SECTION – A

(Short Answer Questions)

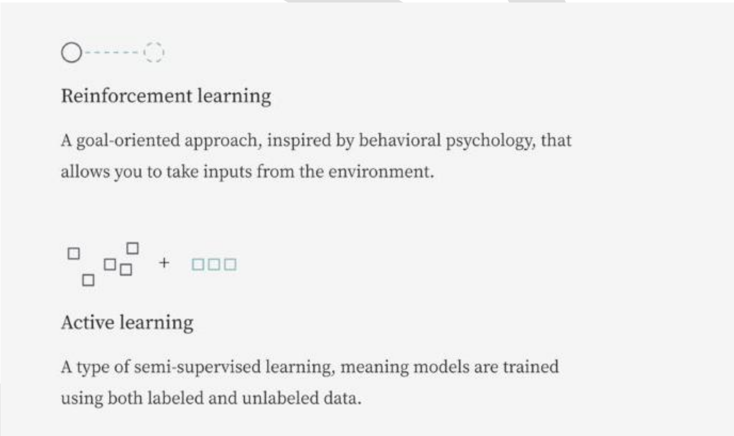
(2 Marks questions)

Unit – V

Category – 1 (Easy)

1. What is active learning?

Active learning is the subset of machine learning in which a learning algorithm can query a user interactively to label data with the desired outputs. In active learning, the algorithm proactively selects the subset of examples to be labeled next from the pool of unlabeled data. The fundamental belief behind the active learner algorithm concept is that an ML algorithm could potentially reach a higher level of accuracy while using a smaller number of training labels if it were allowed to choose the data it wants to learn from. Therefore, active learners are allowed to interactively pose queries during the training stage. These queries are usually in the form of unlabeled data instances and the request is to a human annotator to label the instance. This makes active learning part of the human-in-the-loop paradigm, where it is one of the most powerful examples of success.



Reference: https://algorithmia.com/blog/active-learning-machine-learning

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2. Write the process of reinforcement learning with a diagram.

Reinforcement Learning (RL) is a learning methodology by which the **learner learns to behave in an interactive environment using its own actions** and **rewards for its actions**. The learner, often called, **agent**, discovers which actions give the maximum reward by *exploiting* and *exploring* them

Example - Consider the scenario of teaching new tricks to your cat

As cat doesn't understand English or any other human language, we can't tell her directly what to do. Instead, we follow a different strategy. We emulate a situation, and the cat tries to respond in many different ways. If the cat's response is the desired way, we will give her fish. Now whenever the cat is exposed to the same situation, the cat executes a similar action with even more enthusiastically in expectation of getting more reward(food). That's like learning that cat gets from "what to do" from positive experiences. At the same time, the cat also learns what not do when faced with negative experiences. What is maximum likelihood hypothesis? Use cases of probabilistic graph models.
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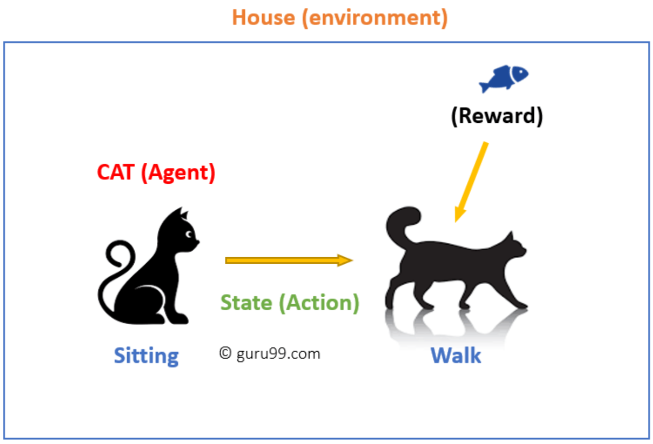

