



## **Pattern and Anomaly Detection Introduction**



# **Unit objectives**



### After completing this unit, you should be able to:

- Understand the concept of pattern recognition and anomaly detection
- Gain knowledge on example of polynomial curve fitting
- Learn about probability theory architecture and working model
- Understand Information theory

# What is pattern?

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- Pattern is all about it in this digital age.
- A pattern can be either visually identified or mathematically detected via the implementation of algorithms.

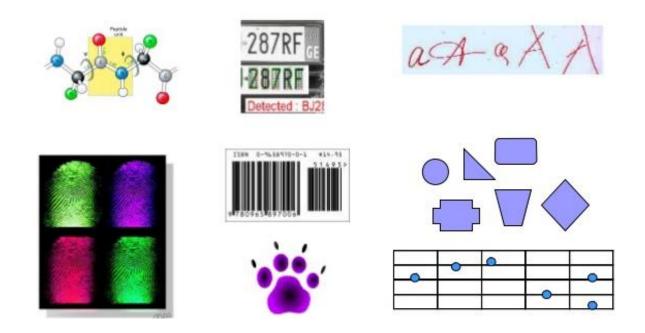


Figure: Pattern definition

Source: https://images.app.goo.gl/NmRdihnyFymA23uRA

## What is pattern recognition?

- As per Wikipedia, pattern recognition is the automated recognition of patterns and regularities in data.
- It has applications in statistical data analysis, signal processing, image analysis, information retrieval, bioinformatics, data compression, computer graphics and machine learning.



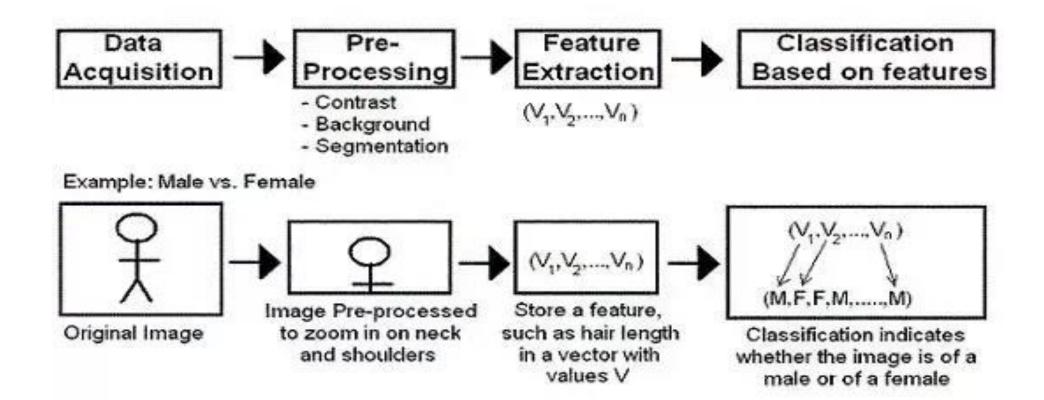


Figure: Pattern recognition process

Source: https://images.app.goo.gl/3x6gZVVao9u3vV8w7

# Training and learning in pattern recognition



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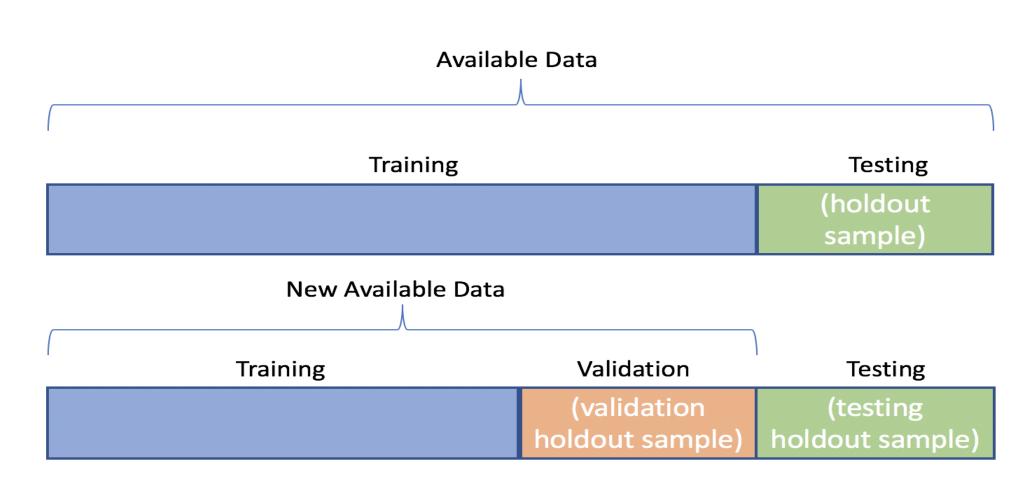


