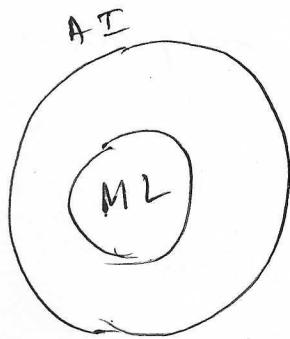


①

Introduction



[AI] \Rightarrow The broad goal

Building machines that can perform tasks that normally require human intelligence.

Ex: Reasoning & problem solving, understanding language, acting in an environment (robots, agents).

[ML] \Rightarrow A subset of AI.

Techniques that allow machines to learn patterns from data instead of being explicitly programmed.

Ex: Learning to classify images, translating languages, recommender systems.

[All ML is AI, but not all AI is ML]

Before ML dominated:

- AI systems were rule based.

- Ex: medical expert systems

- Ex: medical expert systems
If symptoms A AND B \rightarrow disease X

- Problems: hard to scale, fragile, required human experts to encode knowledge.



ML shift: Instead of rules, learn from examples.

Ex: Given 1 million labelled cases, learn disease prediction.

What is learning?

- The acquisition of knowledge or skills through experience, study, or being taught.

What is ML?

- Field or study that gives computers the ability to learn without being explicitly programmed.

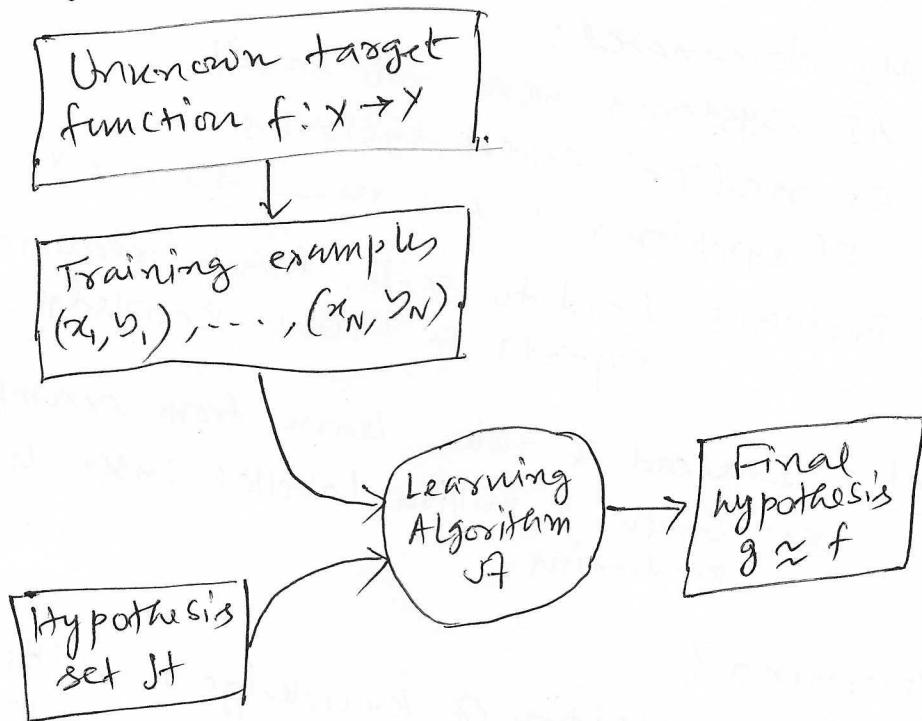
Types of learning

- Supervised: training data includes desired outputs.
- unsupervised: " " does not include " "
- weakly/semi-supervised: " " includes a few " "
- Reinforcement: Rewards from sequence of actions.

Supervised learning

Given examples of a function $(x, f(x))$, predict the function $f(x)$ for new examples. The function can be:

- Discrete \rightarrow classification (e.g. spam/not spam)
- Continuous \rightarrow regression (housing price, weather)
- probability \rightarrow probability estimation (e.g. patient symptom)



Training vs Testing

What do we want?

- good performance on training data?
- good performance on unseen test data.

Training data \rightarrow given to us for learning the function f

Testing data \rightarrow used to see if you have learnt anything

Usually a dataset is split into $\xrightarrow{\text{train}} \xrightarrow{\text{annotate}}$ & $\xrightarrow{\text{test}}$ $\xrightarrow{\text{check performance}}$.

②

Probability Review

Consider a non-deterministic event A (boolean variable)

What does $P(A)$ mean?

Frequentist view: limiting frequency of a repeating non-deterministic event

$$\lim_{N \rightarrow \infty} \frac{\# A \text{ is true}}{N}$$

Bayesian view: $P(A)$ is your "belief" about A.

