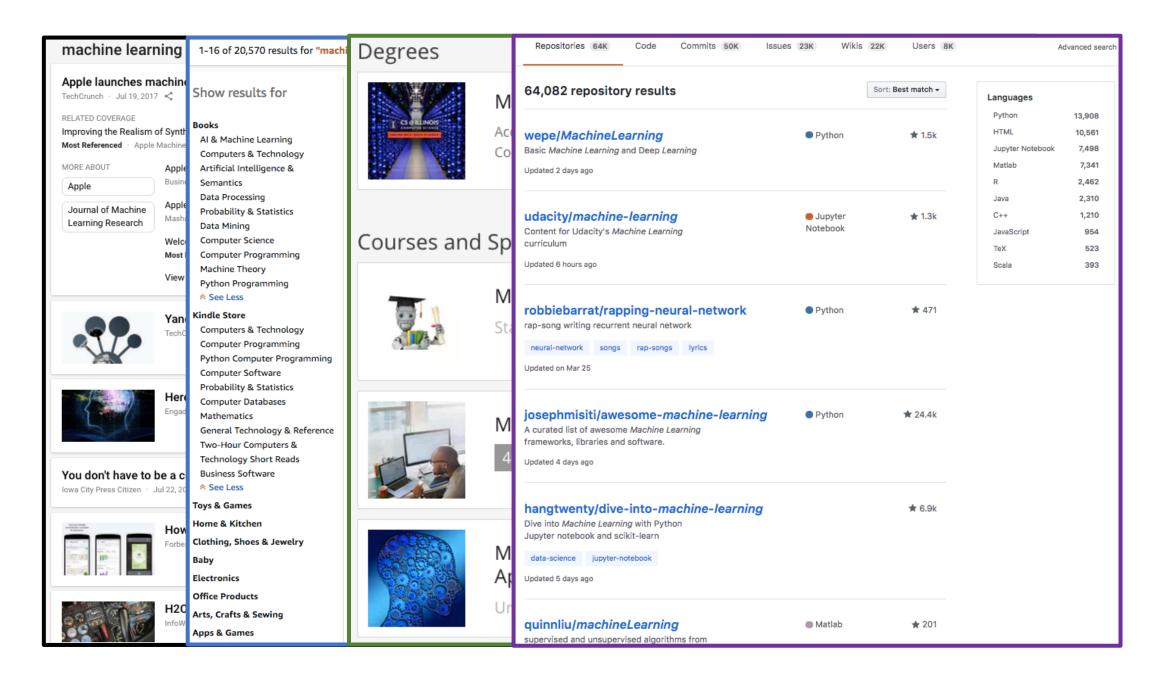
Covve, Athens, 2017-08-02

:HELVIA

today

- part 1: machine-learning algorithms
 - a. basic concepts and the ML pipeline
 - b. algorithms
- part 2: platforms and software
- part 3: hands-on session

part 1: machine learning algorithms



what is machine learning?

'learning'

what do we *learn*?

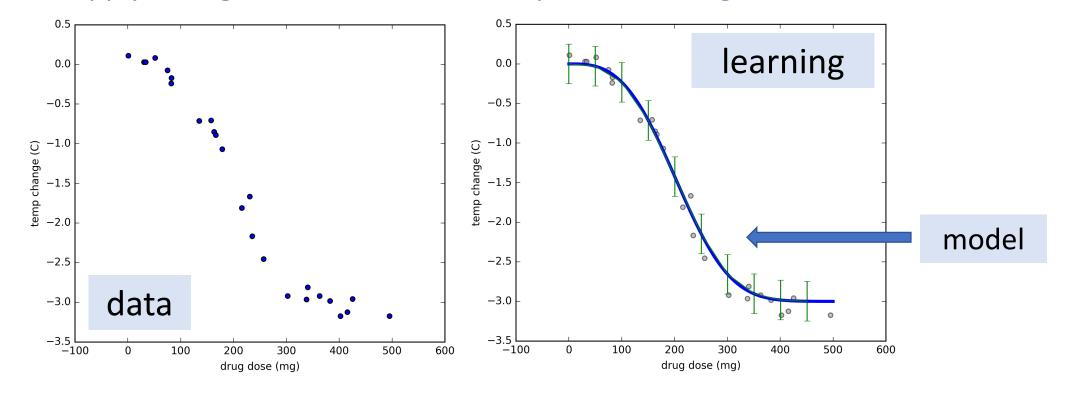
a description of the data

a 'model' that tells us how the data are distributed

why? to make *predictions* and *decisions*

example

the patient's temperature has just exceeded 40C we supply a drug and observe their temperature change after 2 hours



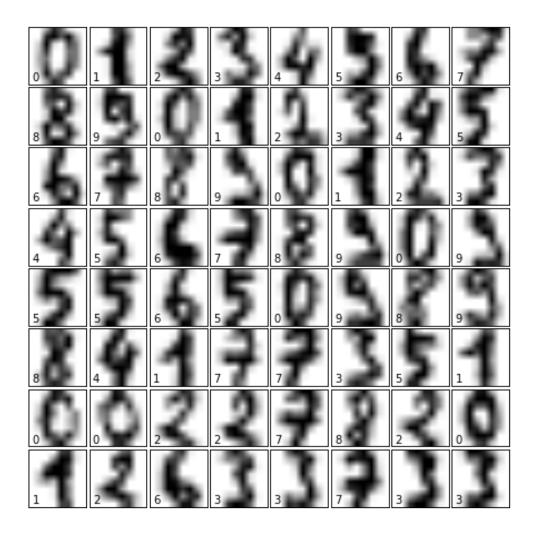
ok, we 'learned' - then what?