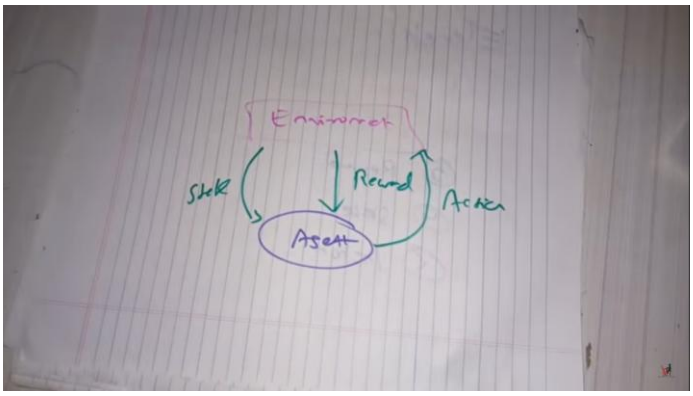

In this case, Your cat is an **agent** that is exposed to the environment. In this case, it is your house. An example of a state could be your cat sitting, and you use a specific word in for cat to walk. Our agent reacts by performing an action transition from one "state" to another "state."For example, your cat goes from sitting to walking. The reaction of an agent is an **action**, and the policy is a method of selecting an action given a state in expectation of better outcomes. After the transition, they may get a reward or penalty in return.

Reinforcement Learning Algorithms

There are three approaches to implement a Reinforcement Learning algorithm.

Value-Based: In a value-based Reinforcement Learning method, you should try to maximize a value function V(s). In this method, the agent is expecting a long-term return of the current states under policy .

Policy-based: In a policy-based RL method, you try to come up with such a policy that the action performed in every state helps you to gain maximum reward in the future.

Two types of policy-based methods are:

Deterministic: For any state, the same action is produced by the policy

Stochastic: Every action has a certain probability, which is determined by the following equation. Stochastic Policy :

n{a\s) = P\A, = a\S, =S]

Model-Based: In this Reinforcement Learning method, you need to create a virtual model for each environment. The agent learns to perform in that specific environment.

Reference: https://www.guru99.com/reinforcement-learning-tutorial.html **[READ THIS 100%]**

https://www.youtube.com/watch?v=3yJTInvfQvw **[ATLEAST WATCH THIS (10 min)]**

3. What are the approaches for scalable machine learning?

Category – 2 (Moderate)

1) Difference between supervised and reinforcement learning?

Criteria	Supervised Learning	Unsupervised Learning	Reinforcement Learning
Definition	The machine learns by using labeled data	The machine is trained on unlabeled data without any guidance	An agent interacts with its environment by performing actions & learning from errors or rewards
Type of problems	Regression & classification	Association & clustering	Reward-based
Type of data	Labeled data	Unlabeled data	No predefined data
Training	External supervision	No supervision	No supervision
Approach	Maps the labeled inputs to the known outputs	Understands patterns & discovers the output	Follows the trial-and-error method

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2) Differentiate between exploration and exploitation in reinforcement learning ?

KAIST AIPR Lab.

Exploration vs. Exploitation

- Exploration
  - ✓ To discover better action selections
  - ✓ To improve its knowledge
- Exploitation
  - ✓ To maximize its reward based on what it already knows
- *Exploration-exploitation dilemma*
  - ✓ Both can't be pursued exclusively without failing

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Exploration versus Exploitation

- Two reasons to take an action in RL
  - **Exploitation**: To try to get reward. We exploit our current knowledge to get a payoff.
  - **Exploration**: Get more information about the world. How do we know if there is not a pot of gold around the corner.
- To explore we typically need to take actions that do not seem best according to our current model.
- Managing the trade-off between exploration and exploitation is a critical issue in RL
- Basic intuition behind most approaches:
  - Explore more when knowledge is weak
  - Exploit more as we gain knowledge

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3) How is semi-supervised learning different from supervised learning ?

	Overview	Process	Subtypes	Examples
Supervised Learning	Majority of algorithms. Machine is trained using **well-labeled data**; inputs and outputs are matched.	Mapping function takes inputs and matches to outputs, creating a target function.	Classification, Regression	Linear regression, Random forest, SVM.
Unsupervised Learning	**Unlabeled data** (inputs only) is analyzed. Learning happens without supervision.	Inputs are used to create a model of the data.	Clustering, Association.	PCA, k-Means, Hierarchical clustering.
Semi supervised	**Some data is labeled**, some not. Goal: better results than labeled data alone. Good for real world data.	Combination of above processes.	All the above.	Self training, Mixture models, Semi-supervised SVM

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4) What is represented in R matrix in reinforcement learning?

