Knobbe Martens

Intellectual Property Strategies for Artificial Intelligence/Machine Learning Technologies in the United States

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Lot Network Bridge

Meet the Speakers

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Firm Profile – By the Numbers

95%+
of attorneys hold technical degrees

Global Practice
through large network of Foreign Associates

7 **Offices Nationwide**
Orange County
Los Angeles
New York
San Diego
San Francisco
Seattle
Washington D.C.

200 Highest number of registered patent attorneys in the US practicing across a **vast array** of industries

250+ lawyers & scientists

Managing ML Product and Service Development

Machine Learning/Artificial Intelligence

- Minimal Requirements for an Algorithm to be ML
  - Representation – Classifiers or basic language that a computer can understand
  - Evaluation – Inputting data and generating output (score)
  - Optimization – Developing a strategy to get from inputs to outputs

Learning Models

1 Supervised Learning

2 Unsupervised Learning

3 Semi-Supervised Learning

4 Reinforcement Learning

Introduction to Machine Learning – Different Machine Learning Models

SUPERVISED LEARNING → UNSUPERVISED LEARNING → SEMI-SUPERVISED → REINFORCEMENT LEARNING

General Characteristics

- Basic Concept: Machine learning is programmed with expected outputs (e.g., labeled training set) to generated learned algorithm
- Quality of performance of the learned algorithm is dependent on the training set

Introduction to Machine Learning – Different Machine Learning Models

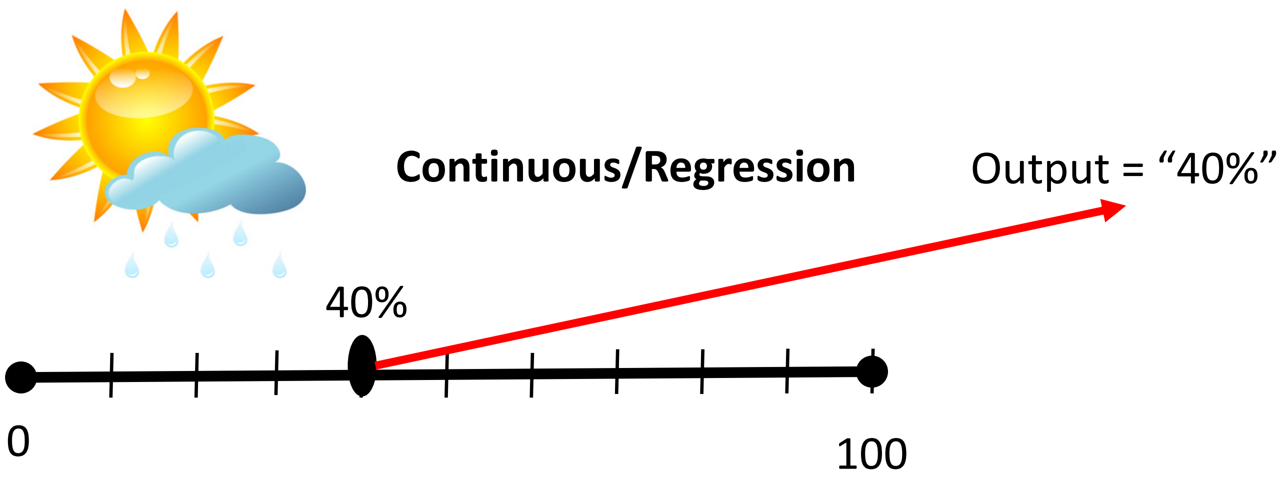
SUPERVISED LEARNING → **UNSUPERVISED LEARNING** → SEMI-SUPERVISED → REINFORCEMENT LEARNING

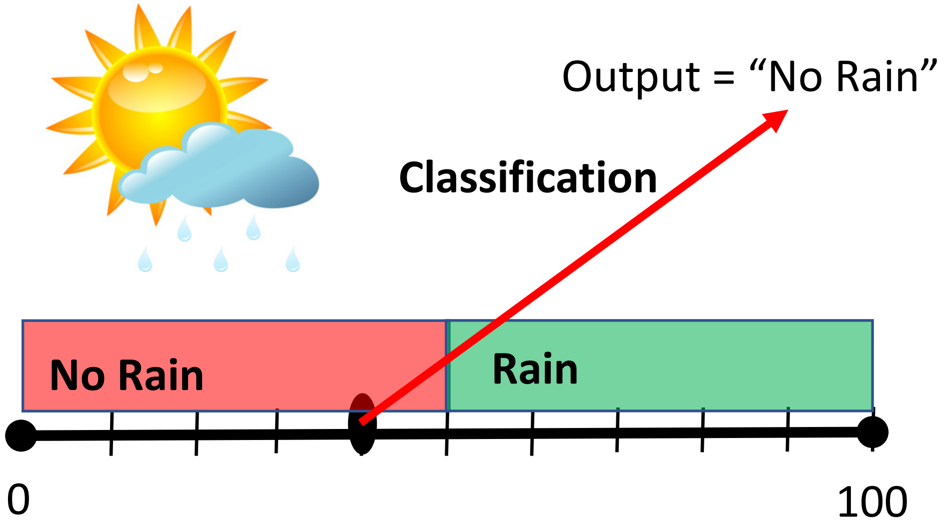
General Characteristics

- Basic Concept: Machine learning is programmed without labeled data (e.g., unlabeled data without human influence) to generate output
- Real-time analysis without pre-existing data using only logic operations
- No training provided to the machine learning algorithm