predict what happens to temperature if we supply 0.20mg?

decide minimum dose to achieve at least 2.5C temp drop?

can do with the model without the data

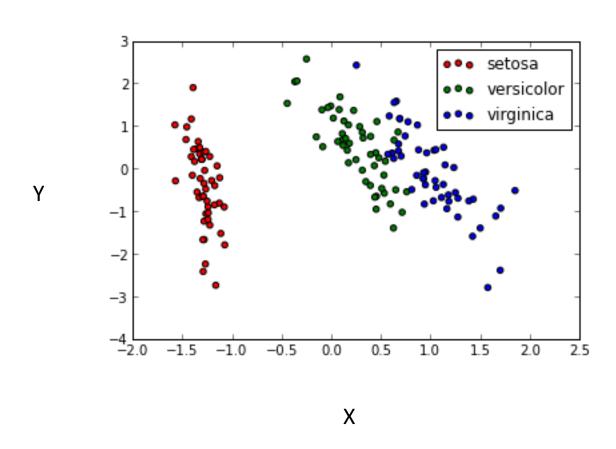
example



digit recognition

classification

example



clustering

density estimation

'machine' learning

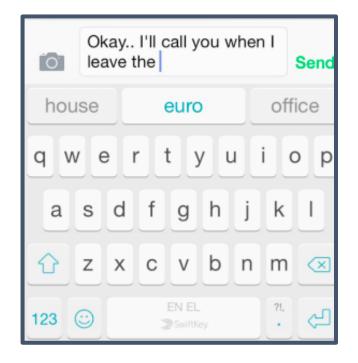
why do we need the machines?

to make learning automated and efficient

big data complex models

example: language





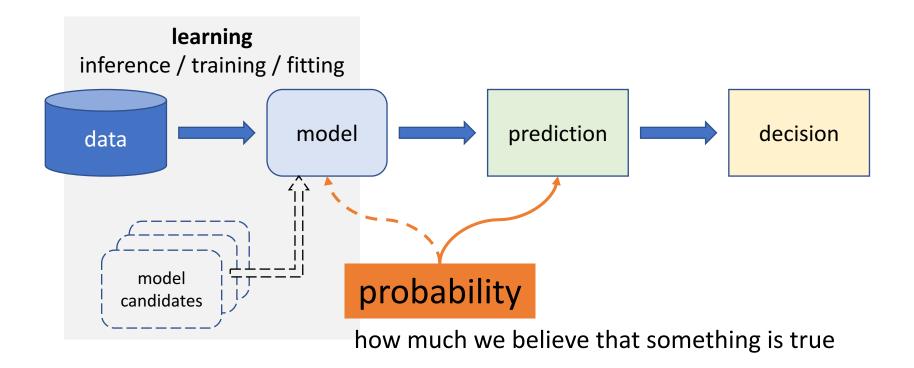
task: complete the sentence

language is complex basic rules (syntax and grammar) do not suffice for good predictions requires complex models

<u>data</u> ns/billions of sentend

millions/billions of sentences/queries user features session attributes

ML pipeline



outline

- what is machine learning
 - examples of tasks: regression, classification, clustering
 - data, learning, prediction, decision; probability
- probability
- algorithms
 - regression
 - classification
 - clustering
- deep learning

probability

'proposition'

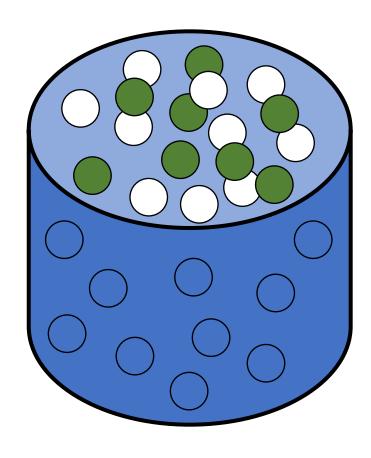
how much we believe that something is true **GIVEN** some information



VERY IMPORTANT!

0: impossible 1: certain

probability



a ball drops out of the box

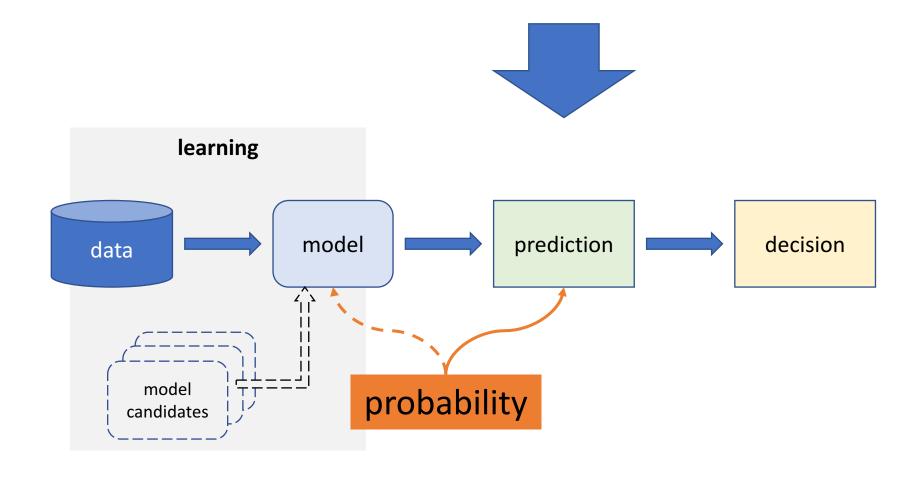
it is green

probability



this shape is '1'

