Different Types of Learning

Machine Learning Techniques to solve problems

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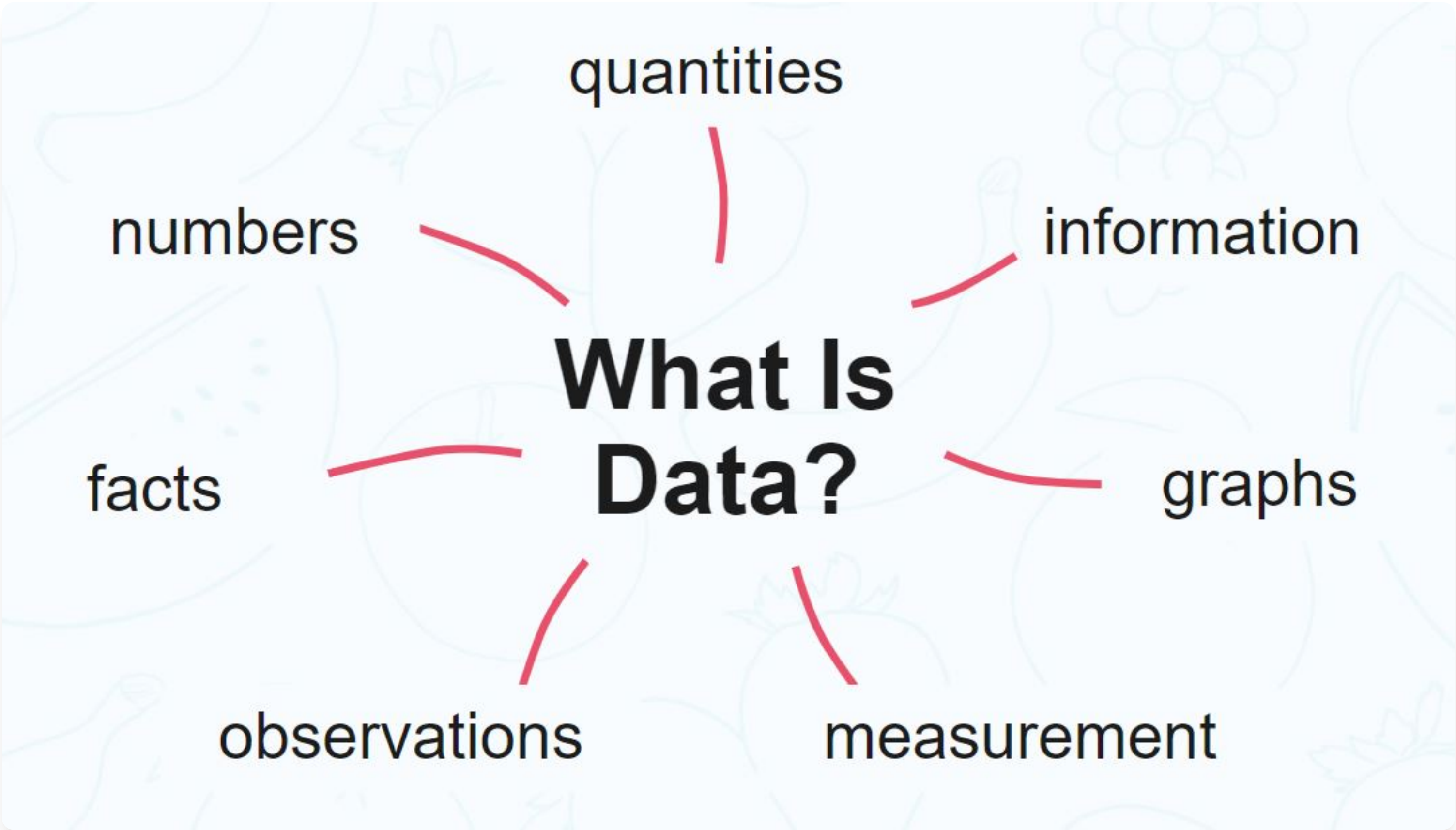

quantities
numbers
information
What Is Data?
facts
graphs
observations
measurement

What is Machine Learning?

- Machine learning is a large field of study that overlaps with and inherits ideas from many related fields such as artificial intelligence.
- The focus of the field is learning, that is, acquiring skills or knowledge from experience. Most commonly, this means synthesizing useful concepts from historical data.
- There are many different types of learning that you may encounter as a practitioner in the field of machine learning: from whole fields of study to specific techniques.

Types of Learning

Learning Problems	Hybrid Learning Problems	Statistical Inference	Learning Techniques
1. Supervised Learning	4. Semi-Supervised Learning	7. Inductive Learning	10. Multi-Task Learning
2. Unsupervised Learning	5. Self-Supervised Learning	8. Deductive Inference	11. Active Learning
3. Reinforcement Learning	6. Multi-Instance Learning	9. Transductive Learning	12. Online Learning
			13. Transfer Learning
			14. Ensemble Learning

1. Supervised Learning

CATEGORY: LEARNING PROBLEMS

Supervised learning describes a class of problem that involves using a model to learn a mapping between input examples and the target variable.

There are two main types of supervised learning problems:

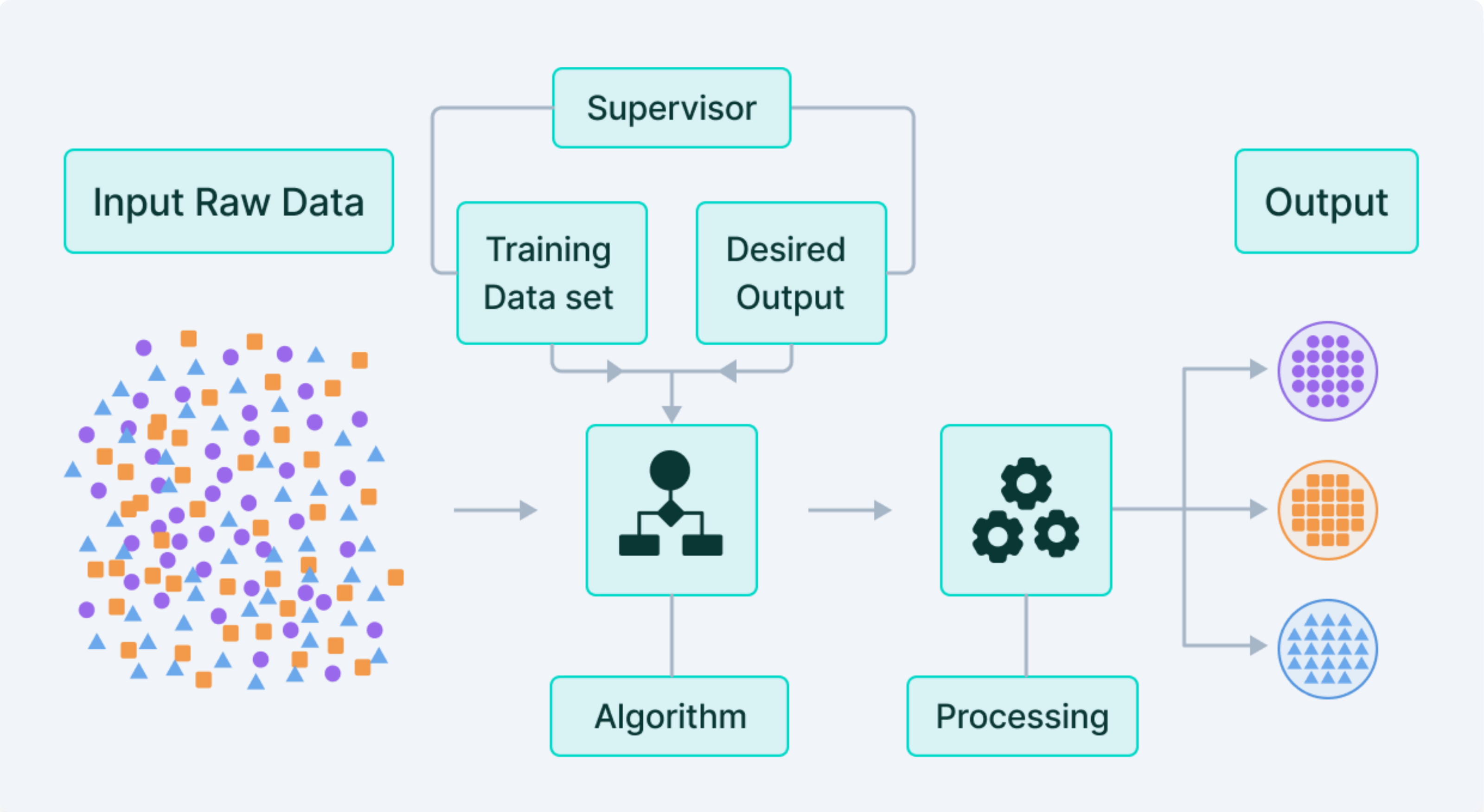
- **Classification:** Supervised learning problem that involves predicting a class label.
- **Regression:** Supervised learning problem that involves predicting a numerical label.