Machine Learning Outputs – Regression vs. Classification

- **Classification**: A model (function) which helps in separating the data into multiple categorical classes.
  - Data is categorized under different labels according to parameters
  - Labels are predicted for the data.
- **Regression/Continuous**: A model (function) distinguishing the data into continuous real values instead of categorical classes.
  - Function attempts to approximate value with the minimum error deviation.
  - No labels





Exemplary Algorithm Types

	Unsupervised Learning Algorithms	Supervised Learning Algorithms

Classification Output	• Association Rule Analysis
	  • Apriori
	  • Equivalence Class Transformation
	  • FP-Growth
	• Hidden Markov Model
		• Classification
		  • K-Nearest Neighbors
		  • Decision/Boosted Trees
		  • Logic Regression/Naive-Bayes
		  • Neural Networks
		  • Support Vector Machine (SVM)

Continuous Output	• Clustering and Dimensionality
	  • K-Means
	  • Singular Value Decomposition
	  • Principle Component Analysis
		• Regression
		  • Linear Regression
		  • Polynomial Regression
		• Decision Trees
		• Random Forests

Introduction to Machine Learning – Different Machine Learning Models

SUPERVISED LEARNING → UNSUPERVISED LEARNING → **SEMI-SUPERVISED** → REINFORCEMENT LEARNING

General Characteristics

- Combination of labeled and unlabeled data sets
- Mitigates cost of labeling data for larger data sets
- Mitigates some human bias for the unlabeled data

Introduction to Machine Learning – Different Machine Learning Models

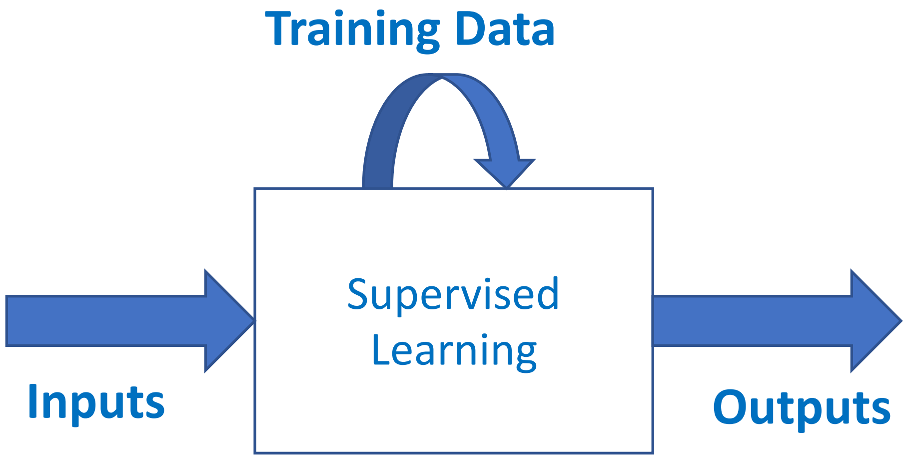
SUPERVISED LEARNING → UNSUPERVISED LEARNING → SEMI-SUPERVISED → **REINFORCEMENT LEARNING**

General Characteristics

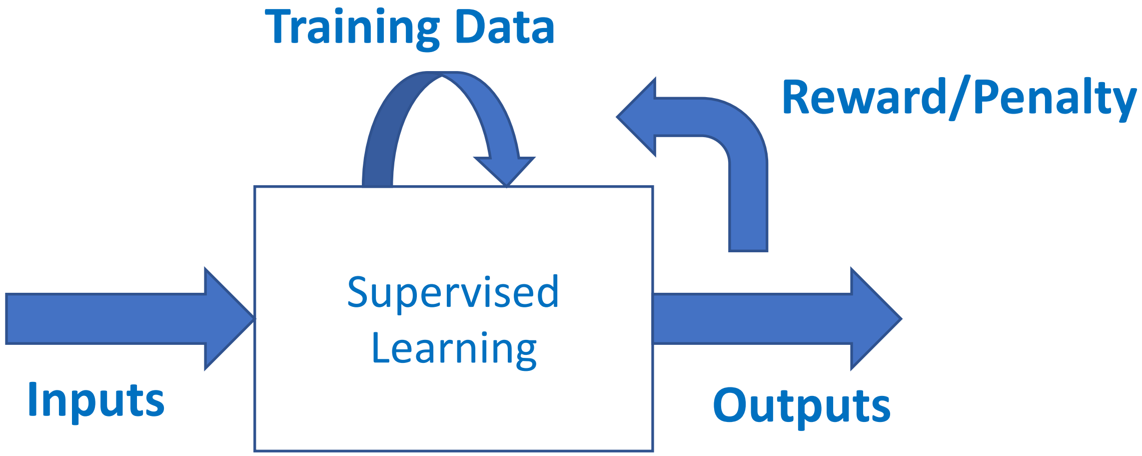
- Introduction of reward function to allow algorithm to adapt
- Includes the utilization of randomization of values based on reward function