Figure: Training and testing dataset

Source: https://images.app.goo.gl/vetePfKYS2t7vmX99

# Pattern recognition applications

- A model is an ideal concrete entity, or theoretical idea. The definition of the animal is an illustration when thinking regarding animal groups.
- The definition of the ball is a trend while speaking about various styles about balls.
- The groups can be baseball, cricket game, table tennis match, in sample case balls.
- Before approaching a new species, the species class has to be established.
- Choosing attributes and describing patterns is a very critical phase in classifying the layout.
- Effective presentation requires the use of non-discriminatory attributes, and the sample classification computational pressure.

## Pattern recognition use cases



- Customer research and stock market analysis.
- Chat bots, NLP with text generation, text analysis, text translation.
- Optical Character Recognition (OCR), document classification and signature verification.
- Image recognition, visual search, face recognition.
- Voice recognition and ai assistants.
- Recommendation sentiment analysis, audience research.

## What is anomaly detection?



## Example of Anomaly detection

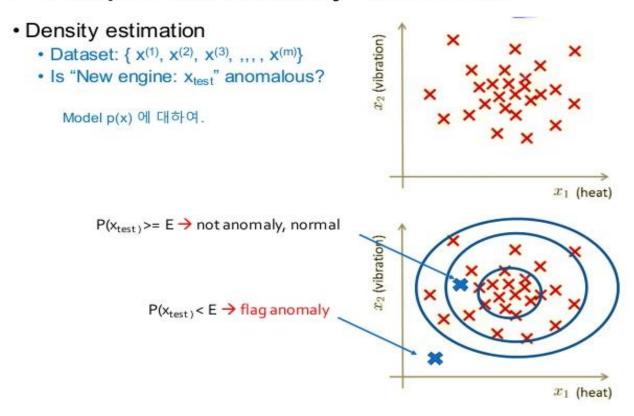


Figure: Anomaly detection example

Source: https://images.app.goo.gl/WpR4Rk1Xth1Fj4rt6

# What are some other practical uses for anomaly detection?



- Traffic dropped or spiked.
- Transactions or revenue dropped.
- Traffic from social media increased or decreased.
- Traffic from organic search increased or decreased.

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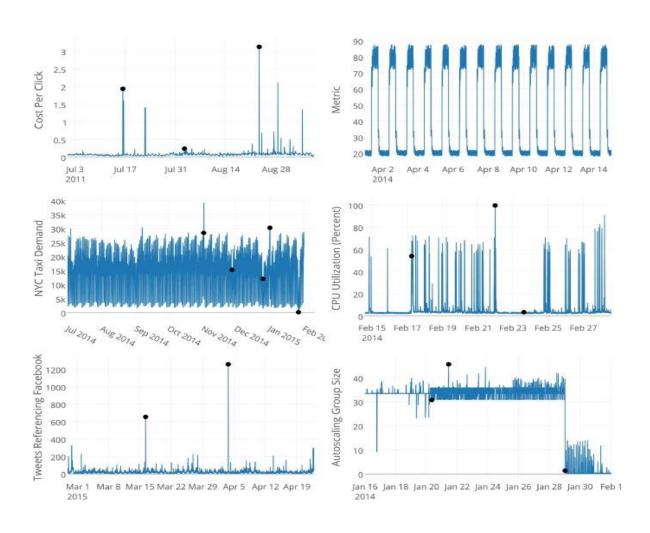


Figure: CPU time frame for anomaly detection

Source: https://images.app.goo.gl/a5wk76ZUmKZLj63v6

## **Self evaluation: Exercise 1**

- To continue with the training, after learning the various steps involved in pattern recognition and anomaly detection, it is instructed to utilize the concepts to perform the following activity.
- You are instructed to write the following activities using python code.
- Exercise 1: Polynomial curve fitting.