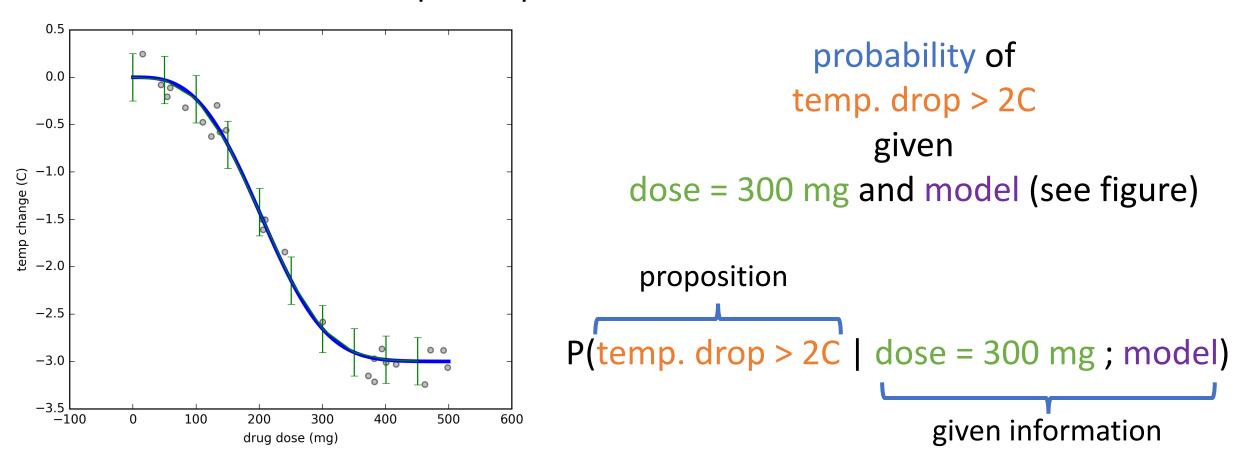
ML pipeline



assign probabilities to propositions

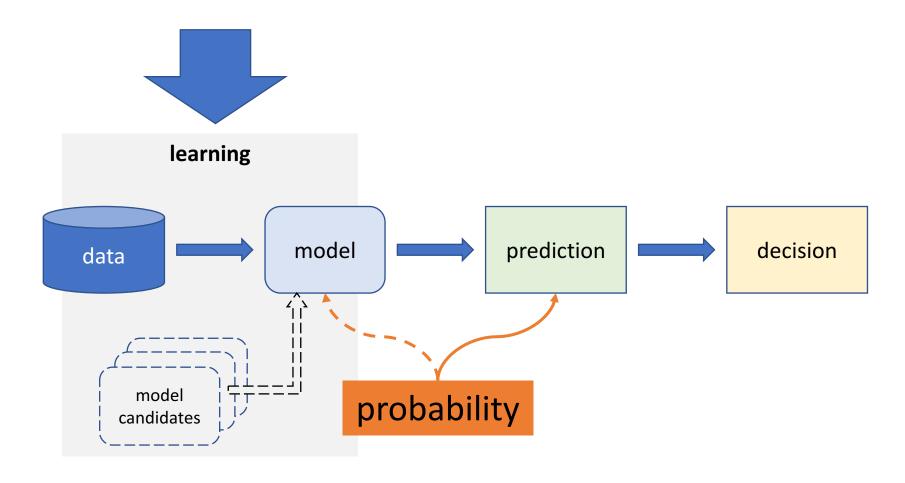
probability :: prediction

what is the probability that a dose of 300mg drops temperature more than 2C?



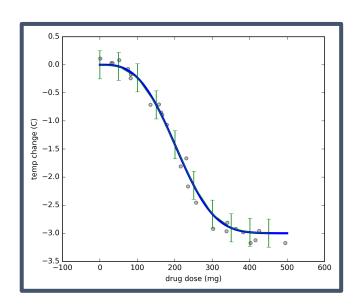
the value for this probability is provided by the model!