Comparison of Supervised Learning to Reinforcement Learning

Supervised Learning Algorithms

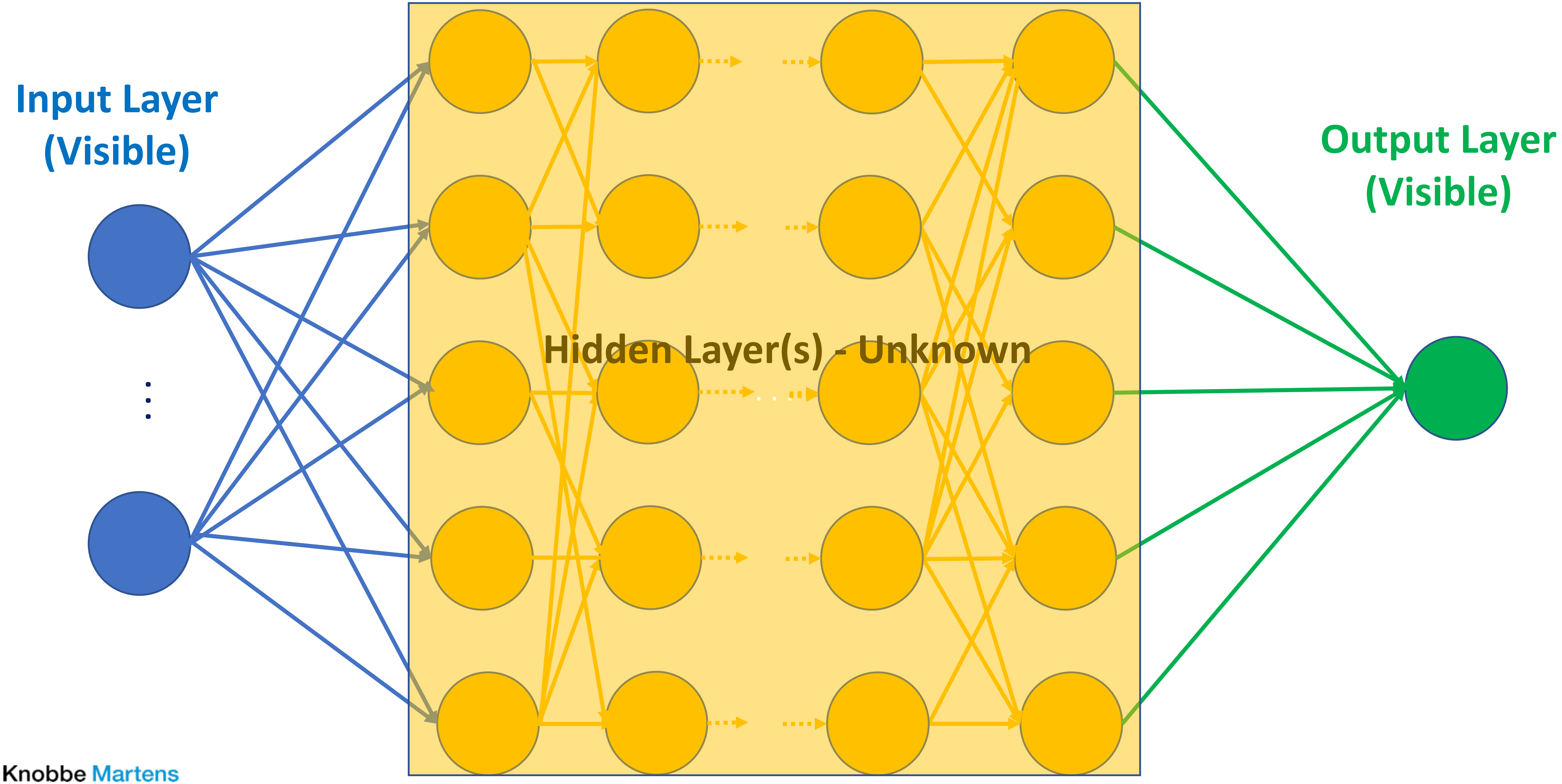


Reinforcement Learning Algorithms



In Depth Description - Neural Networks

General Architecture of Neural Network – Supervised Learning Model



Protecting ML Technologies

Data Set Generation and Inputs

- Contract/Copyright
- Data Privacy
- Potential Patentable Subject Matter

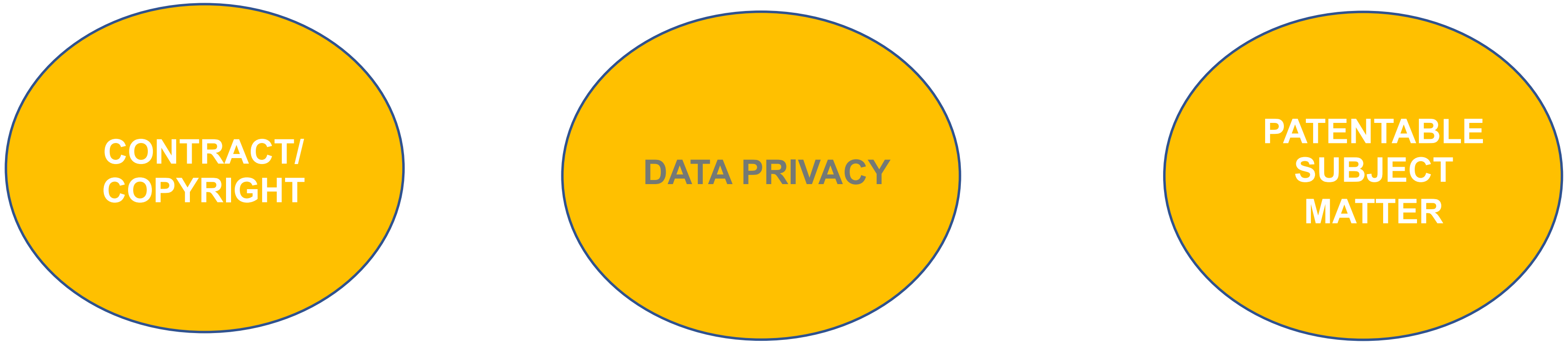
ML Processing

- Contract/Copyright
- Data Privacy
- Potential Patentable Subject Matter

ML Results and Post Processing

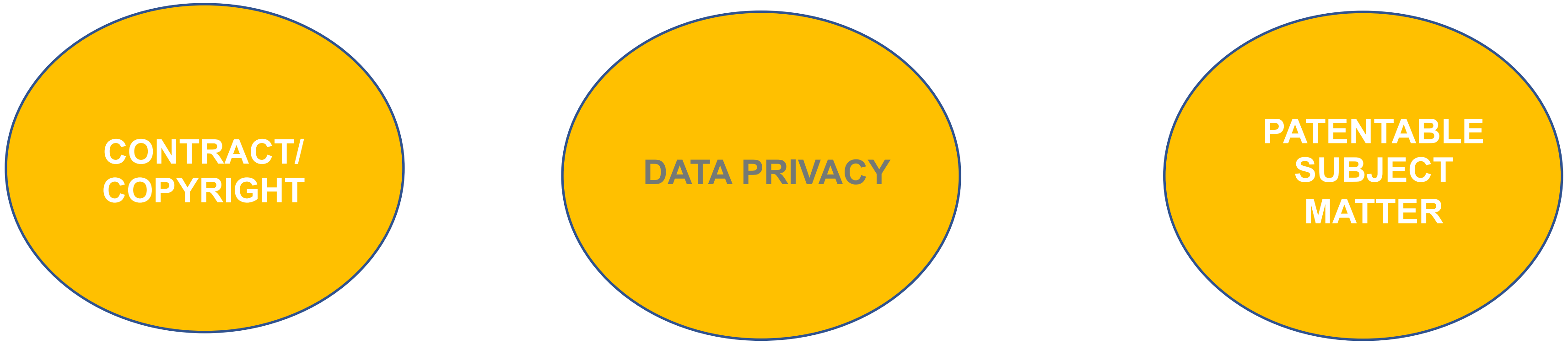
- Contract/Copyright
- Data Privacy
- Potential Patentable Subject Matter

Protecting ML Technologies - Data Set Generation and Inputs



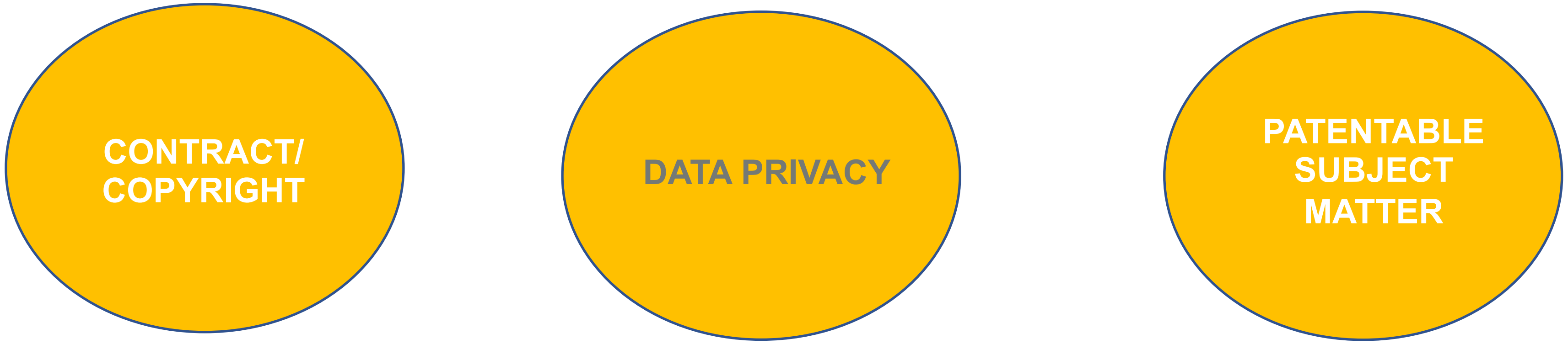
- Contract/Copyright
  - Securing data rights from users or third-parties
- Data Privacy
  - Providing necessary information
  - Maintaining data appropriately
- Potential Patentable Subject Matter
  - Collecting or Forming Data Set
  - Supplementing Data Set

Protecting ML Technologies - ML Processing



- Contract/Copyright
  - Third-party ML processing services
- Data Privacy
  - Providing data to third-party services
  - Maintaining data appropriately
- Potential Patentable Subject Matter
  - Modifications/Improvements to AI algorithms

Protecting ML Technologies - ML Results and Post Processing



- Contract/Copyright
  - Limitations/restrictions of the generated result
- Data Privacy
  - Maintaining processed data appropriately
- Potential Patentable Subject Matter
  - Post-processing feedback
  - Use of ML processed data