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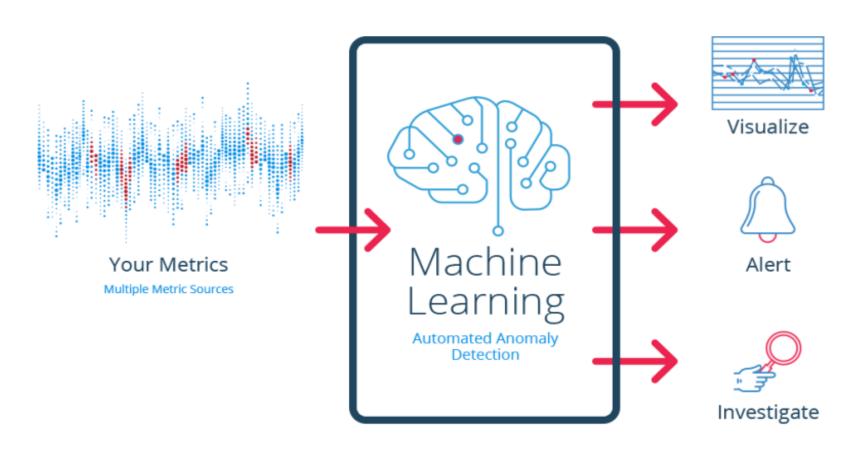


Figure: Anomaly detection flow with Machine learning

Source: https://images.app.goo.gl/ewiV18h8cpAkEyCL9



### Tasks for Artificial Intelligence



Analyze datasets, dynamically fine-tune normal behavior parameters and identify breaches in patterns



#### Real-time analysis

Sending a signal once a pattern isn't recognized by the system



#### Scrupulousness

End-to-end gap-free monitoring to identify smallest anomalies



### Accuracy

Avoiding nuisance alerts and false positives/negatives triggered by static thresholds



#### Self-learning

Al-driven algorithms learn from data patterns and deliver predictions or answers as required