The R-matrix represents the environment in which the agent will be operating, viewed in terms of the states which the agent can be in, the actions available to the agent from each state (which are generally viewed as moves to other states) and the rewards received for arriving at a state. The agent does not know the whole R-matrix; all it can see are the moves immediately available to it.

States	Actions: Arsenal	Finsbury Park	Manor House	Seven Sisters	Stamford Hill	Tottenham Hale
Arsenal	0	0	-	-	-	-
Finsbusry Park	0	0	0	0	-	-
Manor House	-	0	0	-	-	-
Seven Sisters	-	0	-	0	0	100
Stamford Hill	-	-	-	0	0	-
Tottenham Hale	-	-	-	0	-	100

The table above is an R-matrix for navigating the small section of the London underground shown in the image, where the goal is to reach Tottenham Hale station. Each row of the table describes a single state, with the values in each column representing the rewards received by the agent for moving to another state. For example, when at Stamford Hill, the agent can either stay at Stamford Hill, or move to Seven Sisters.

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5) Differentiate between on-line machine learning off-line machine learning.

Offline Learning	Features	Online Learning
Less complex as model is constant	**Complexity**	Dynamic complexity as the model keeps evolving over time
Fewer computations, single time batch-based training	**Computational Power**	Continuous data ingestions result in consequent model refinement computations
Easier to implement	**Use in Production**	Difficult to implement and manage
Image Classification or anything related to Machine Learning - where data patterns remains constant without sudden concept drifts	**Applications**	Used in finance, economics, heath where new data patterns are constantly emerging
Industry proven tools. E.g. Sci-kit, TensorFlow, Pytorch, Keras, Spark Mlib	**Tools**	Active research/New project tools: E.g. MOA, SAMOA, scikit-multiflow, streamDM
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SECTION – B

(8 Marks questions)**Easy Questions**

1. What are components of reinforcement learning?

Reinforcement learning consists of three primary components: (i) the agent (learning agent); (ii) the environment (agent interacts with environment); and (iii) the actions (agents can take actions). An agent learns from the environment by interacting with it and receiving rewards for performing actions.

Reference: https://www.guru99.com/reinforcement-learning-tutorial.html **[same as qn 1 in 2 marks]**

https://www.youtube.com/watch?v=3yJTInvfQvw [full clarity, and example is also there]

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2. Write the steps in Q-learning algorithm.

Here are the 3 basic steps:

- Agent starts in a state (s1) takes an action (a1) and receives a reward (r1)
- Agent selects action by referencing Q-table with highest value (max) OR by random (epsilon, ε)
- Update q-values.

Reference: https://towardsdatascience.com/simple-reinforcement-learning-q-learning-fcddc4b6fe56 **[refer this max]**

https://www.youtube.com/watch?v=ibBEEZNQZtk [best video for q learning]

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3. In a dataset with few labeled examples, what are the methods to generating labels for unlabelled examples.

- Given a dataset of 100.000 emails but only 10.000 of them are labeled.
- The unlabelled examples need not be annotated.
- Instead the labeled elements could be used to train the AI.
- After this, the expectation-maximization machine learning algorithm can be used to automate the process of annotation for the whole set of unlabeled data.
- This way, a unique combination of predictive and descriptive algorithms from supervised and unsupervised learning respectively is obtained.
- This approach is known as **semi supervised learning. -**Semi-supervised machine learning is a combination of supervised and unsupervised learning. It uses a small amount of labeled data and a large amount of unlabeled data, which provides the benefits of both unsupervised and supervised learning while avoiding the challenges of finding a large amount of labeled data. That means you can train a model to label data without having to use as much labeled training data.

Reference: https://algorithmia.com/blog/semi-supervised-learning

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4. Write the real world applications of reinforcement learning.

https://www.google.com/amp/s/neptune.ai/blog/reinforcement-learning-applications/amp
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Moderate Questions

1. Difference between supervised , unsupervised and semi-supervised learning.

	Overview	Process	Subtypes	Examples
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Styles of Learning

Supervised	Unsupervised	Semi-Supervised	Reinforcement
• Data has **known labels** or output	• Labels or output unknown • Focus on **finding patterns and gaining insight** from the data	• Labels or output known for **a subset of** data • A blend of supervised and unsupervised learning	• Focus on **making decisions** based on previous experience • Policy-making with feedback
• Insurance underwriting • Fraud detection	• Customer clustering • Association rule mining	• Medical predictions (where tests and expert diagnoses are expensive, and only part of the population receives them)	• Game AI • Complex decision problems • Reward systems