Both classification and regression problems may have one or more input variables and input variables may be any data type, such as numerical or categorical.

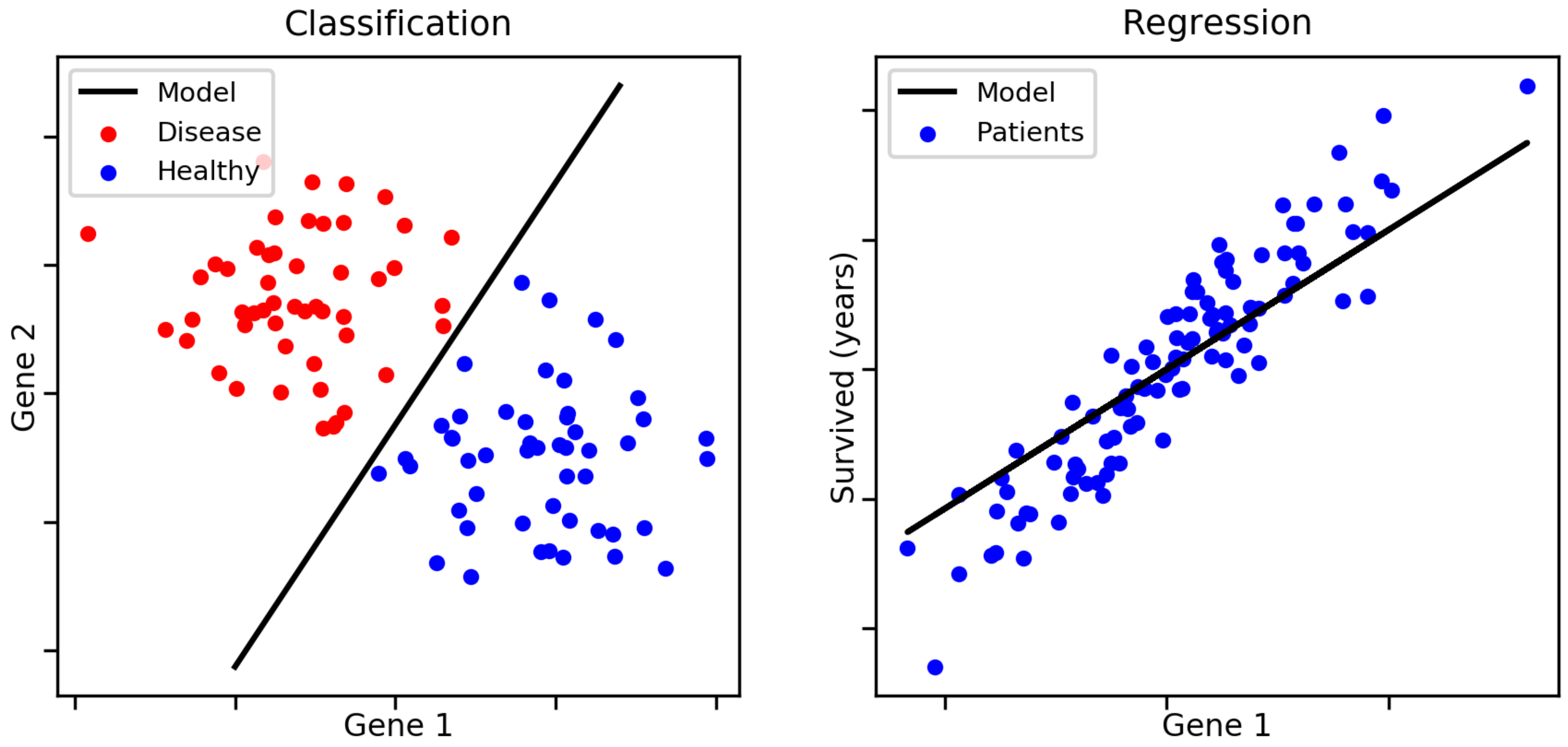
Dataset Example

age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	target
30	unemployed	married	primary	no	1787	no	no	cellular	19	oct	79	1	-1	0	unknown	no
33	services	married	secondary	no	4789	yes	yes	cellular	11	may	220	1	339	4	failure	no
35	management	single	tertiary	no	1350	yes	no	cellular	16	apr	185	1	330	1	failure	no
30	management	married	tertiary	no	1476	yes	yes	unknown	3	jun	199	4	-1	0	unknown	no
59	blue-collar	married	secondary	no	0	yes	no	unknown	5	may	226	1	-1	0	unknown	no
35	management	single	tertiary	no	747	no	no	cellular	23	feb	141	2	176	3	failure	no
36	self-employed	married	tertiary	no	307	yes	no	cellular	14	may	341	1	330	2	other	no
39	technician	married	secondary	no	147	yes	no	cellular	6	may	151	2	-1	0	unknown	no
41	entrepreneur	married	tertiary	no	221	yes	no	unknown	14	may	57	2	-1	0	unknown	no
43	services	married	primary	no	-88	yes	yes	cellular	17	apr	313	1	147	2	failure	no
39	services	married	secondary	no	9374	yes	no	unknown	20	may	273	1	-1	0	unknown	no
43	admin.	married	secondary	no	264	yes	no	cellular	17	apr	113	2	-1	0	unknown	no
36	technician	married	tertiary	no	1109	no	no	cellular	13	aug	328	2	-1	0	unknown	no
20	student	single	secondary	no	502	no	no	cellular	30	apr	261	1	-1	0	unknown	yes
31	blue-collar	married	secondary	no	360	yes	yes	cellular	29	jan	89	1	241	1	failure	no
40	management	married	tertiary	no	194	no	yes	cellular	29	aug	189	2	-1	0	unknown	no
56	technician	married	secondary	no	4073	no	no	cellular	27	aug	239	5	-1	0	unknown	no
37	admin.	single	tertiary	no	2317	yes	no	cellular	20	apr	114	1	152	2	failure	no
25	blue-collar	single	primary	no	-221	yes	no	unknown	23	may	250	1	-1	0	unknown	no
31	services	married	secondary	no	132	no	no	cellular	7	jul	148	1	152	1	other	no
38	management	divorced	unknown	no	0	yes	no	cellular	18	nov	96	2	-1	0	unknown	no
42	management	divorced	tertiary	no	16	no	no	cellular	19	nov	140	3	-1	0	unknown	no
44	services	single	secondary	no	106	no	no	unknown	12	jun	109	2	-1	0	unknown	no
44	entrepreneur	married	secondary	no	93	no	no	cellular	7	jul	125	2	-1	0	unknown	no
26	housemaid	married	tertiary	no	543	no	no	cellular	30	jan	169	3	-1	0	unknown	no
41	management	married	tertiary	no	5883	no	no	cellular	20	nov	182	2	-1	0	unknown	no
55	blue-collar	married	primary	no	627	yes	no	unknown	5	may	247	1	-1	0	unknown	no
67	retired	married	unknown	no	696	no	no	telephone	17	aug	119	1	105	2	failure	no
56	self-employed	married	secondary	no	784	no	yes	cellular	30	jul	149	2	-1	0	unknown	no

Dataset Example



Classification vs Regression



2. Unsupervised Learning

CATEGORY: LEARNING PROBLEMS

Unsupervised learning describes a class of problems that involves using a model to describe or extract relationships in data.