Figure: AI Task

Source: https://images.app.goo.gl/F9Z664sSWR53yGqLA

# Al system learning process (1 of 2)



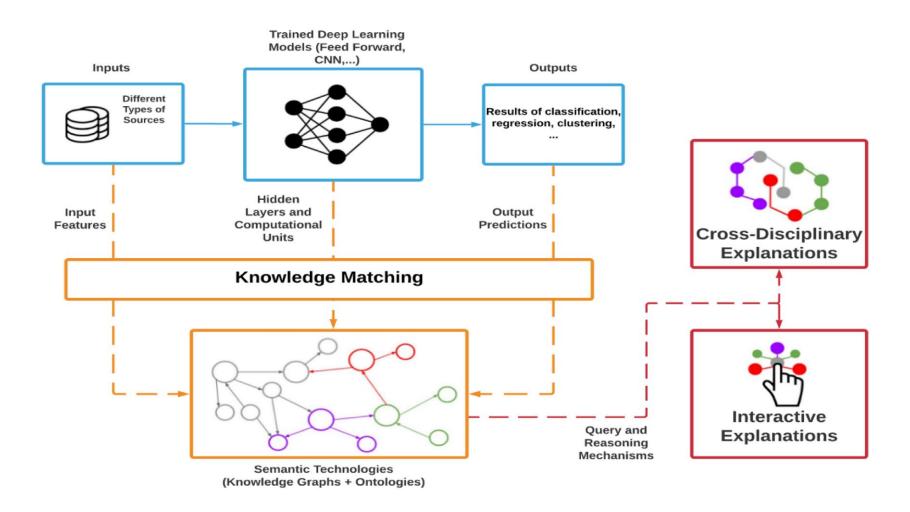


Figure: AI Learning Process

Source: https://images.app.goo.gl/dBtnk7CPRtqe7xM59

# Al system learning process (2 of 2)



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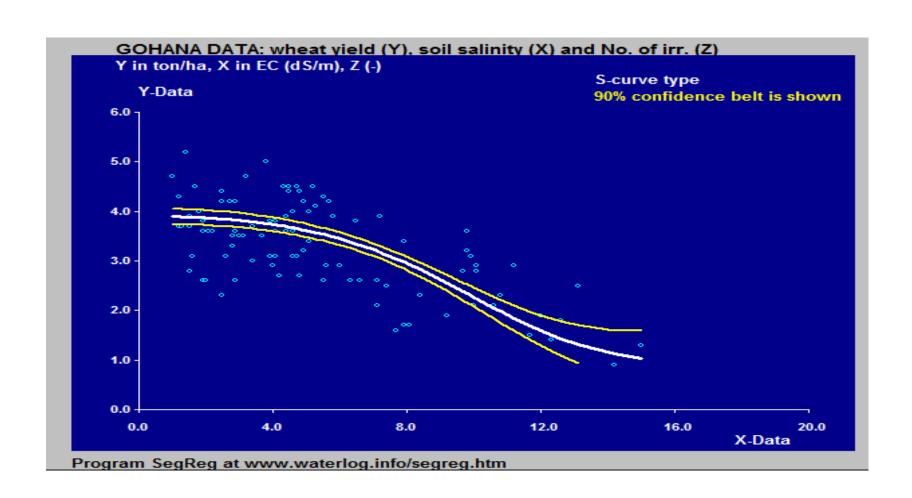


Figure: Relation between wheat yield and soil salinity

Source: https://upload.wikimedia.org/wikipedia/commons/thumb/4/46/Gohana\_inverted\_S-curve.png/560px-Gohana\_inverted\_S-curve.png

## **Self evaluation: Exercise 2**

- To continue with the training, after learning the various steps involved in pattern recognition and anomaly detection, it is instructed to utilize the concepts to perform the following activity.
- You are instructed to write the following activities using python code.
- Exercise 2: Probability and distribution.

# Test to geometric requirements for curves algebraic



Scheme of curve plotting	Equation of a curve in a parametrical look
1	2
$y_{i}$ $y_{i}$ $x_{i}$ $x_{i}$	Straight line: $x_{i} = \frac{f}{\cos(u_{i} - v)} \cdot \cos(u_{i})$ $y_{i} = \frac{f}{\cos(u_{i} - v)} \cdot \sin(u_{i})$
$y_0$	Circle arch: $x_i = x_0 + R_0 \times \cos(u_i)$ $y_i = y_0 + R_0 \times \sin(u_i)$
R Ya 72	Epicycloid: $x_{i} = (R + r_{1})\cos(u_{i} + u_{0}) -$ $-r_{2}\cos\left[\left(\frac{R + r_{1}}{r_{1}}\right)(u_{i} + u_{0})\right]$ $y_{i} = (R + r_{1})\sin(u_{i} + u_{0}) -$ $-r_{2}\sin\left[\left(\frac{R + r_{1}}{r_{1}}\right)(u_{i} + u_{0})\right]$

Figure: Algebraic curves in a parametrical form used for creation of the forming line in the edge section of different rated surfaces

Source: https://images.app.goo.gl/Rn75dzFLCv9y6nu5A

# Curves matched to data points (1 of 2)



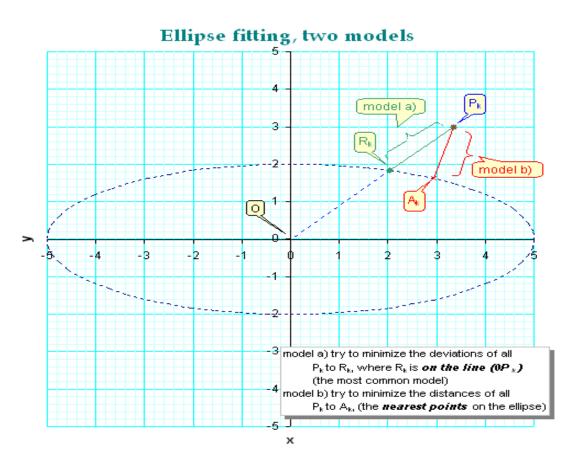


Figure: Different models of ellipse fitting

Source: https://lh3.googleusercontent.com/HkRug5Yd6SlGy0AkSgLZ9FYwrq3Os5jeSoEiHqg5ft1se9C8uSUcXjY9p3yfYfhg13eyUA=s86

