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Answer 1) (a) Types of learning
(i) Supervised learning
(ii) Unsupervised learning
(iii) Semi-supervised learning
(iv) Reinforcement learning

(i) Supervised learning:-
Training data includes desired outputs learning using labeled data
Some example of SL is text classification problem. In this set of problem, the goal is to predict the class of a given piece of text.

(ii) Unsupervised learning:-
Training data does not include desired outputs learning using unlabled data.
Some examples:- clustering, Dimensionallity Reduction Finding customer segments clustering is an unsupervised technique.

(iii) Semi-supervised learning:-
Training data includes a few desired outputs.
A common example is text document classifier Because semi-supervised's ideal it would be nearly impossible to find a large amount of labeled documents.

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(iv) Reinformement learning
Rewards from sequence of actions
doesn't use labeled or unlabled data
in the traditional sense
In RL an agent learns via interaction
with an envioonment.
Ex:-
is your cat is an agent that is
exposed to the environment. the
biggest characteristic of RC is that
there is no subervision, only a real
no. or reward signal

(B) ⇒ In Maching learning, Generalization is
a definition to demonstrate how
well is a trained model to classify
or forecast unseen data. Training a
~~a~~ generalized machine learning
model means, in general, it works
for all subset of unseen data.

⇒ Generalization performale is the
fundamental problem in inductive
learning.
because,
Given a collection of examples
$(x^{(i)} f(x)^{(i)})$; $i=1,2,\dots n$ of a function
$f(x)$, return a function $h(x)$ that
approximates $f(x)$.

from a conceptual point of view,
it is not easy to tell wheather any

particular $h(x)$ is a good approximation of function, A good approximation will generalize well. It will predict novel patterns correctly.

=> let us assume given set of random example (x, y) from (x, y) to (x_n, y_n) draw from a probability distribution P over R.

Now,

True Risk fun w.r.t P as R

$$E\left[L(y, f(x, w))\right] = \int_{x*y} L(y, f(x,w))\, p(x, y)\, dx\, dy = R(w)$$

$$R(w) = E\left[(xw - y)^2\right] \quad -(1)$$

Therefore a learning machine can at ~~least is~~ best guarantee that the estimates o/p values $\hat{y}$ fit the true values y over training data.

As dataset is the only source of information the risk function given by (1) must be ~~approx~~ approximat the empirical risk ~~R~~ fun (w) :-

$$R_{emp}(w) = \frac{1}{N} \sum_{i=1}^{N} L(y^{(i)}, f(x^{(i)}, w)).$$