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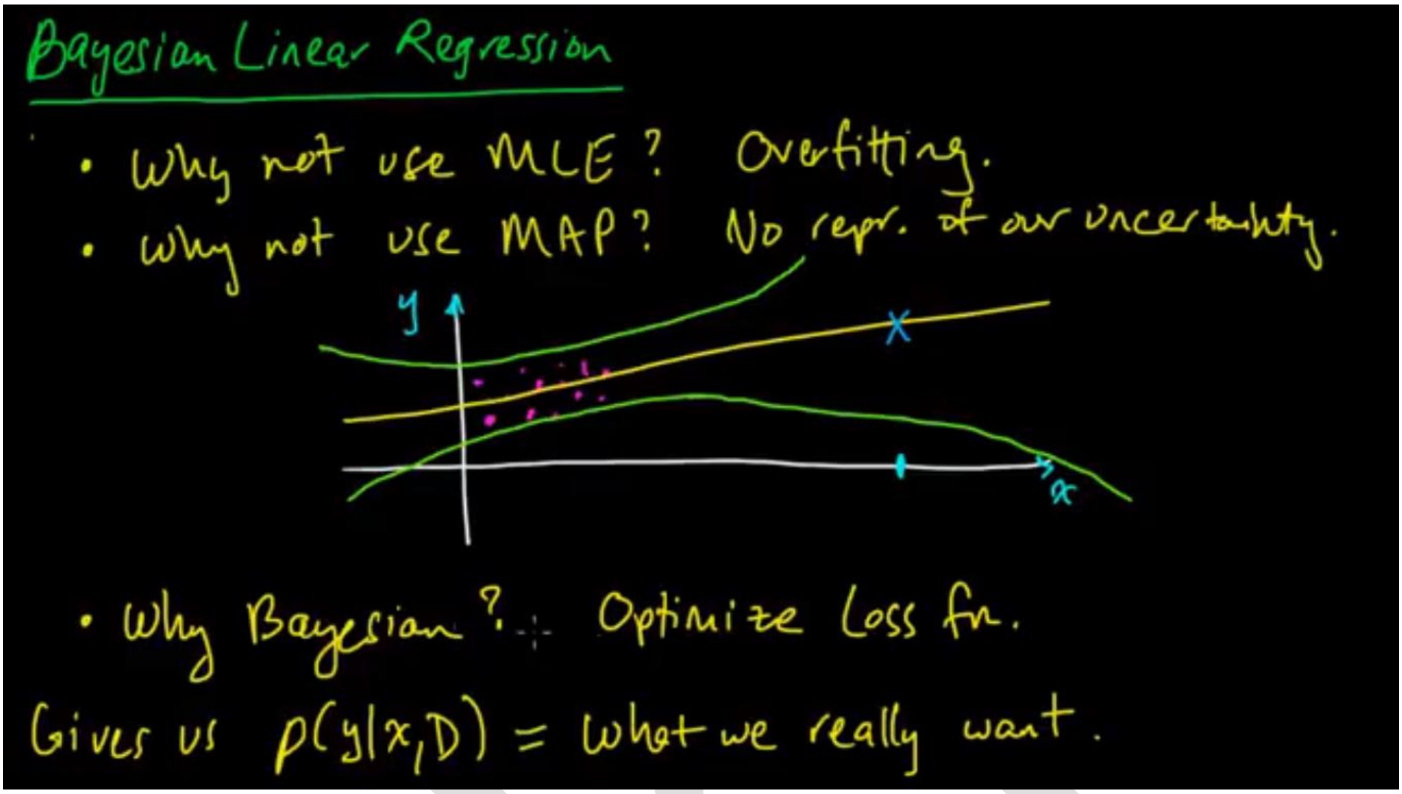
MACHINE LEARNING