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# Curves matched to data points (2 of 2)

	= 7 =

SUMMARY OUTPUT						
Regression St	atistics					
Multiple R	0.977411977					
R Square	0.955334173					
Adjusted R Square	0.952025593					
Standard Error	13.21744878					
Observations	30					
ANOVA						
	df	SS	MS	F	Significance F	
Regression	2	100887.8743	50443.93714	288.7444885	5.95206E-19	
Residual	27	4716.925714	174.7009524			
Total	29	105604.8				
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	21.92	10.57395903	2.073017301	0.047839767	0.224028187	43.61597181
Month	-24.5485714	6.91777293	-3.54862348	0.001441196	-38.742669	-10.3544738
MonSq	8.057142857	0.967418193	8.328500456	6.14519E-09	6.072164688	10.04212103

Figure: Linear regression output

Figure: Quadratic regression output

SUMMARY OUTPUT						
Regression St	tatistics					
Multiple R	0.91683485					
R Square	0.840586142					
Adjusted R Square	0.83489279					
Standard Error	24.52030396					
O bservations	30					
ANOVA						
	df	SS	MS	F	Sig nifican ce F	
Regression	1	88769.93143	88769.93143	147.6434502	1.1088E-12	
Residual	28	16834.86857	601.2453061			
Total	29	105604.8				
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-53.28	10.20861661	-5.21912048	1.52374E-05	-74.1914032	-32.3685968
Month	31.85142857	2.621330755	12.15086212	1.1088E-12	26.48187593	37.22098121

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# Case study: Anomaly detection with IBM Watson



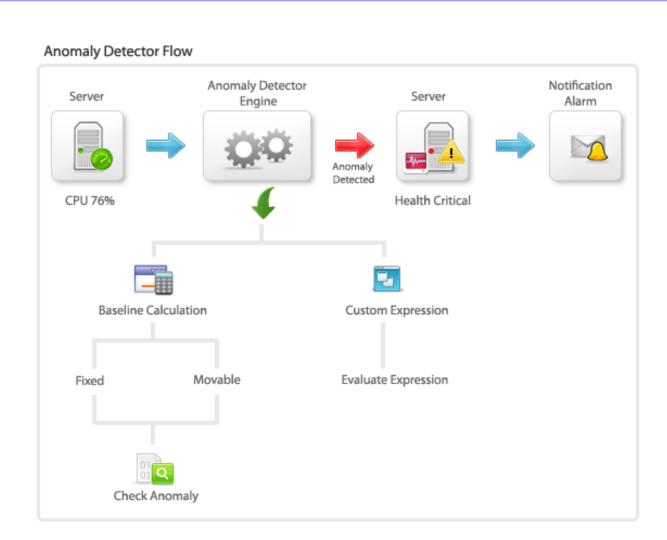


Figure: Anomaly detection workflow engine

Source: https://images.app.goo.gl/ukrNQnHbjnP5XXKf6

## **Self evaluation: Exercise 3**

- To continue with the training, after learning the various steps involved in pattern recognition and anomaly detection, it is instructed to utilize the concepts to perform the following activity.
- You are instructed to write the following activities using python code.
- Exercise 3: Simple linear regression.



# Probability Theory



The probability of getting number "3" with one throw?

The probability of getting number "3" with double throw?

$$\frac{1}{6} \times \frac{1}{6} = \frac{1}{36}$$





Source: https://images.app.goo.gl/DKudJzQZCPZEQyvt6



## Probability theory (2 of 2)



Sample Space: 12 There are 12 marbles total (4+5+1+2 = 12)

Probability= Total Possible outcome

- P (black) = 2/12 = 1/6 There are 2 black marbles in the bag, 12 is your sample space.
- P (blue) = 4/12 = 1/3 There are 4 blue marbles in the bag, 12 is your sample space.
- P (blue or black) = 6/12= 1/2 4 blue + 2 black = 6 , 12 is your sample space.
- P (not green) = 11/12 There's 1 green. So 12-1 = 11 that aren't green,12 is your sample space.
- P (not purple) = 1
- I will select a marble that is not purple because there are no purple marbles in the bag.
   Whenever the chance of something occurring is definite, the probability is i.