Protecting ML Technologies

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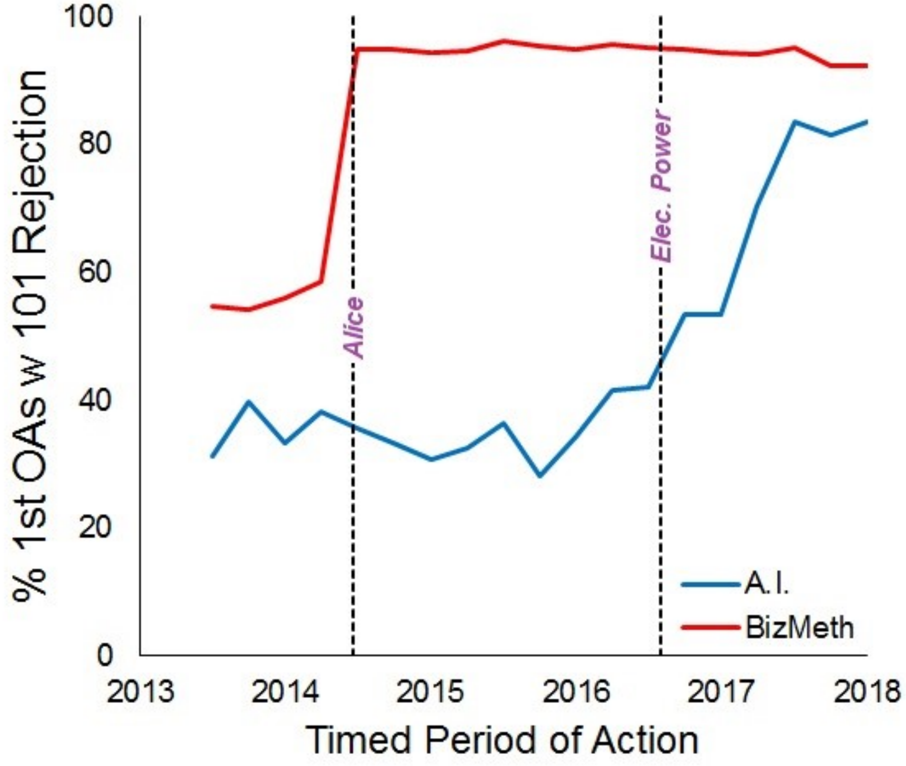
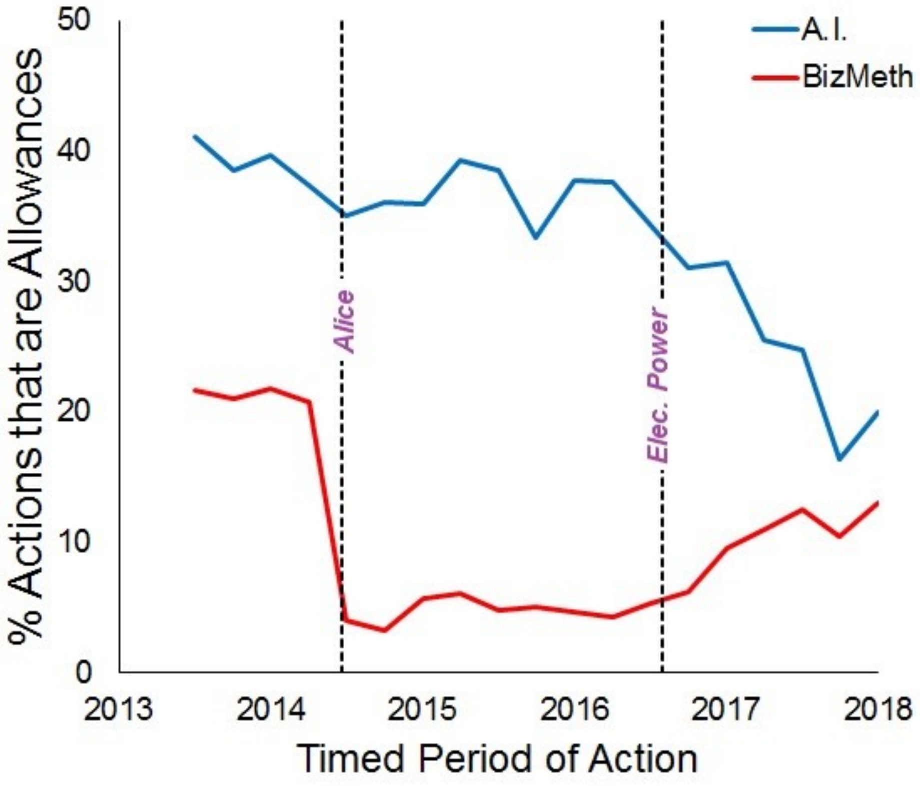
Comparison of Section 101 Rejections "Business Method" vs. ML



Allowance Percentage "Business Method" vs. ML



Source: *Artificial Intelligence Technologies Facing Heavy Scrutiny at the USPTO*, IP Watchdog, November 28, 2018.

Example 39 - Method for Training a Neural Network for Facial Detection

A computer-implemented method of training a neural network for facial detection comprising:

collecting a set of digital facial images from a database;

applying one or more transformations to each digital facial image including mirroring, rotating, smoothing, or contrast reduction to create a modified set of digital facial images;

creating a first training set comprising the collected set of digital facial images, the modified set of digital facial images, and a set of digital non-facial images;

training the neural network in a first stage using the first training set;

creating a second training set for a second stage of training comprising the first training set and digital non-facial images that are incorrectly detected as facial images after the first stage of training; and

training the neural network in a second stage using the second training set.