Axioms of probability

- $0 \leq P(A) \leq 1$
- $P(\text{empty set}) = 0$
- $P(\text{everything}) = 1$
- $P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$

Sample space \rightarrow space of events

Random variables \rightarrow Mapping from events to numbers (set of possible values from a random experiment)

discrete continuous

Probability distribution \rightarrow List all possible outcomes of a random variable along with their corresponding values. e.g.: $\{H, T\}, \{1:1/6, 2:1/6, \dots, 6:1/6\}$

Probability Mass function (PMF) \rightarrow Probability that a discrete random variable equals a specific value.

$$P(X=x) = p(x)$$

Probability Density function (PDF) \rightarrow How dense probability is around values (in the continuous case, probability at an exact point is zero).

$$P(a \leq X \leq b) = \int_a^b f(x) dx$$

Expectations \rightarrow Long run average outcome (over many repetitions). weighted average, where weights are probabilities.

$$E_p[f(x)] = \sum_{x=1}^{\infty} p(x) f(x) \quad (\text{discrete})$$

$$= \int_{-\infty}^{\infty} p(x) f(x) dx \quad (\text{continuous})$$

Joint distribution (in discrete space) & Marginalization:

Ex: Suppose we observe 2 random variables.

W = Weather: Rainy, Sunny

U = Whether a person carries an umbrella: Yes, No.

Qn: What is the probability of a specific combination of Weather & umbrella choice?

Ex:- rainy AND carries an umbrella

- sunny AND does NOT carry an umbrella

- sunny AND carries an umbrella

Let's say after observing many days, we get:

W	U	$p(w, u)$
Rainy	Yes	0.4
Rainy	No	0.1
Sunny	Yes	0.1
Sunny	No	0.1

← This table is the joint distribution $p(w, u)$

Marginalization

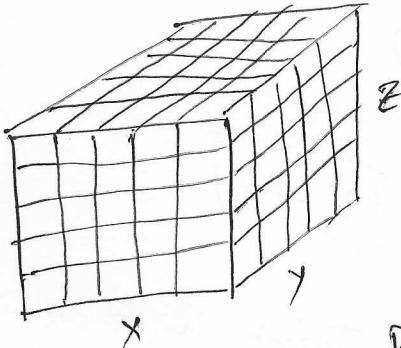
Suppose we ask what is the probability that it is

rainy, regardless of the umbrellas?

Then we marginalize out (ignore) the umbrella variable.
 $P(W=\text{Rainy}) = P(\text{Rainy}, \text{Yes}) + P(\text{Rainy}, \text{No}) = 0.4 + 0.1 = 0.5$

similar for $P(W=\text{Sunny})$ as well.

This is called marginal distribution of weather.



$$p(x, y) \downarrow \text{marginalize out } y$$

$$p(x=x) = \sum_y p(x=x, y=y)$$

↑
sum of all values where
 $x=x$ occurs with
all possible values of y

$$p(x, y, z)$$

↓ we want to compute $p(x)$

$$p(x, y) = \sum_z p(x, y, z)$$

$$p(x) = \sum_y p(x, y)$$

If there are n variables, we want marginalization of everything other than a single variable, we need $(n-1)$ summations.

Conditional probabilities:

$p(x=x | y=y)$: What do you believe about $y=y$, if I tell you $x=x$?

$$p(x, y | z) \quad (\text{conditioning on that slice out})$$

$$p(x, y | z=z) = \frac{p(x, y, z)}{p(z)}$$

Joint Marginal

chain rule

$$p(y=y | x=x) = \frac{p(y=y, x=x)}{p(x=x)}$$

$$\Rightarrow p(y=y, x=x) = p(y=y | x=x) p(x=x)$$

for d -dimensional case of joint distribution, we need to recursively apply the chain rule:

$$p(x_1=x_1, \dots, x_d=x_d) = p(x_2=x_2, \dots, x_d=x_d | x_1=x_1) p(x_1=x_1)$$

$$= p(x_3=x_3, \dots, x_d=x_d | x_2=x_2, x_1=x_1) p(x_2=x_2 | x_1=x_1) p(x_1=x_1)$$

$$= p(x_4=x_4, \dots, x_d=x_d | x_3=x_3, x_2=x_2, x_1=x_1) p(x_3=x_3 | x_2=x_2, x_1=x_1) p(x_2=x_2 | x_1=x_1) p(x_1=x_1)$$

$$= \prod_{j=1}^d p(x_j=x_j | x_1=x_1, \dots, x_{j-1}=x_{j-1})$$

Conditional independence

$$p(y=b, x=a) = p(y=b | x=a) p(x=a)$$

India wins World cup ↑
 ↓ ↑
 Joint is factorized into marginal.

$$= p(y=b) p(x=a)$$

$\boxed{X \perp Y}$

Bayes rule

From chain rule,

$$p(y=b, x=a) = p(y=b | x=a) p(x=a)$$

$$\xrightarrow{\text{swap}} p(x=a, y=b) = p(x=a | y=b) p(y=b)$$

$$\Rightarrow p(y=b | x=a) = \frac{p(x=a | y=b) p(y=b)}{p(x=a)}$$

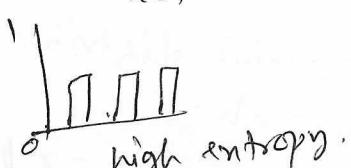
(what do you believe
of the classes after
you ~~see~~ see the data)

Likelihood
(how much does a
certain hypothesis
explain the data)

Normalization

Prior
(what do you
believe before
seeing any data)

Entropy: Measures amount of uncertainty in a distribution.

$$H(X) = - \sum_{x \in X} p(x) \log p(x)$$


KL divergence: An asymmetric measure of distance between two distributions.

$$KL[p || q] = \sum_x p(x) [\log p(x) - \log q(x)]$$

$KL > 0$ unless $p = q$ (in that case $KL = 0$)