Supervised Learning		Unsupervised Learning		Deep Learning (semi-supervised)		
Regressors	Classifiers	Dimension Reducers	Clustering Methods	Unsupervised Pretrained Networks	Convolutional Neural Networks	Recurrent Neural Networks
Wireline log prediction Spatial interpolation Sesimic inversion (with numeric labels)	Automatic facies prediction from wireline logs Seismic inversion (with categ-orical labels)	Compressing high-dimensional data Increasing signal-to-noise ratio in data	AVO class prediction Seismic inversion (uncalibrated)	Seismic denoising Seismic multiple removal Seismic migration	Seismic structural feature/fault detection Automatic facies prediction from borehole imagery	Microseismic analysis Sedimentary process modelling Earthquake prediction

2. Deduce linear regression cost function using Bayesian learning.

https://www.youtube.com/watch?v=1WvnpjljKXA **[SEE FROM 3:30]**



In Bayesian learning, the classifiers assume that the probability of the presence or absence of the state of a feature which is modified by the states of other features.

Once the classical machine learning model is represented as probabilistic models with random variables, Bayesian learning is used to infer the unknown model parameters. Such a **process of learning unknown parameters of a model is known as Bayesian inference.**

Bayesian learning for linear regression:

The simple linear regression tries to fit the relationship between **dependent variable Y** and **single predictor (independent) variable X** into a straight line. We can write that linear relationship as:

$$y_i=\tau+w.x_i+\epsilon_i \quad (1)$$

Here τ is the **intercept** and w is the **coefficient of the predictor variable**. The term ϵ_i represents **the individual error** when modelling real-world data that does not fit perfectly to a straight line.

Now we have to determine the values for these unknown parameters τ and w minimizing the total error. In Bayesian learning, we represent variables as random variables with probability distributions.

We have defined three prior distributions corresponding to each unknown variable in the linear regression model:

1. Coefficient of x (x_coeff) - Normal distribution
2. Intercept - Normal distribution
3. Error term (sigma) - Half Cauchy distribution

Once we have defined the priors, we need to specify the likelihood of our model. This is done **by modifying the above linear regression model to a logistic regression model by simply replacing the normal likelihood with the Bernoulli likelihood:**

$$P = \text{sigmoid}\,(w.x_i+\tau)$$

Using concept of normal distribution, we get:

$$y_i \sim N\,(w.x_i+\tau,\sigma^2)$$

If we apply the Bayes' theorem to **$P\,(w,\tau,\sigma^2|Y,X)P(w,\tau,\sigma^2|Y,X)$,** we get the following expression,

$$\underbrace{P(w,\tau,\sigma^2|Y,X)}_{\text{posterior}} = \frac{\overbrace{P(Y|w,\tau,\sigma^2,X)}^{}_{\text{likelihood}}\underbrace{P(w,\tau,\sigma^2)}_{\text{prior}}}{\underbrace{P(Y|X)}_{\text{evidence}}}$$

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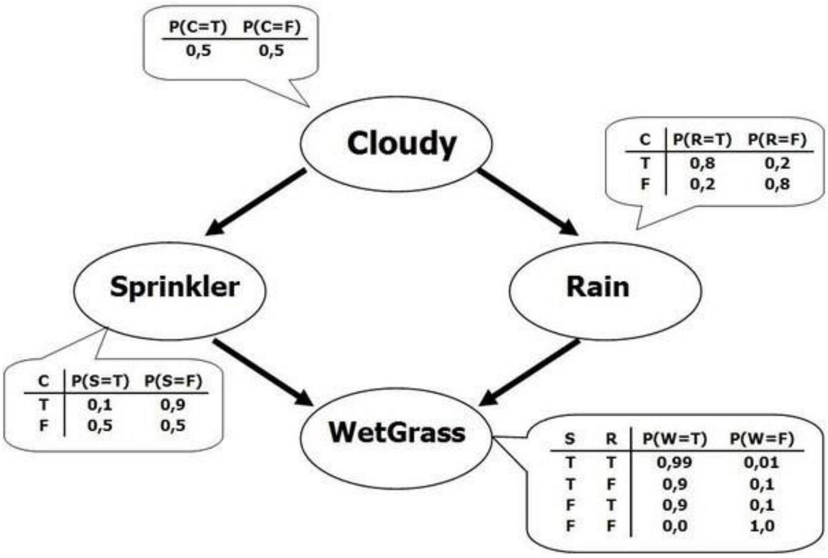
STANDARD

3. Does Bayesian network give compact representation of dependencies? Illustrate with example.

- Using the relationships specified by our Bayesian network, we can obtain a compact, factorized representation of the joint probability distribution by taking advantage of conditional independence.