Example 39 v US 2017/0369275

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A computer-implemented method of training a neural network for facial detection comprising:

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creating a second training set for a second stage of training comprising the first training set and digital non-facial images that are incorrectly detected as facial images after the first stage of training; and

training the neural network in a second stage using the second training set.

US 2017/0369275 - Usage and contextual-based management of elevator operations

1. An apparatus to manage operations of one or more elevators servicing a plurality of floors, the apparatus comprising:

one or more computer processors;

a usage pattern module coupled with the one or more processors, to identify usage patterns of the one or more elevators, wherein the usage pattern module is to receive and store, for at least one elevator, information of a plurality of journeys;

a contextual awareness module coupled with the one or more processors, to identify a context proximate to the one or more elevators, wherein the contextual awareness module is to receive and store information about a plurality of events proximate to, but outside the operation of, the one or more elevators; and

an operations module coupled with the one or more processors, to control operation of the one or more elevators, wherein the operations module is to send one or more commands to change a position or an operational state of at least one of the one or more elevators based at least in part on data in the usage pattern data store and in the contextual awareness data store.

Best Practices

- **U.S. Best Practices**

1. Include description of the technical substance underlying the AI technology. Simply relying on black box description of “artificial intelligence” or “machine learning” will likely not be sufficient.

2. Avoid personification of “modules” or “processors”

3. Include detailed step-by-step algorithms and concrete examples of how the AI/machine learning can be applied.

US Pub 2018/0373233

Claim

1. A failure predicting apparatus for predicting a failure timing of a printed circuit board included in a management target device, the failure predicting apparatus comprising:

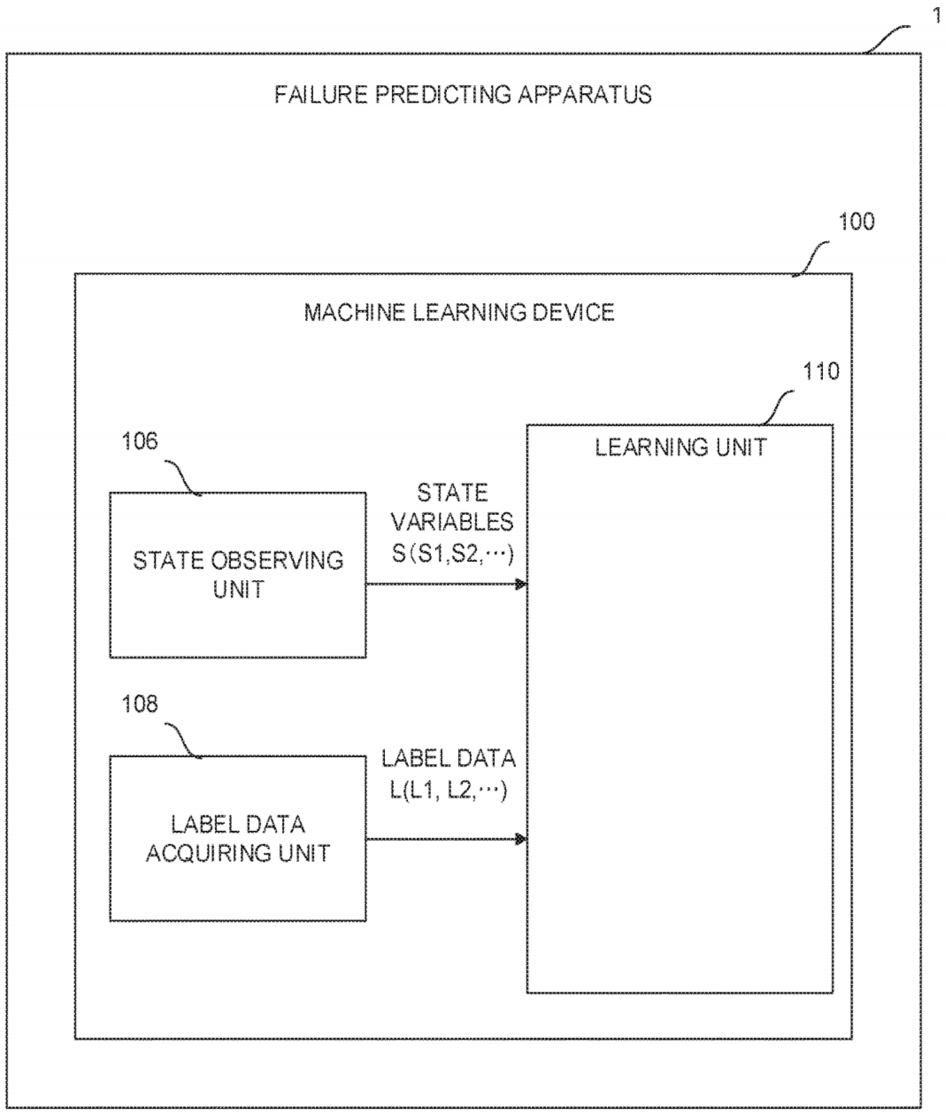
a machine learning device that learns the failure timing of the printed circuit board included in the management target device with respect to an operating state of the management target device,

wherein the machine learning device includes a state observing unit that observes, as state variables indicating a current environmental state, operating state data indicating an operating state of the management target device and device configuration data indicating a device configuration of the management target device,

a label data acquiring unit that acquires, as label data, maintenance history data indicating a maintenance history of the management target device, and

a learning unit that, by using the state variables and the label data, learns the failure timing of the printed circuit board included in the management target device, the operating state data, and the device configuration data such that the failure timing is associated with the operating state data and the device configuration data.