Compared to supervised learning, unsupervised learning operates upon only the input data without outputs or target variables. As such, unsupervised learning does not have a teacher correcting the model, as in the case of supervised learning.

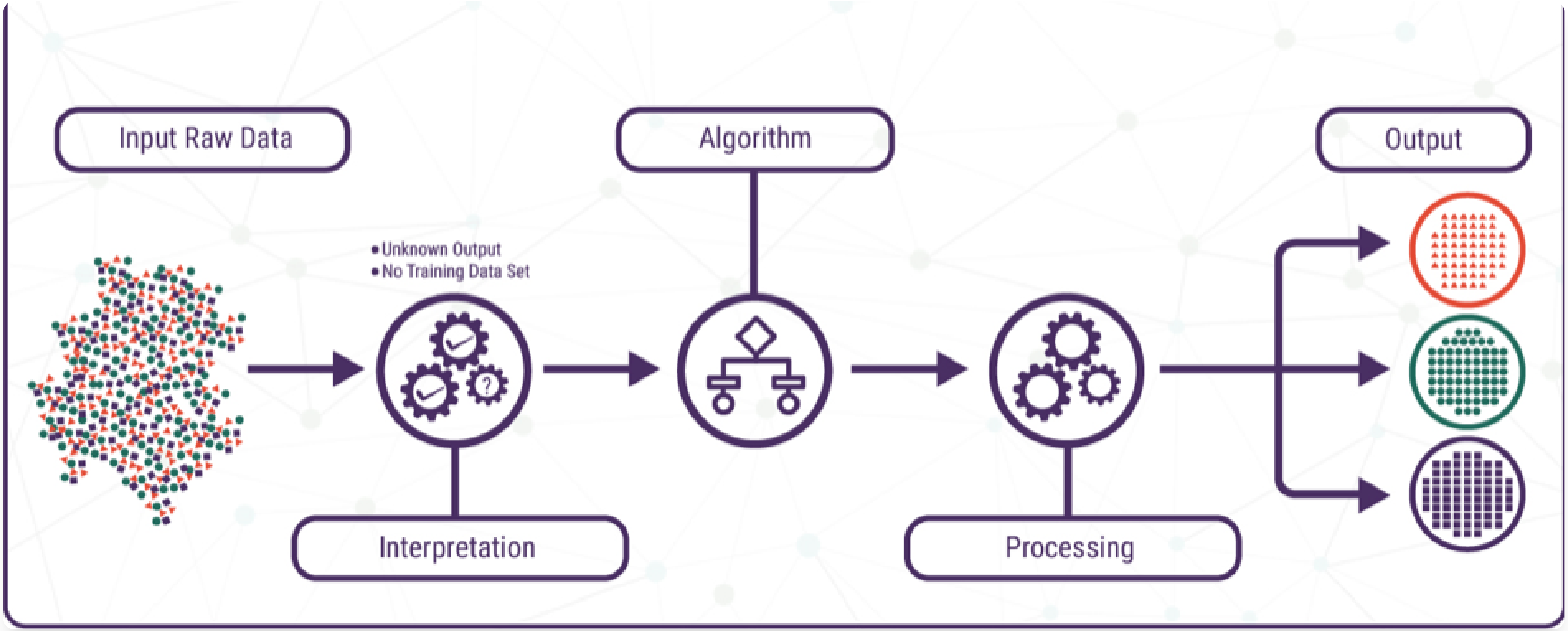
There are many types of unsupervised learning, although there are two main problems that are often encountered by a practitioner:

- **Clustering:** Unsupervised learning problem that involves finding groups in data.
- **Density Estimation:** Unsupervised learning problem that involves summarizing the distribution of data.

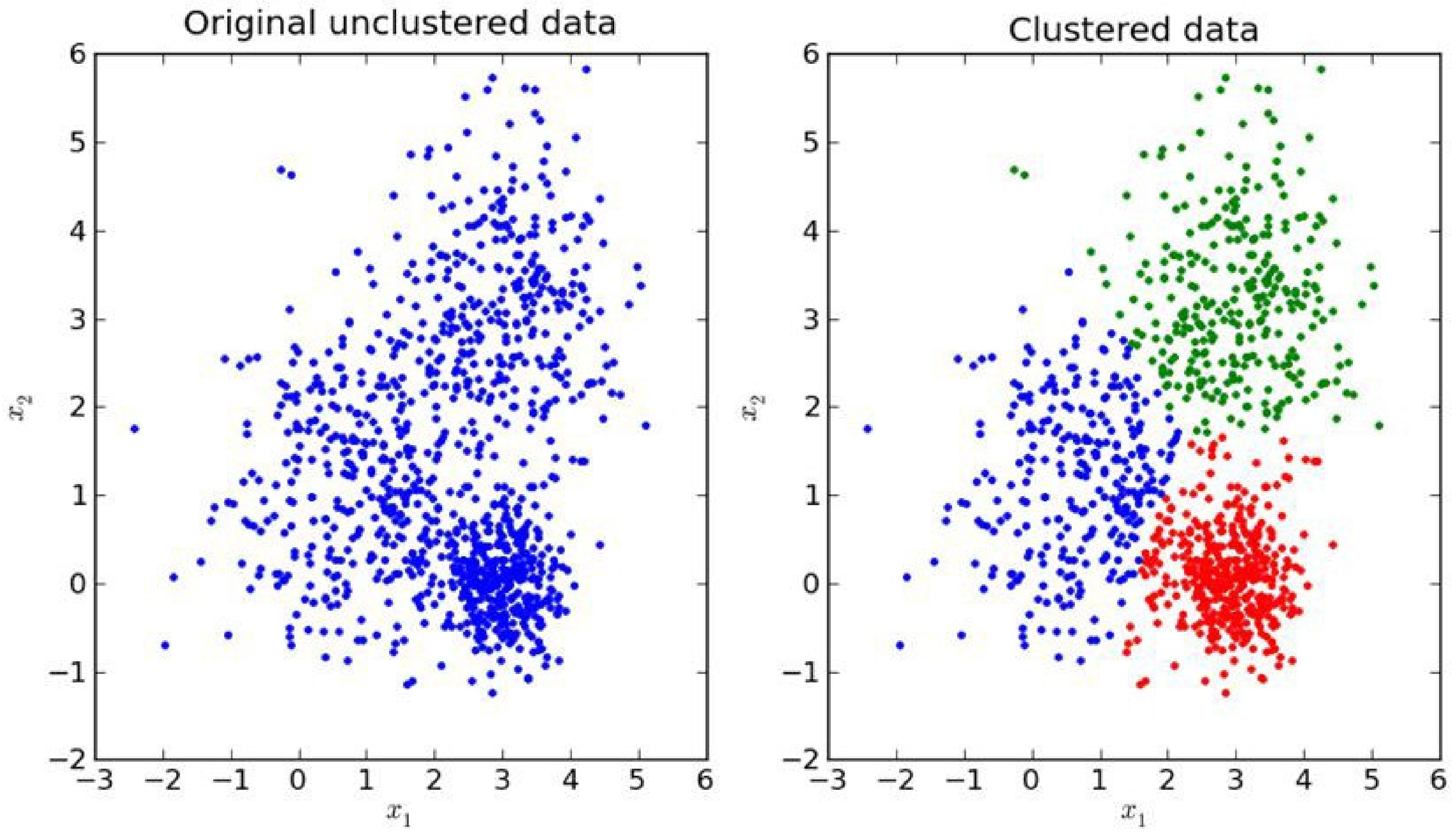
Additional unsupervised methods may also be used, such as visualization that involves graphing or plotting data in different ways and projection methods that involves reducing the dimensionality of the data.