- A Bayesian network is a **directed acyclic graph** in which each edge corresponds to a conditional dependency, and each node corresponds to a unique random variable.
- Formally, if an edge (A, B) exists in the graph connecting random variables A and B, it means that P(B|A) is a **factor** in the joint probability distribution, so we must know P(B|A) for all values of B and A in order to conduct inference.
- In the above example, since Rain has an edge going into WetGrass, it means that P(WetGrass|Rain) will be a factor, whose probability values are specified next to the WetGrass node in a conditional probability table.
- Bayesian networks satisfy the **local Markov property**, which states that a node is conditionally independent of its non-descendants given its parents.
- In the above example, this means that P(Sprinkler|Cloudy, Rain) = P(Sprinkler|Cloudy) since Sprinkler is conditionally independent of its non-descendant, Rain, given Cloudy.
- This property allows us to simplify the joint distribution, obtained in the previous section using the chain rule, to a smaller form.
- After simplification, the joint distribution for a Bayesian network is equal to the product of P(node|parents(node)) for all nodes, stated below:

$$P(X_1,\ldots,X_n) = \prod_{i=1}^{n} P(X_i \mid X_1,\ldots,X_{i-1}) = \prod_{i=1}^{n} P(X_i \mid Parents(X_i))$$

- In larger networks, this property allows us to greatly reduce the amount of required computation, since generally, most nodes will have few parents relative to the overall size of the network.
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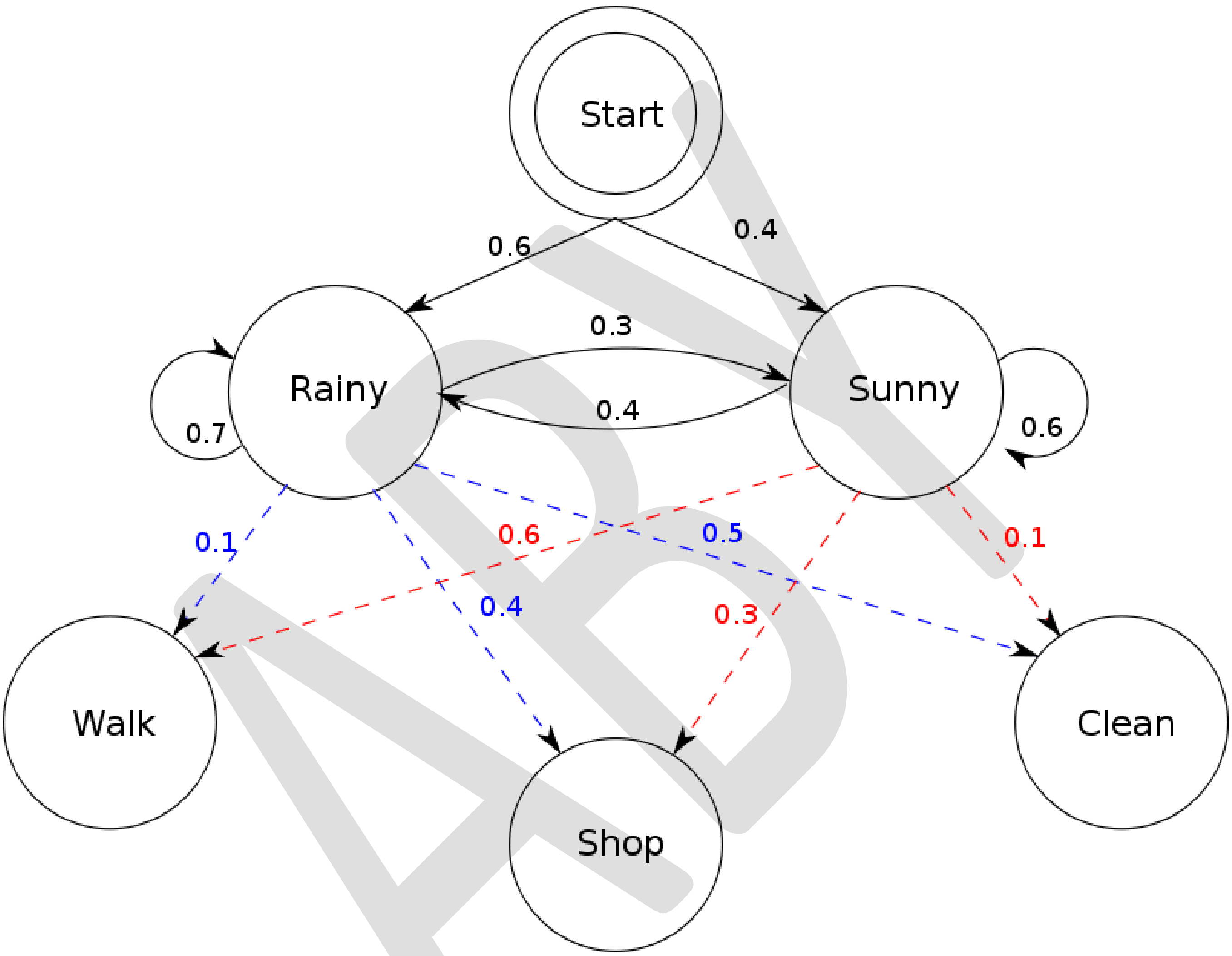
3. Is HMM a graph model? Write the components of a graph model?