ML pipeline

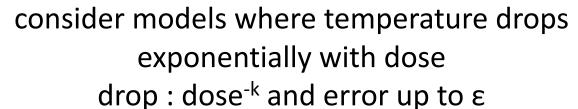


assign probabilities to models

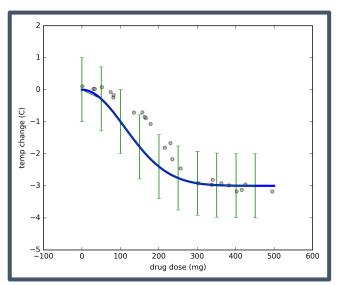
probability :: learning



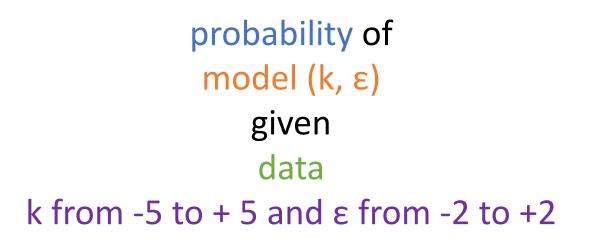
model M1



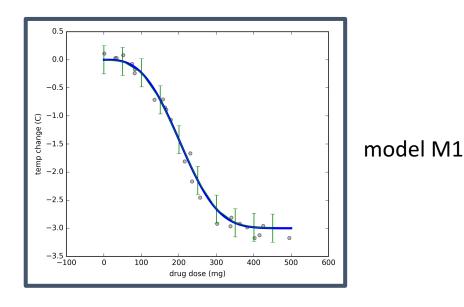
what is the probability that the right model is M1 / M2 / ...?



model M2



probability :: learning





from Bayes' Rule, this is proportional to

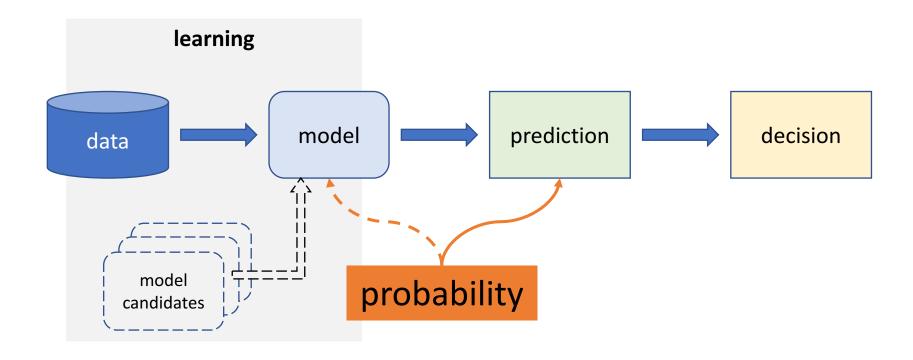
likelihood

prior

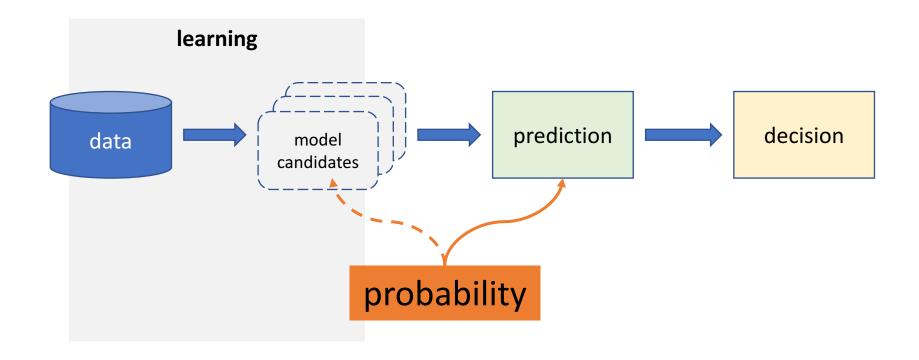
model M2

we choose the model of maximum probability (do we have to?)

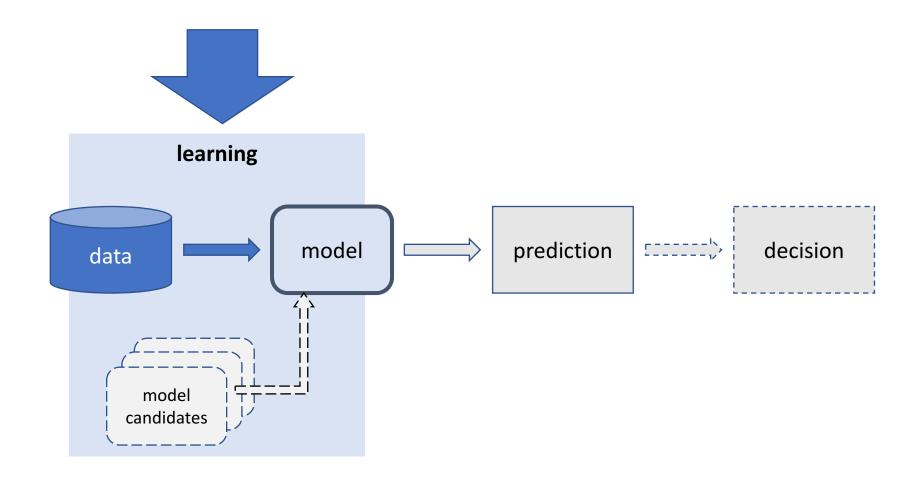
ML pipeline



ML pipeline – the Bayesian way



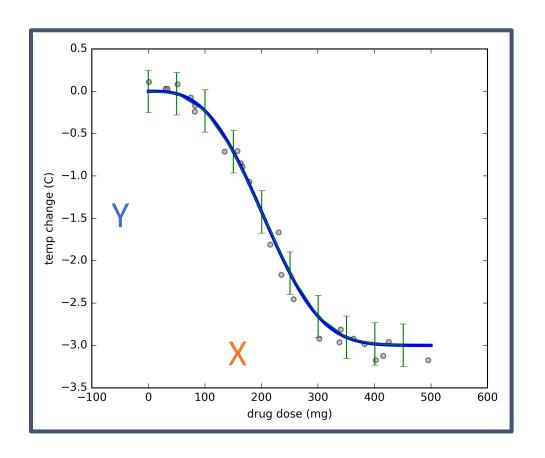
in what follows...