- **Visualization:** Unsupervised learning problem that involves creating plots of data.

Unsupervised Learning



Clustering and Density Estimation



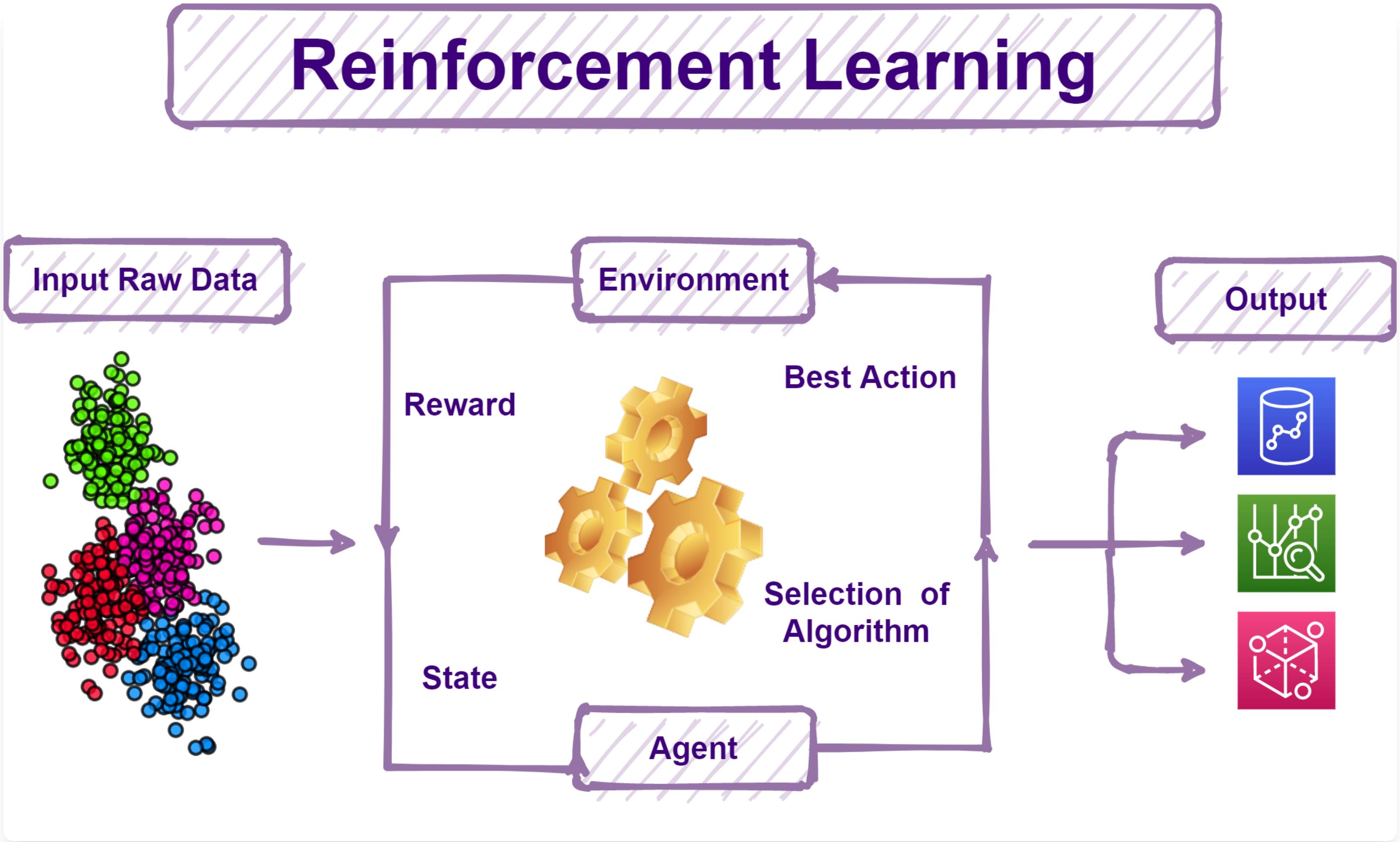
3. Reinforcement Learning

CATEGORY: LEARNING PROBLEMS

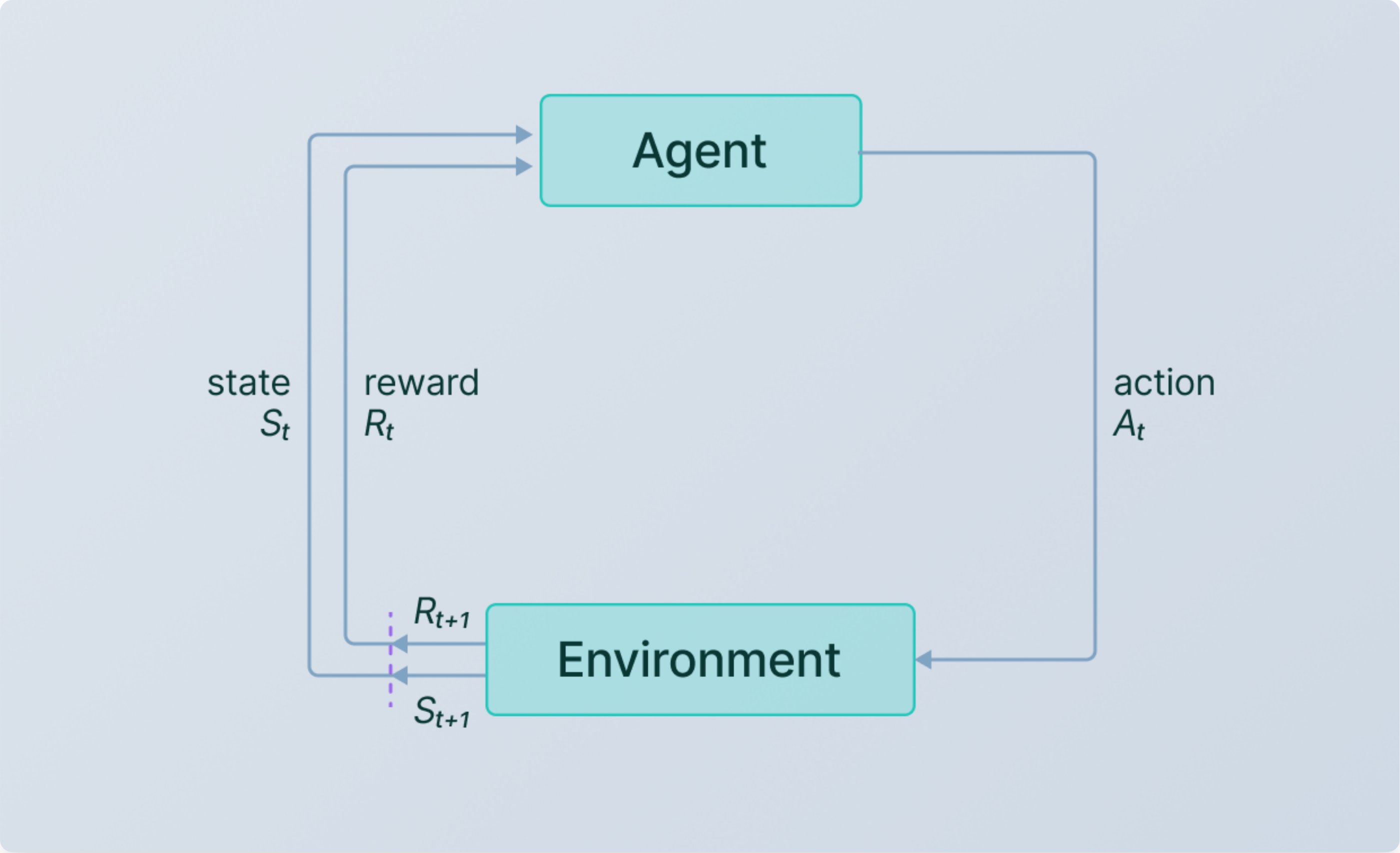
Reinforcement learning describes a class of problems where an agent operates in an environment and must learn to operate using feedback.