Figure 2



Disclosure in 2018/0373233

FIG.6A

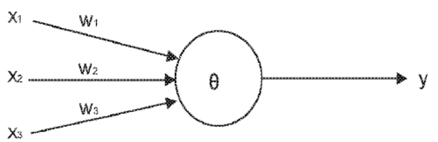


FIG.6B

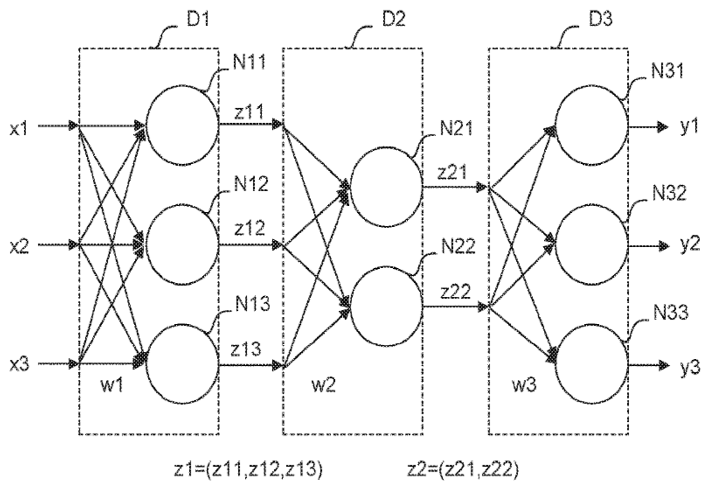


FIG.3

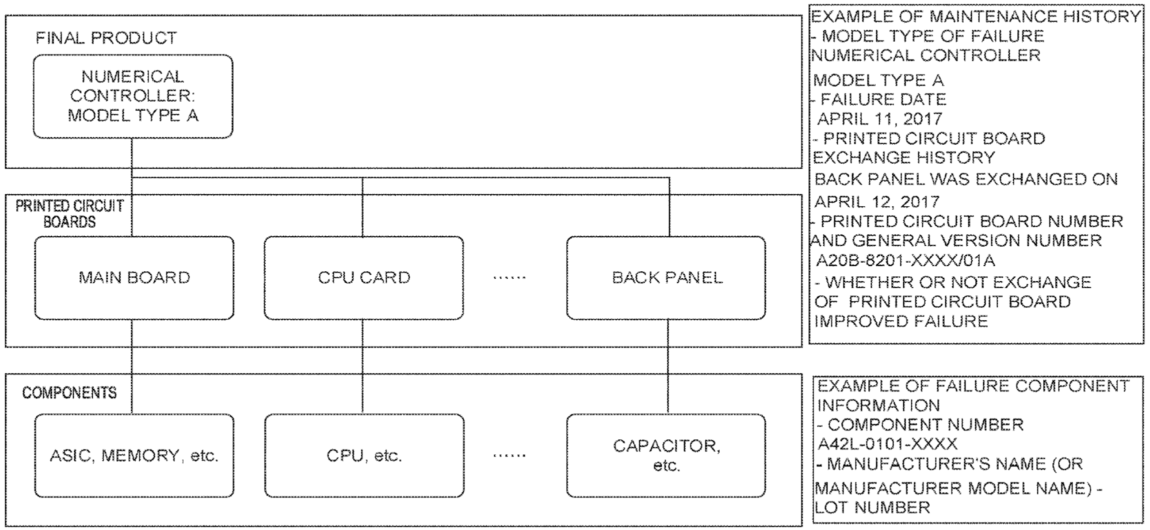
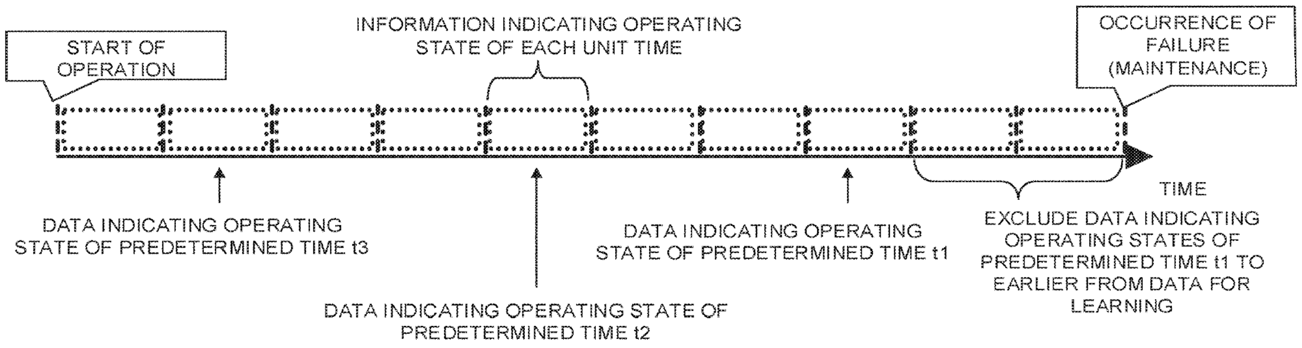