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regression



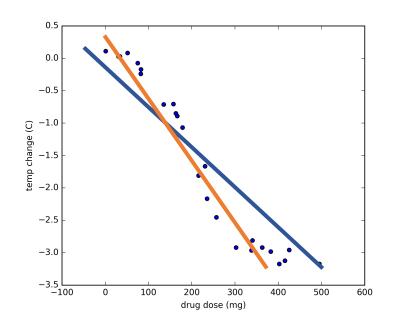
build model that provides dp(Y = y | X = x; Model M) for real-valued Y

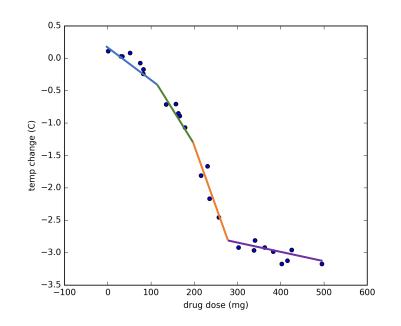
regression methods differ in the set of model candidates they consider

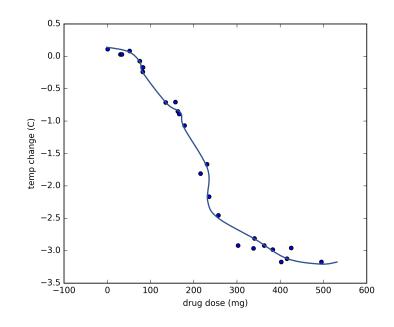
each method has corresponding algorithm(s)

to search for best model

some regression methods







linear regression line + error

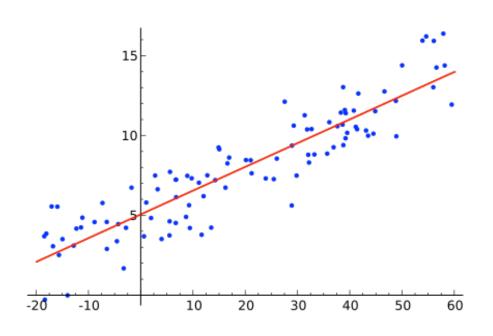
segmented regression k segments + errors

multinomial regression curve + error

this is where methods differ

$$p(M \mid data; I) \propto p(data \mid M; I) \times p(M \mid I)$$

linear regression



$$Y = E(Y|X_1, ..., X_p) + \varepsilon$$
$$= \beta_0 + \sum_{j=1}^p X_j \beta_j + \varepsilon,$$

solved with linear algebra if the data points are more than the dimensions

$$RSS(\beta) = \sum_{i=1}^{N} (y_i - f(x_i))^2$$

ridge regression

ridge regression

$$\hat{eta}^{ ext{ridge}} = \operatorname*{argmin}_{eta} \Bigl\{ \sum_{i=1}^N \bigl(y_i - eta_0 - \sum_{j=1}^p x_{ij} eta_j ig)^2 + \lambda \sum_{j=1}^p eta_j^2 \Bigr\}.$$

$$\hat{eta}^{ ext{ridge}} = rgmin_{eta} \sum_{i=1}^N \Bigl(y_i - eta_0 - \sum_{j=1}^p x_{ij} eta_j \Bigr)^2,$$
 subject to $\sum_{j=1}^p eta_j^2 \leq t,$

lasso

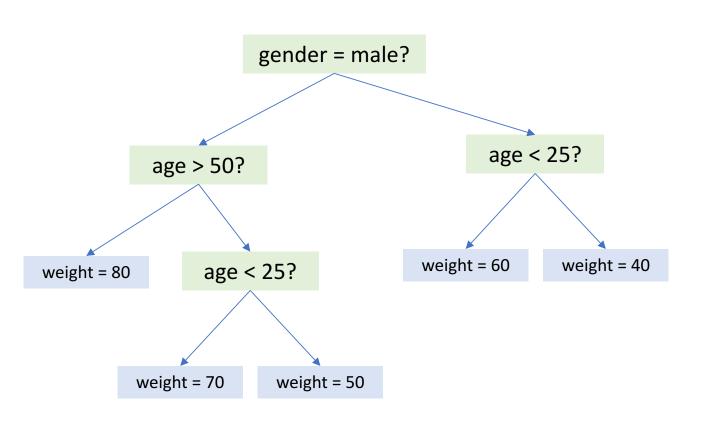
$$\hat{\beta}^{\text{lasso}} = \operatorname*{argmin}_{\beta} \left\{ \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij} \beta_j \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\}$$

$$\hat{eta}^{ ext{lasso}} = \operatorname*{argmin} \sum_{i=1}^N \Big(y_i - eta_0 - \sum_{j=1}^p x_{ij} eta_j \Big)^2$$
 subject to $\sum_{j=1}^p |eta_j| \le t$.