# Maximum likelihood theory and estimation (1 of 2)



- The estimate of density is the issue of evaluating the distribution of likelihood for a sub-set of a sample in a question domain.
- Two Important concepts:
  - Probability density estimation problem.
  - Maximum likelihood calculation.

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# Maximum likelihood theory and estimation (2 of 2)

- Suppose that we are given a sequence (x1...xn) of IID random variables and a priori distribution of it is given by Us wish to find the MAP estimate of it. Note that the normal distribution is its own conjugate prior, so we will be able to find a closed-form solution
- The function to be maximized is then given by:

analytically.

$$f(\mu)f(x\mid\mu) = \pi(\mu)L(\mu) = \frac{1}{\sqrt{2\pi}\sigma_m} \exp\left(-\frac{1}{2}\left(\frac{\mu-\mu_0}{\sigma_m}\right)^2\right) \prod_{j=1}^n \frac{1}{\sqrt{2\pi}\sigma_v} \exp\left(-\frac{1}{2}\left(\frac{x_j-\mu}{\sigma_v}\right)^2\right),$$

Which is equivalent to minimizing the following function of it:

$$\sum_{i=1}^{n} \left( \frac{x_j - \mu}{\sigma_v} \right)^2 + \left( \frac{\mu - \mu_0}{\sigma_m} \right)^2.$$

Thus, we see that the MAP estimator for p is given by:

$$\hat{\mu}_{ ext{MAP}} = rac{\sigma_m^2 \, n}{\sigma_m^2 \, n + \sigma_v^2} \left(rac{1}{n} \sum_{j=1}^n x_j
ight) + rac{\sigma_v^2}{\sigma_m^2 \, n + \sigma_v^2} \, \mu_0 = rac{\sigma_m^2 \left(\sum_{j=1}^n x_j
ight) + \sigma_v^2 \, \mu_0}{\sigma_m^2 \, n + \sigma_v^2}.$$

 Which turns out to be a linear interpolation between the prior mean and the sample mean weighted by their respective covariance's. The case of is called a non-informative prior and leads to an ill-defined a priori probability distribution.

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## Self evaluation: Exercise 4

- To continue with the training, after learning the various steps involved in pattern recognition and anomaly detection, it is instructed to utilize the concepts to perform the following activity.
- You are instructed to write the following activities using python code.
- Exercise 4: Multiple linear regression.

## Model selection (1 of 2)



The MDL (Minimum Description Length) statistic is calculated as follows:

$$MDL = L(h) + L(D | h)$$

- Where h is the model, D is the predictions made by the model, L(h) is the number of bits required to represent the model, and L(D | h) is the number of bits required to represent the predictions from the model on the training dataset.
- The score as defined above is minimized, e.g., the model with the lowest MDL is selected.
- The number of bits required to encode (D | h) and the number of bits required to encode (h)
  can be calculated as the negative log-likelihood. For example:

$$MDL = -log(P(theta)) - log(P(y | X, theta))$$

• Or the negative log-likelihood of the model parameters (theta) and the negative log-likelihood of the target values (y) given the input values (X) and the model parameters (theta).