Reinforcement learning is learning what to do — how to map situations to actions—so as to maximize a numerical reward signal. The learner is not told which actions to take, but instead must discover which actions yield the most reward by trying them.

The use of an environment means that there is no fixed training dataset, rather a goal or set of goals that an agent is required to achieve, actions they may perform, and feedback about performance toward the goal.


Reinforcement Learning
Input Raw Data
Environment
Output
Reward
Best Action
Selection of Algorithm
State
Agent

Reinforcement Learning Cycle



4. Semi-Supervised Learning

CATEGORY: HYBRID LEARNING PROBLEMS

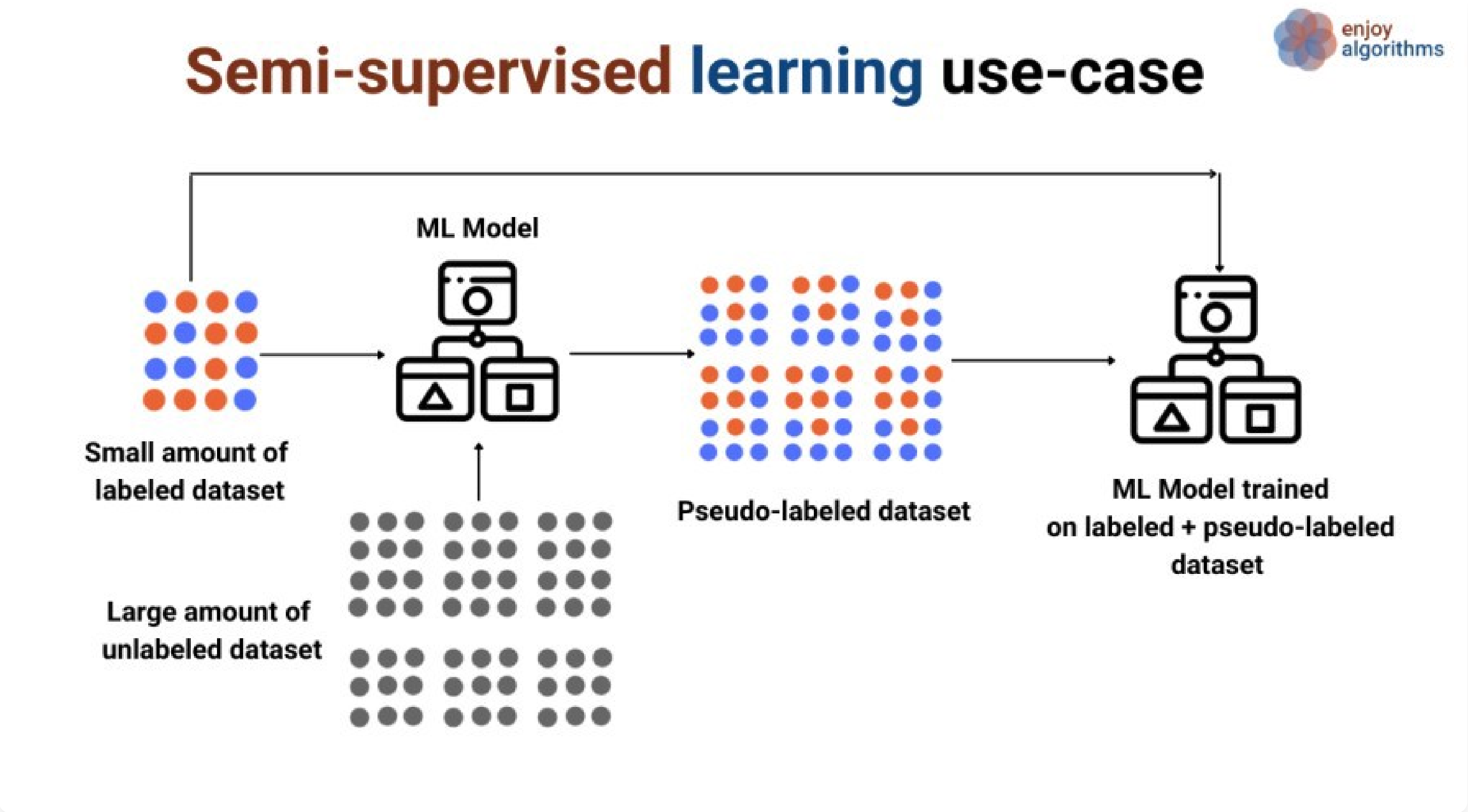
Semi-supervised learning is supervised learning where the training data contains very few labeled examples and a large number of unlabeled examples.

The goal of a semi-supervised learning model is to make effective use of all of the available data, not just the labelled data like in supervised learning.

Many problems from the fields of computer vision (image data), natural language processing (text data), and automatic speech recognition (audio data) fall into this category and cannot be easily addressed using standard supervised learning methods.

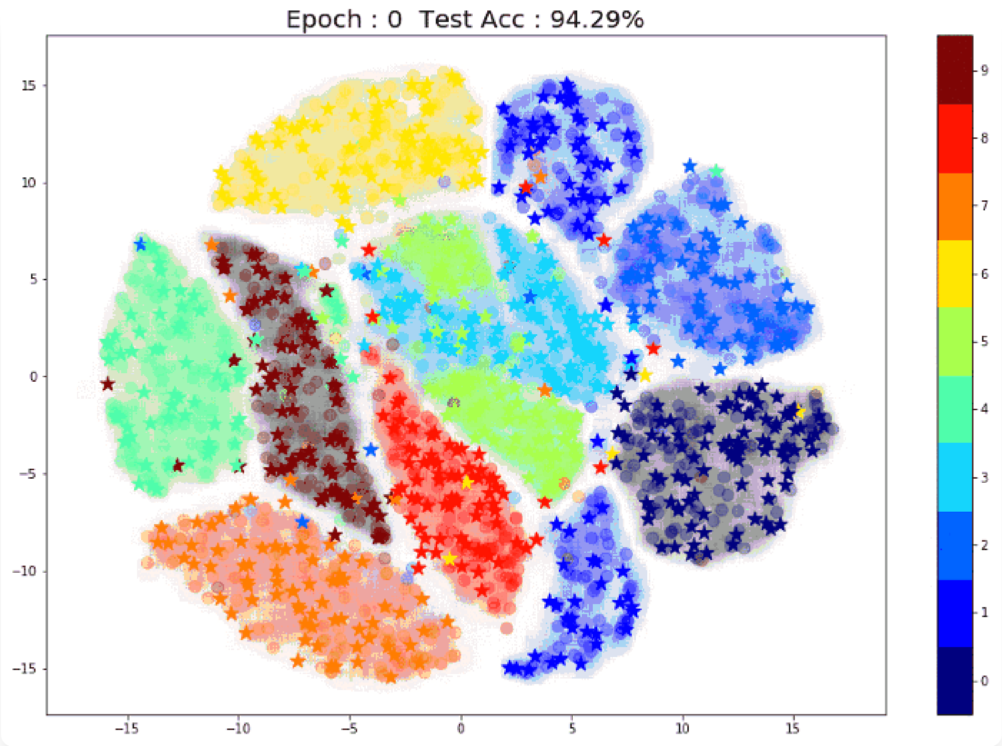
LABELED DATA + UNLABELED DATA

SUPERVISED + UNSUPERVISED


Semi-supervised learning use-case
enjoy algorithms
ML Model
Small amount of labeled dataset
Large amount of unlabeled dataset
Pseudo-labeled dataset
ML Model trained on labeled + pseudo-labeled dataset

Pseudo Labelling

Pseudo labelling is the process of using the labelled data model to predict labels for unlabelled data.