linear regression with shrinkage

the penalty on the size of β expresses a prior

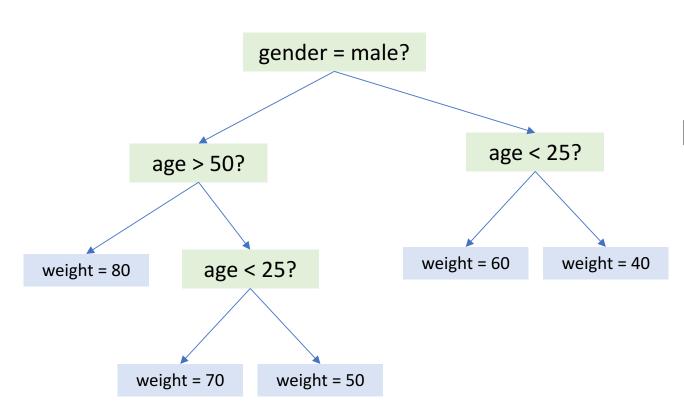
decision trees



predict the value of the leaf

build tree to minimize error (e.g., square error) subject to restrictions

random forests



build many decision trees on random subset of data random subset of features

combine predictions

neural networks

idea

apply a linear model on a non-linear transformation of the input

$$h_i = g(\boldsymbol{x}^{\! op} \boldsymbol{W}_{:,i} + c_i)$$
 $g(z) = \max\{0, z\}$

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{c}, \boldsymbol{w}, b) = \boldsymbol{w}^{\top} \max\{0, \boldsymbol{W}^{\top} \boldsymbol{x} + \boldsymbol{c}\} + b.$$

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naïve-bayes

within each class, features are distributed independently

$$\mathsf{p}(\mathsf{X} \mid \mathsf{C} = \mathsf{j}) = f_j(X) = \prod_{k=1}^p f_{jk}(X_k).$$

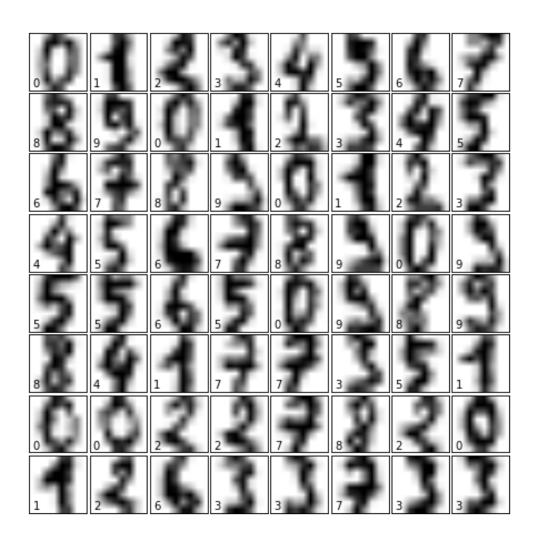
$$\log \operatorname{tr} \frac{\Pr(G = \ell | X)}{\Pr(G = J | X)} = \log \frac{\pi_{\ell} f_{\ell}(X)}{\pi_{J} f_{J}(X)}$$

$$= \log \frac{\pi_{\ell} \prod_{k=1}^{p} f_{\ell k}(X_{k})}{\pi_{J} \prod_{k=1}^{p} f_{J k}(X_{k})}$$

$$= \log \frac{\pi_{\ell}}{\pi_{J}} + \sum_{k=1}^{p} \log \frac{f_{\ell k}(X_{k})}{f_{J k}(X_{k})}$$

$$= \alpha_{\ell} + \sum_{k=1}^{p} g_{\ell k}(X_{k}).$$

classification



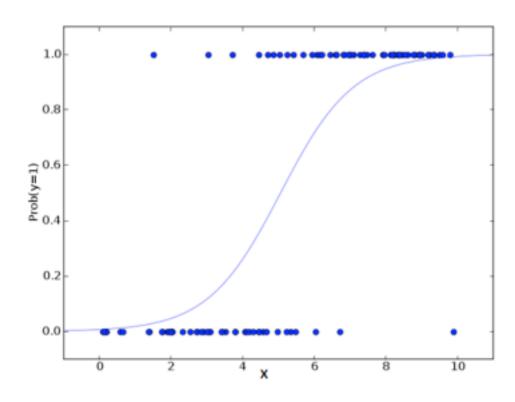
build model that provides p(Y = y | X = x; Model M) for categorically-valued Y

classification methods differ in the set of model candidates they consider

each method has corresponding algorithm(s)
to search for best model

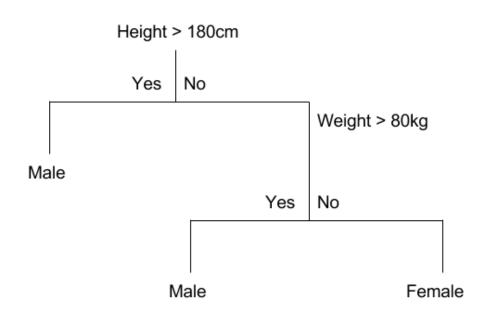
what is X and Y for digit recognition?