# Model selection (2 of 2)



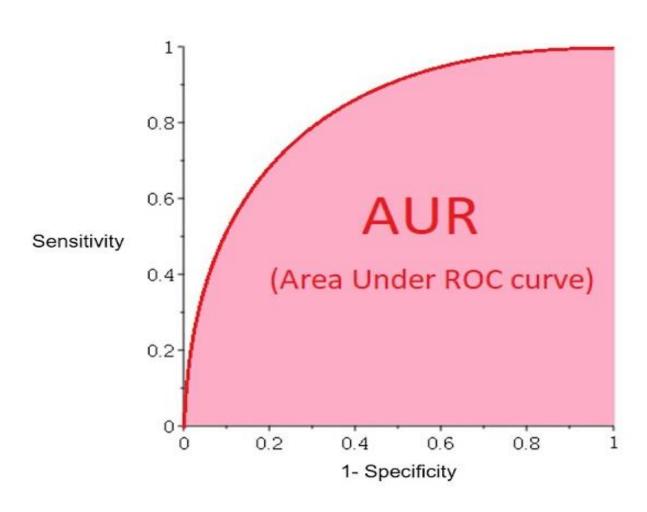


Figure: AU ROC

Source: https://images.app.goo.gl/iMXwj7jLYADko1uCA

# Matrices of uncertainty (confusion matrices)



- A few other metrics are computed from these values:
- Accuracy: How often is the classifier correct? (TP+TN)
- Misclassification rate (or "error rate"): How often is the classifier wrong?  $\left(\frac{\text{FP+FN}}{\text{total}} = 1 \text{accuracy}\right)$
- Recall (or "sensitivity" or "true positive rate"): How often are positive-labeled samples predicted as positive?
- False positive rate: How often are negative-labeled samples predicted as positive?

$$\frac{\text{FP}}{\text{num negative-labeled examples}}$$

- Specificity (or "true negative rate"): How often are negative-labeled samples predicted as negative?
- Precision: How many of the predicted positive samples are correctly predicted? (TP+FP)
- Prevalence: How many labeled-positive samples are there in the data?

# Loss of logging (log-loss)



$$H_p(q) = -\frac{1}{N} \sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

Binary Cross-Entropy / Log Loss

Figure: Log Loss formula

Source: https://images.app.goo.gl/UpFaWENnNrSm935R9

## Rate for F1 (F1 score)

====

 The F1 score is the weighted average accuracy and warning, even the balanced F-score or F-measure.

$$F_1 = 2 \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

Figure: F1 score

## **Metric selection**



- Metric selection is more complex for biased groups (or strongly predetermined bias data).
- For example, you have a dataset with only 0.5% of the data in category 1.
- You run your experiment and remember that 99.5 percent of the tests are correctly graded.



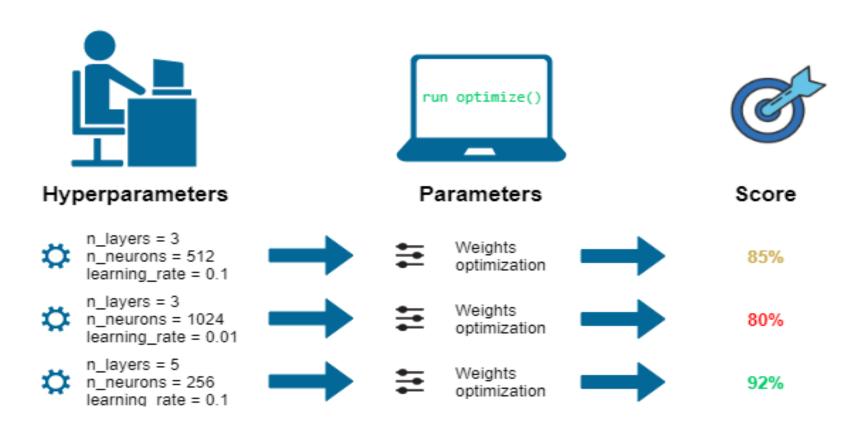


Figure: Hyperparameter selection

Source: https://images.app.goo.gl/o3DaxpbGLPVRxKnPA

# Hyperparameter selection (2 of 2)

- Optimization of Bayesian hyperparameter.
- There are two parts:
  - Exploration: Test the feature with the most uncertain outcome in collection of hyperparameters.
  - Operating: Test this function on a set of high-value hyperparameters.

# The problem with high dimensionality



- The dimension of a problem refers to the number of input variables (actually, degrees of freedom).
- The exponential increase in data required to densely populate space as the dimension increases.