FIG.4



Disclosure in 2018/0373233

FIG.2

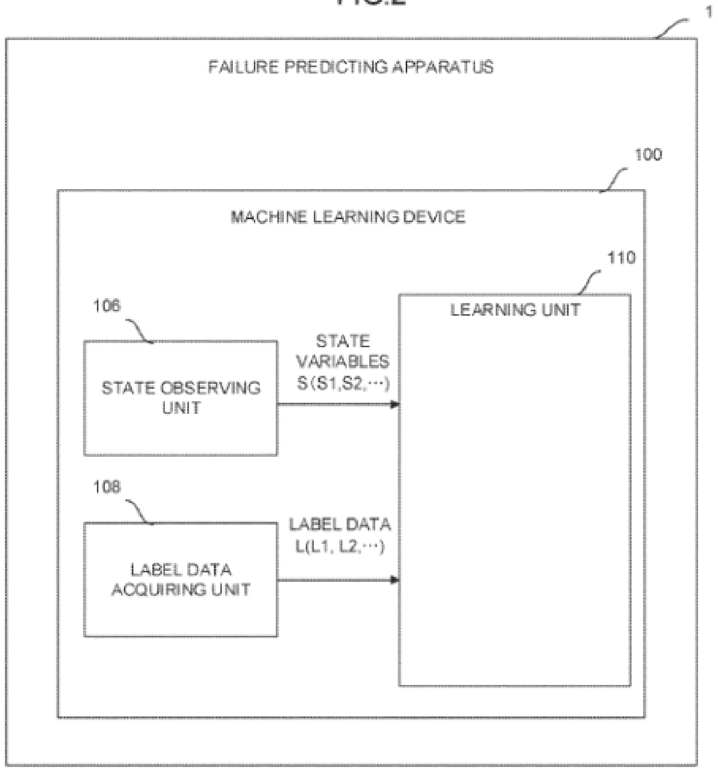


FIG.6A

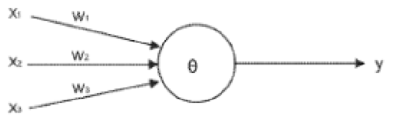
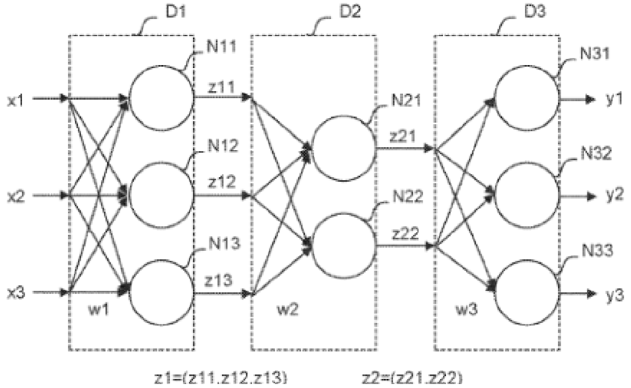


FIG.6B



[0048] FIG. **6**A schematically illustrates a neuron model. FIG. **6**B schematically illustrates a model of a three-layer neural network formed by combining the neurons illustrated in FIG. **6**A. The neural network may be formed by a computation device or a storage device, etc., simulating the model of neurons, for example.

[0049] The neuron illustrated in FIG. **6**A outputs a result y in response to a plurality of inputs x (here, inputs x_1 to x_3, as examples). Weights w (w_1 to w_3) corresponding to the inputs x are applied to the x_1 to x_3, respectively. As a result, the neuron outputs the output y expressed by Expression 2 below. In Expression 2, all the inputs x, the output y, and the weights w are vectors. In addition, θ represents a bias and f_k represents an activation function.

$$y = f_k(\Sigma_{i=1}^{n} x_i w_i - \theta) \qquad \text{[Expression 2]}$$

[0050] In the three-layer neural network illustrated in FIG. **6**B, a plurality of inputs x (here, inputs x**1** to x**3** as examples) are inputted from the left side, and results y (here, results y**1** to y**3**, as examples) are outputted from the right side. In the example illustrated in FIG. **6**B, the inputs x**1**, x**2**, x**3** are multiplied by corresponding weights (collectively expressed by w**1**), and all of the inputs x**1**, x**2**, x**3** are inputted into each of three neurons N**11**, N**12**, N**13**.

[0051] In FIG. **6**B, respective outputs from the neurons N**11** to N**13** are collectively expressed by z**1**. z**1** can be regarded as feature vectors obtained by extracting respective feature amounts of the input vectors. In the example illustrated in FIG. **6**B, the feature vectors z**1** are multiplied by corresponding weights (collectively expressed by w**2**) and all the feature vectors z**1** are inputted into each of two neurons N**21**, N**22**. The feature vectors z**1** each represent a feature between the weight w**1** and the weight w**2**.

[0052] In FIG. **6**B, outputs from the neurons N**21**, N**22** are collectively expressed by z**2**. z**2** can be regarded as feature

Best Practices

Overlapping Best Practices Between the U.S. and Europe

1. Much of the above advice for U.S. patent applications also applies in Europe.

2. Identifying technical problems in the specification coupled with the specific, technical solutions—and claiming those solutions—remain viable approaches for AI inventions in both the U.S. and Europe.

3. Describing improvements to how a computer performs machine learning or executes AI (e.g., by running faster, using less memory, etc.) helps both in the U.S. and Europe.

4. Reciting specific use cases may be specifically helpful in Europe

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Thank you!

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