Pseudo Labelling

Pseudo labelling is the process of using the labelled data model to predict labels for unlabelled data.

Now instead of simply adding the unlabeled loss with the labeled loss, Lee proposes using weights. The overall loss function looks like this:

$$L = \frac{1}{n}\sum_{m=1}^{n}\sum_{i=1}^{C} L(y_i^m, f_i^m) + \alpha(t)\frac{1}{n'}\sum_{m=1}^{n'}\sum_{i=1}^{C} L(y_i'^m, f_i'^m), \tag{15}$$

Equation [15] Lee (2013) [1]

Or in simpler words:

$$\text{Loss per Batch} = \text{Labeled Loss} + Weight * \text{Unlabeled Loss}$$

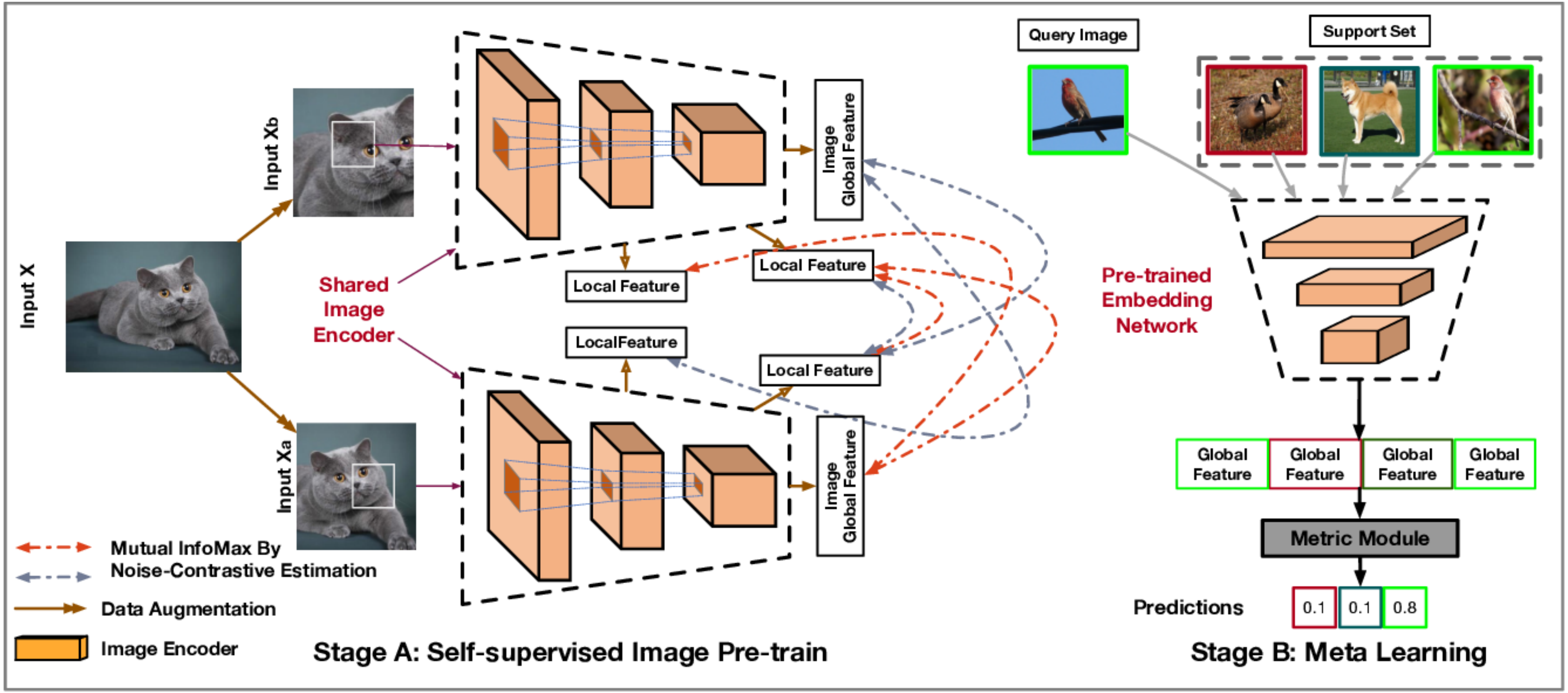
5. Self-Supervised Learning

CATEGORY: HYBRID LEARNING PROBLEMS

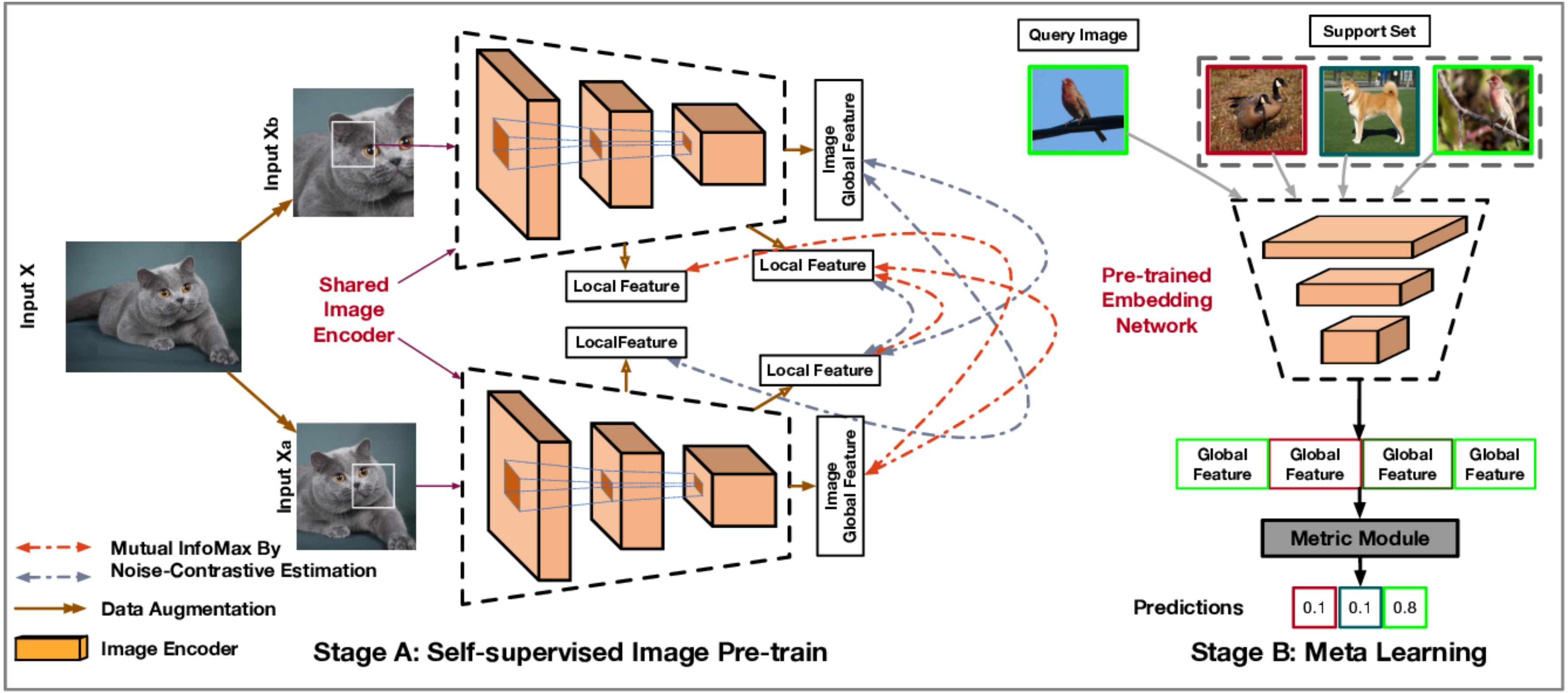
Self-supervised learning refers to an unsupervised learning problem that is framed as a supervised learning problem in order to apply supervised learning algorithms to solve it.