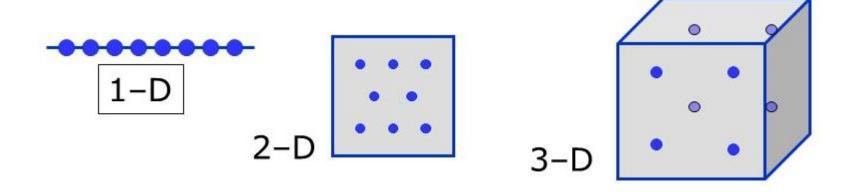


Figure: The Problem with High Dimensionality

Source: https://images.app.goo.gl/T6QLvXses34dSeXXA



### Information:

$$I(x) = -\log P(x). \tag{3.48}$$

### Entropy:

$$H(\mathbf{x}) = \mathbb{E}_{\mathbf{x} \sim P}[I(x)] = -\mathbb{E}_{\mathbf{x} \sim P}[\log P(x)]. \tag{3.49}$$

### KL divergence:

$$D_{\mathrm{KL}}(P||Q) = \mathbb{E}_{\mathbf{x} \sim P} \left[ \log \frac{P(x)}{Q(x)} \right] = \mathbb{E}_{\mathbf{x} \sim P} \left[ \log P(x) - \log Q(x) \right]. \tag{3.50}$$

Figure: Information theory Formulas

Source: https://images.app.goo.gl/DnbEL1fyXk23ory49

## **Self evaluation: Exercise 5**

- To continue with the training, after learning the various steps involved in pattern recognition and anomaly detection, it is instructed to utilize the concepts to perform the following activity.
- You are instructed to write the following activities using python code.
- Exercise 5: Logistic regression model.

## Checkpoint (1 of 2)



### Multiple choice questions:

- 1. The recalled output in pattern association problem depends on?
  - a) Nature of input-output
  - b) Design of network
  - c) Both input & design
  - d) None of the mentioned
- 2. What is the objective of feature maps?
  - a) To capture the features in space of input patterns
  - b) To capture just the input patterns
  - c) Update weights
  - d) To capture output patterns
- 3. Use of nonlinear units in the feedback layer of competitive network leads to concept of?
  - a) Feature mapping
  - b) Pattern storage
  - c) Pattern classification
  - d) None of the mentioned

# **Checkpoint solutions (1 of 2)**



- 1. The recalled output in pattern association problem depends on?
  - a) Nature of input-output
  - b) Design of network
  - c) Both input & design
  - d) None of the mentioned
- 2. What is the objective of feature maps?
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- 3. Use of nonlinear units in the feedback layer of competitive network leads to concept of?
  - a) Feature mapping
  - b) Pattern storage
  - c) Pattern classification
  - d) None of the mentioned

## Checkpoint (2 of 2)



### Fill in the blanks:

1.	learning is involved in pattern clustering task.
2.	If the weight matrix stores the given patterns, then the network becomes
3.	Activation models are
4.	Information theory is using in detection.

### True or False:

- 1. From given input-output pairs pattern recognition model should capture characteristics of the system? True/False
- 2. Can system be both interpolative & accretive at same time? True/False
- 3. Does pattern classification belong to category of non-supervised learning? True/False

# **Checkpoint solutions (2 of 2)**



#### Fill in the blanks:

- 1. <u>Unsupervised</u> learning is involved in pattern clustering task.
- 2. If the weight matrix stores the given patterns, then the network becomes <u>auto associative</u> <u>memory.</u>
- 3. Activation models are deterministic.
- Information theory is using in <u>pattern</u> detection.

#### True or False:

- From given input-output pairs pattern recognition model should capture characteristics of the system? True
- 2. Can system be both interpolative & accretive at same time? False
- 3. Does pattern classification belong to category of non-supervised learning? False

## **Question bank**



### Two mark questions:

- What is pattern detection?
- 2. What is information theory?
- 3. What is linear regression model?
- 4. What is the math formula for curve designing?

### Four mark questions:

- 1. What is the difference between pattern and anomaly detection?
- 2. What is polynomial curve fitting?
- 3. Describe high dimensionality problems.
- Describe information theory components.

### **Eight mark questions:**

- Explain model selection techniques.
- Explain probability theory in details.

# **Unit summary**



### After completing this unit, you should be able to:

- Understand the concept of pattern recognition and anomaly detection
- Gain knowledge on example of polynomial curve fitting
- Learn about probability theory architecture and working model
- Understand Information theory