logistic regression



$$\Pr(Y_i = c) = rac{e^{oldsymbol{eta}_c \cdot \mathbf{X}_i}}{\sum_{k=1}^K e^{oldsymbol{eta}_k \cdot \mathbf{X}_i}}$$

decision trees & random forests



very similar to regression methods leafs assign probabilities to classes

neural networks

idea

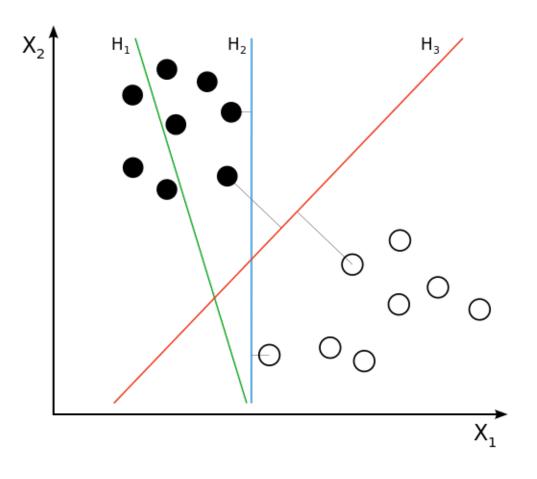
apply a linear model on a non-linear transformation of the input

$$h_i = g(\boldsymbol{x}^{\! op} \boldsymbol{W}_{:,i} + c_i)$$
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$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{c}, \boldsymbol{w}, b) = \boldsymbol{w}^{\top} \max\{0, \boldsymbol{W}^{\top} \boldsymbol{x} + \boldsymbol{c}\} + b.$$

evidence for one class

support-vector machines



separate the classes with hyperplanes

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supervised and unsupervised learning

the methods we saw for regression and classification are cases of 'supervised' learning

build model that provides $p(Y = y \mid X = x; Model M)$

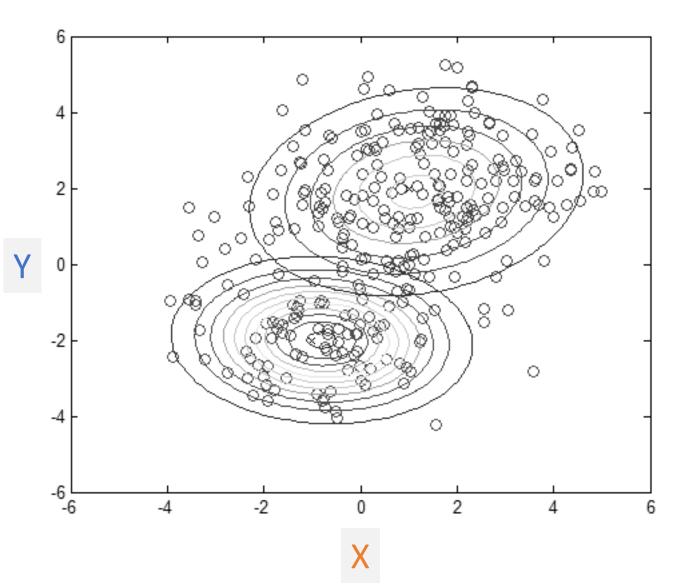
other data features

some data features

build model that provides p(X = x, Y = y; Model M)

'unsupervised' learning

unsupervised learning

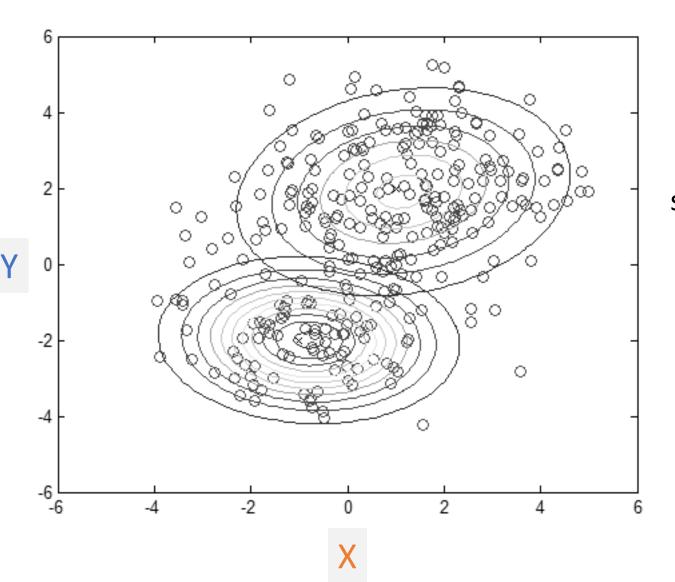


build model that provides

p(X = x, Y = y; Model M)

find structure in the data

k-means clustering

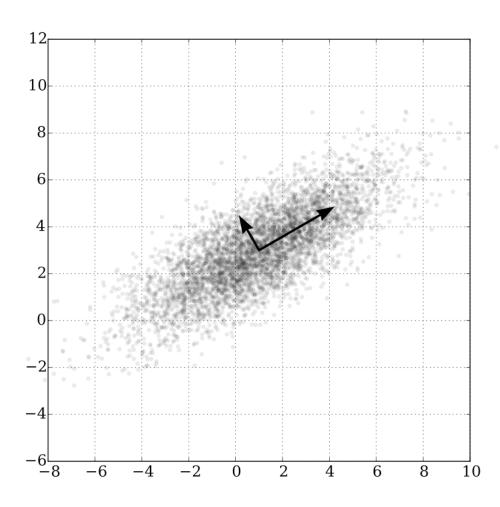


clustering

assign points to clusters so that total distance from cluster center is minimized

k-means
assign points to cluster of nearest center
compute centers from assigned points
repeat