A hidden Markov model (HMM) is a probabilistic **graphical model** that is commonly used in **statistical pattern recognition and classification**.

It is a powerful tool for **detecting weak signals**, and has been successfully **applied in temporal pattern recognition** such as speech, handwriting, word sense disambiguation, and computational biology.



A HMM consists of two components. Each HMM contains a series of discrete-state, time-homologous, first-order Markov chains (MC) with suitable transition probabilities between states and an initial distribution.

A MC is a discrete-time process for which the next state is conditionally independent of the past given the current state.

Each state has a discrete or continuous probability distribution over possible emissions or outputs.

These outputs are generated when a particular state is visited or during transition from one state to another.

State-to-state transitions are guided by a set of transition and emission probabilities. The transition probability is the probability of moving from one state to another via a connected edge, and the emission probability is the probability of emitting a particular symbol at a state. The sequences of states through which the model passes are hidden and cannot be observed, hence the name hidden Markov model. The probability of any sequence, given the model, is computed by multiplying the emission and transition probabilities along the path.

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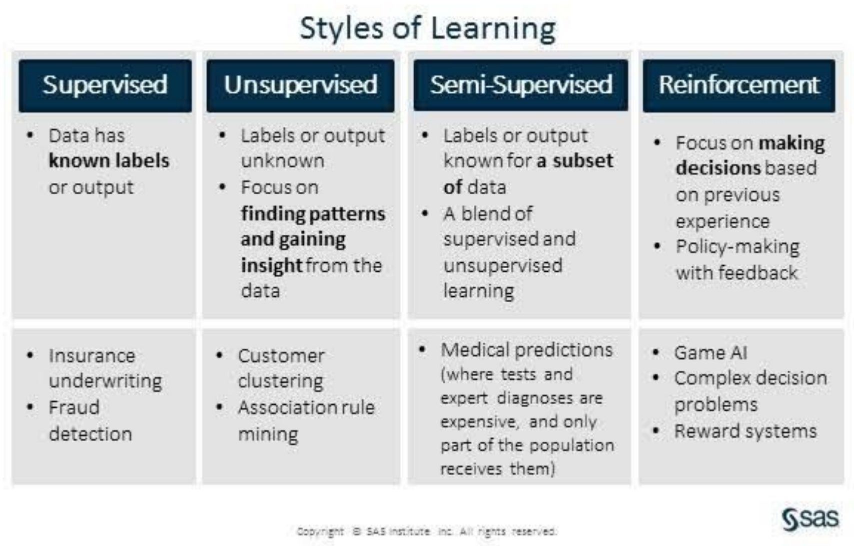
Standard Questions

1. How do you get optimal classifier in Bayesian learning?

https://machinelearningmastery.com/bayes-optimal-classifier/#:~:text=Bayes%20Optimal%20Classifier-,The%20Bayes%20optimal%20classifier%20is%20a%20probabilistic%20model%20that%20makes,the%20Bayes%20optimal%20discriminant%20function.

2. What applications are suited for semi-supervise learning ?



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