The self-supervised learning framework requires only unlabeled data in order to formulate a pretext learning task such as predicting context or image rotation, for which a target objective can be computed without supervision.

Self Supervised Learning



Self Supervised Learning



6. Multi-Instance Learning

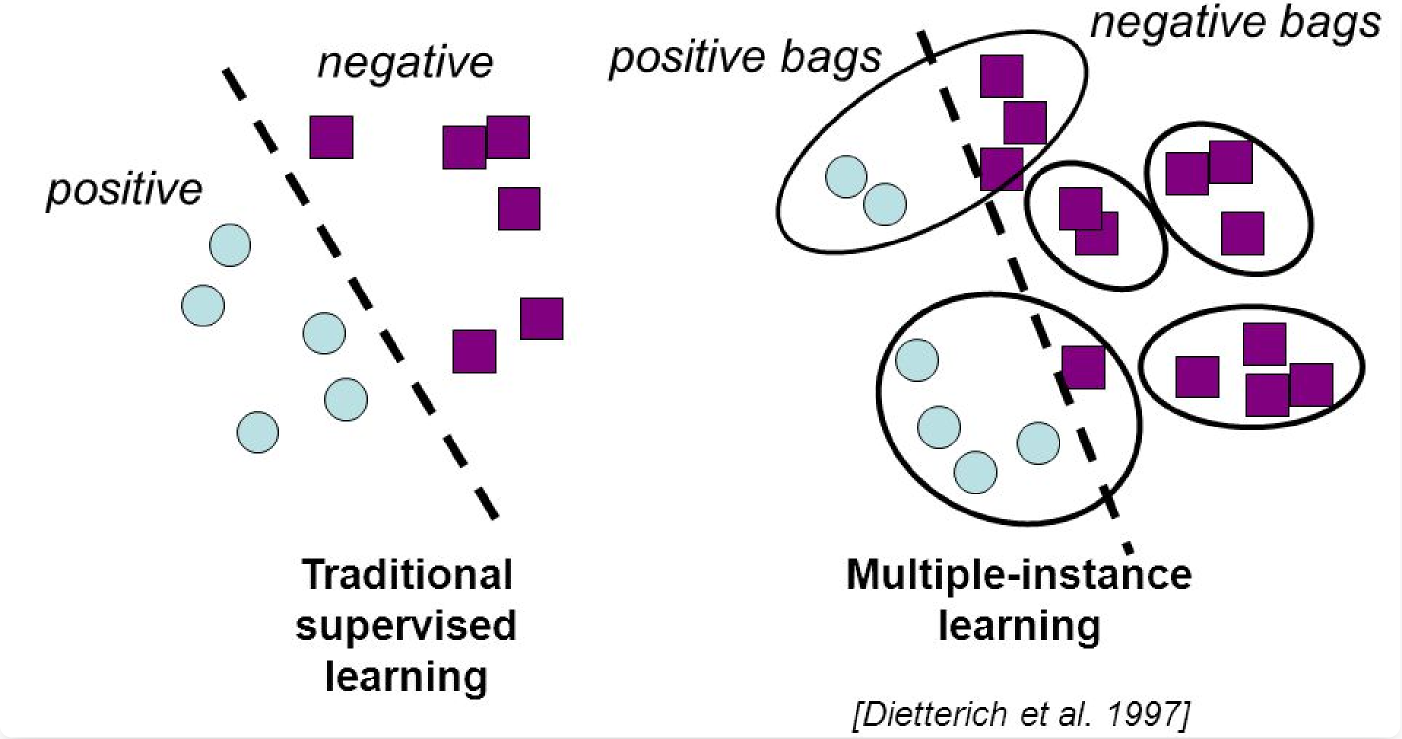
CATEGORY: HYBRID LEARNING PROBLEMS

Multi-instance learning is a supervised learning problem where individual examples are unlabeled; instead, bags or groups of samples are labeled.

In multi-instance learning, an entire collection of examples is labeled as containing or not containing an example of a class, but the individual members of the collection are not labeled.

Modeling involves using knowledge that one or some of the instances in a bag are associated with a target label, and to predict the label for new bags in the future given their composition of multiple unlabeled examples.

Multiple-Instance Learning

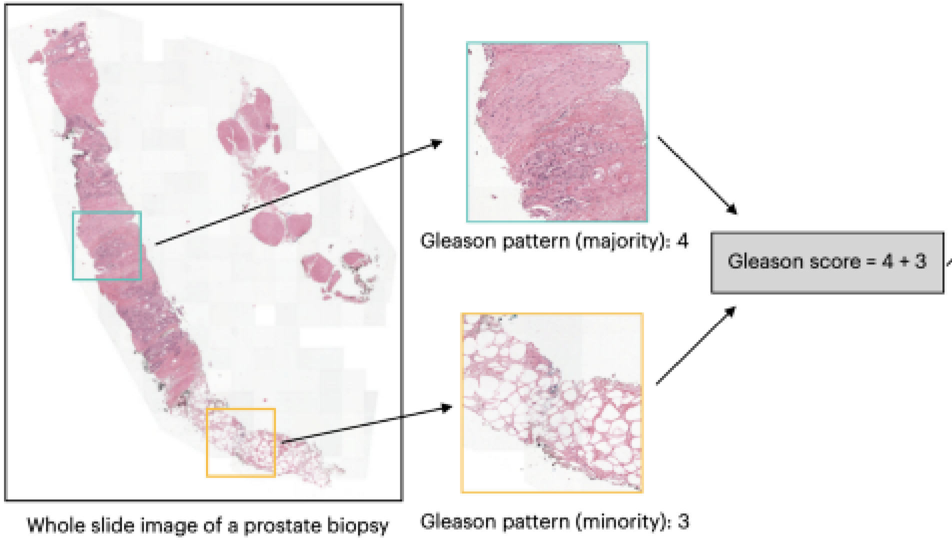


MIL: Example #1

Binary Classification

The goal of the MIL is to predict the labels of new, unseen bags.

Example #2



Gleason score	ISUP grade
3 + 3	1
3 + 4	2
4 + 3	3
4 + 4	4
3 + 5	4
5 + 3	4
4 + 5	5
5 + 4	5
5 + 5	5

7. Inductive Learning

CATEGORY: STATISTICAL INFERENCE

Inductive learning, also known as discovery learning, is a process where the learner discovers rules by observing examples.

Inductive learning involves using evidence to determine the outcome.

Inductive reasoning refers to using specific cases to determine general outcomes, e.g. specific to general.