PCA



project the data on orthogonal system so that successive dimensions maximize remaining variance

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deep learning

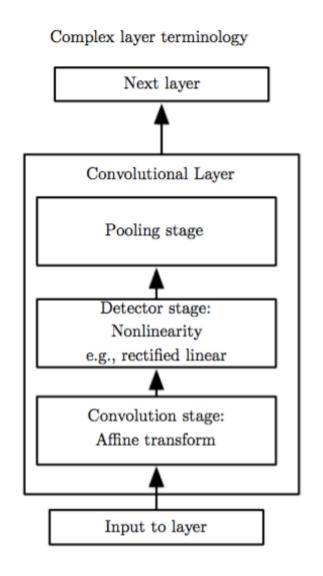
basically another name for 'neural networks' with many layers and generalized structure

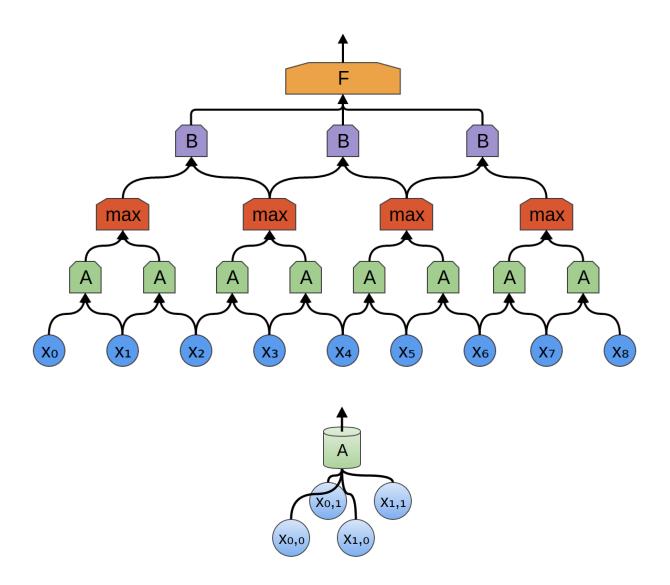
rebranded due to efficiency and good results on difficult tasks

language (translation, sentence completion) image recognition

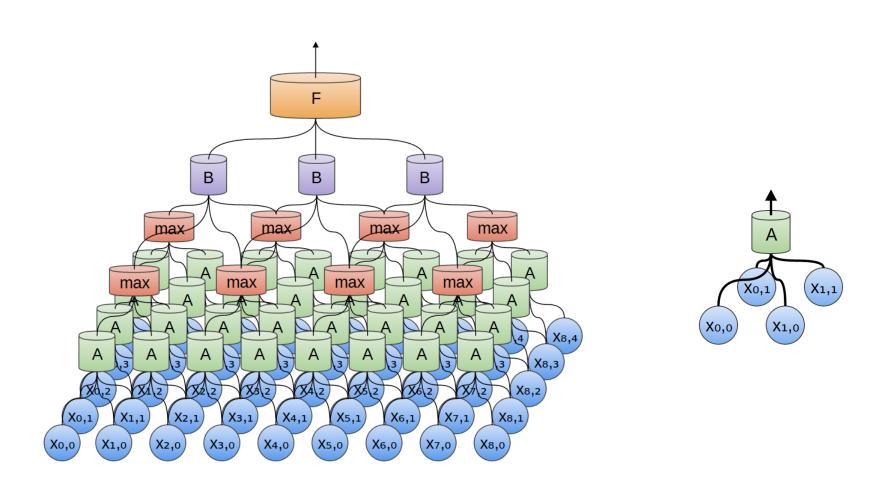
recurrent neural networks

convolutional neural networks





convolutional neural networks



part 2: platforms and software

outline

- scikit-learn
- deep-learning libraries
- ML on the cloud
 - amazon, azure, google
- apache spark

scikit-learn



python ML library on top of scipy stack

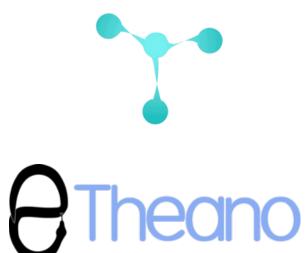
many general ML algorithms standardized pipeline ideal for fast prototyping on moderate datasets

deep learning :: tensorflow



deep learning library uses computation graphs

deep learning :: other







torch.ch

open source machine learning library scientific framework, programming language (Lua) used by Facebook Research

theano

http://deeplearning.net/software/theano/ deep learning with efficient numerical operations

microsoft cognitive toolkit (cntk)

https://cntk.ai/ tensorflow alternative

keras

simpler tensorflow, theano, cntk in python

cloud :: google



Cloud ML Engine

basically offers the ML pipeline with Deep Learning models as implemented in Tensorflow

other services
trained models for other applications
speech, video or image tagging, translation
https://cloud.google.com/products/machine-learning/
pricing: about 0.5\$ per hour

cloud :: other





amazon aws

classification and regression with logistic and linear regression

microsoft azure

'cortana intelligence'

ML pipeline

apache spark



machine learning algorithms on top of Spark

iterative optimization

part 3: hands-on session

outline

- scikit-learn
- tensorflow

scikit-learn

http://scikit-learn.org/

tensorflow

https://www.tensorflow.org/

the end...

ML pipeline