Most machine learning models learn using a type of inductive inference or inductive reasoning where general rules (the model) are learned from specific historical examples (the data).

This can be very **complex** depending on the data.

it is an effective method used in ML and used in various fields of ML like facial recognition technology, disease cure, and diagnosis, etc. It uses a **bottom-up approach**.

The results are not certain, it can range from **strong to weak**.

8. Deductive Learning

CATEGORY: STATISTICAL INFERENCE

Deduction or deductive inference refers to using general rules to determine specific outcomes.

Deduction is the reverse of induction. If induction is going from the specific to the general, deduction is going from the general to the specific.

Deduction is a top-down type of reasoning that seeks for all premises to be met before determining the conclusion, whereas induction is a bottom-up type of reasoning that uses available data as evidence for an outcome.

Deductive learning uses the already available facts and information in order to give a valid conclusion. It uses a **top-down approach**.

The one major thing to note is that in deductive learning, the results are certain i.e, it is either **yes or no**.

If induction is going from the specific to the general, deduction is going from the general to the specific.

Inductive vs Deductive

inductive: From observation to conclusion.

In my opinion, Inductive Learning is similar to data-driven learning. Most of popular ML algorithms are belong to this.

deductive: From conclusion to observation.

In my opinion, it is similar to expert systems. We give rules (conclusion) , and then get the answer (observation)

Few differences between inductive machine learning and deductive machine learning are

Inductive Machine Learning	Deductive Machine Learning
Observe and learn from the set of instances and then draw the conclusion	Derives conclusion and then work on it based on the previous decision
It is Statistical machine learning like KNN (K-nearest neighbor) or SVM (Support Vector Machine)	Machine learning algorithm to deductive reasoning using a decision tree
$A \wedge B \vdash A \rightarrow B$ (Induction)	$A \wedge (A \rightarrow B) \vdash B$ (Deduction)

9. Transductive Learning

CATEGORY: STATISTICAL INFERENCE

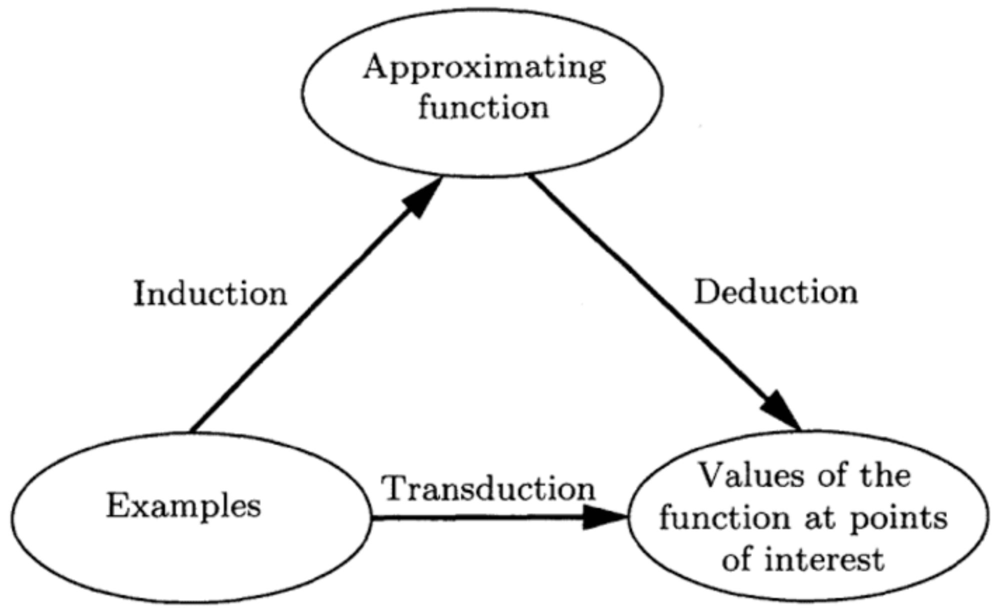
Transduction or transductive learning is used in the field of statistical learning theory to refer to predicting specific examples given specific examples from a domain.

- **Induction**, deriving the function from the given data.
- **Deduction**, deriving the values of the given function for points of interest.
- **Transduction**, deriving the values of the unknown function for points of interest from the given data.

We can contrast these three types of inference in the context of machine learning.

- **Induction:** Learning a general model from specific examples.
- **Deduction:** Using a model to make predictions.
- **Transduction:** Using specific examples to make predictions.

Relationship of Induction and Deduction and Transduction



10. Multi-Task Learning

CATEGORY: LEARNING TECHNIQUES

Multi-task learning is a type of supervised learning that involves fitting a model on one dataset that addresses multiple related problems.

It involves devising a model that can be trained on multiple related tasks in such a way that the performance of the model is improved by training across the tasks as compared to being trained on any single task.

Multi-task learning can be a useful approach to problem-solving when there is an abundance of input data labeled for one task that can be shared with another task with much less labeled data.

For example, it is common for a multi-task learning problem to involve the same input patterns that may be used for multiple different outputs or supervised learning problems. In this setup, each output may be predicted by a different part of the model, allowing the core of the model to generalize across each task for the same inputs.

11. Active Learning

CATEGORY: LEARNING TECHNIQUES

Active learning is a technique where the model is able to query a human user operator during the learning process in order to resolve ambiguity during the learning process.

The learner adaptively or interactively collects training examples, typically by querying an oracle to request labels for new points.

Active learning is a type of supervised learning and seeks to achieve the same or better performance of so-called “passive” supervised learning, although by being more efficient about what data is collected or used by the model.

It is not unreasonable to view active learning as an approach to solving semi-supervised learning problems, or an alternative paradigm for the same types of problems.

Note: Of course, we human experts tell all of the label, it make nonsense for the algorithm to learn, i.e., algorithm just ask a small part of the unlabeled data, Under this timely small help, active learning algorithm will get a big boost.

12. Online Learning

CATEGORY: LEARNING TECHNIQUES

Online learning involves using the data available and updating the model directly before a prediction is required or after the last observation was made.

Traditionally machine learning is performed offline, which means we have a batch of data, and we optimize an equation [...] However, if we have streaming data, we need to perform online learning, so we can update our estimates as each new data point arrives rather than waiting until "the end" (which may never occur).

Generally, online learning seeks to minimize "regret," which is how well the model performed compared to how well it might have performed if all the available information was available as a batch.

13. Transfer Learning

CATEGORY: LEARNING TECHNIQUES

Transfer learning is a type of learning where a model is first trained on one task, then some or all of the model is used as the starting point for a related task.

In transfer learning, the learner must perform two or more different tasks, but we assume that many of the factors that explain the variations in P1 are relevant to the variations that need to be captured for learning P2.

If there is significantly more data in the first setting (sampled from P1), then that may help to learn representations that are useful to quickly generalize from only very few examples drawn from P2. Many visual categories share low-level notions of edges and visual shapes, the effects of geometric changes, changes in lighting, etc.

transfer learning is particularly useful with models that are incrementally trained and an existing model can be used as a starting point for continued training, such as deep learning networks.

14. Ensemble Learning

CATEGORY: LEARNING TECHNIQUES

Ensemble learning is an approach where two or more models are fit on the same data and the predictions from each model are combined.

The objective of ensemble learning is to achieve better performance with the ensemble of models as compared to any individual model. This involves both deciding how to create models used in the ensemble and how to best combine the predictions from the ensemble members.

Ensemble learning is a useful approach for improving the predictive skill on a problem domain and to reduce the variance of stochastic learning algorithms, such as artificial neural networks.

Further Reading

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- The Elements of Statistical Learning: Data Mining, Inference, and Prediction, 2nd edition, 2016.
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Thank You

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