

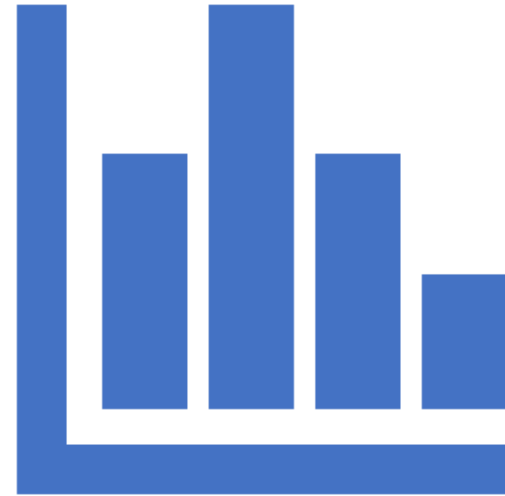
EL Activity: Hand Written Digit Recognition (Machine Learning and Evaluation Metrics)

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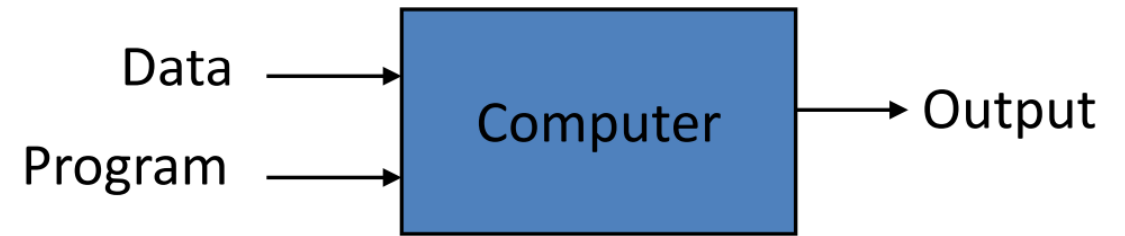
Topics Covered

- Machine Learning
- Types of Learning
- Classification Problem
- Handwritten Digit Recognition
- Dataset
- KNN
- Accuracy
- Confusion Matrix
- Precision-Recall
- F-1 Score

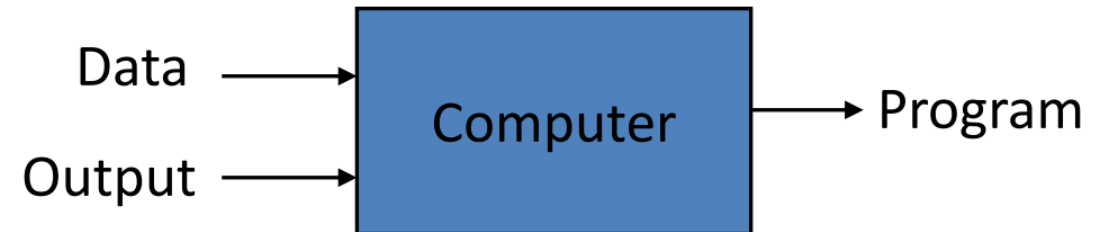
MACHINE LEARNING

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P , if its performance at tasks in T , as measured by P , improves with experience E .

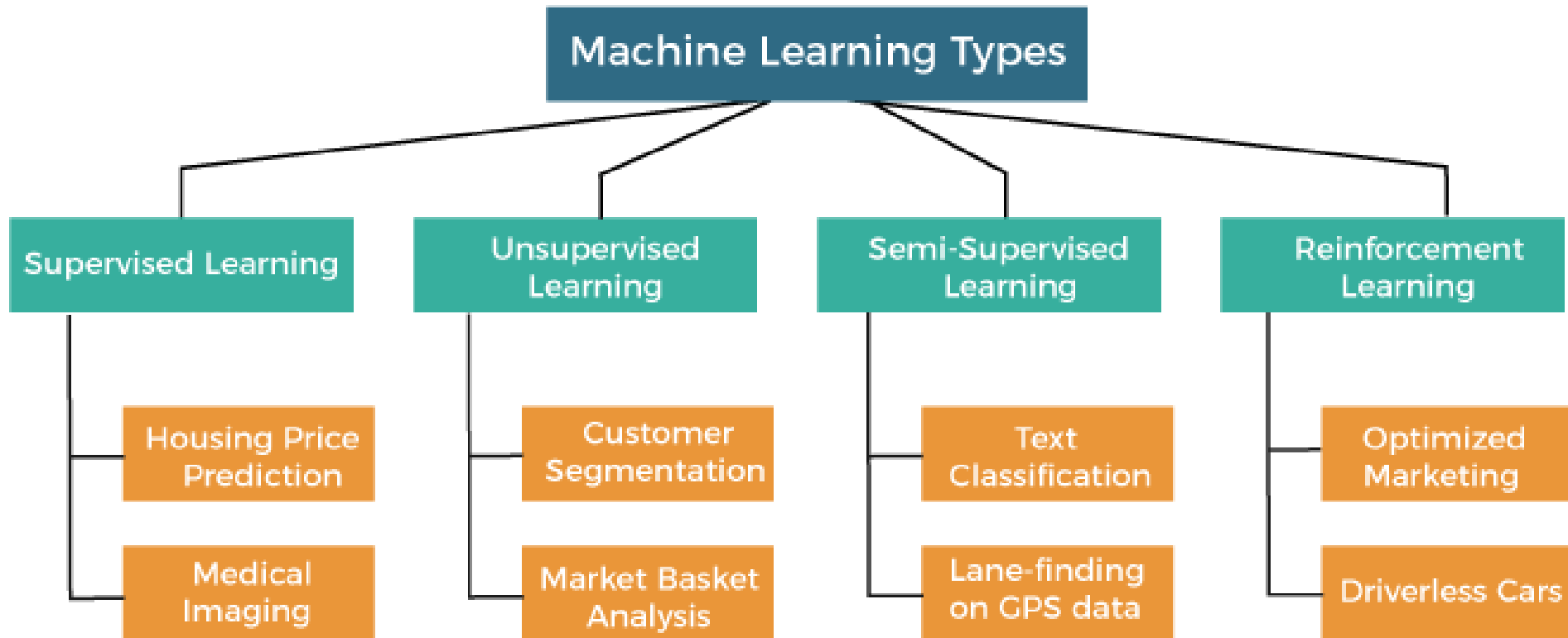
Traditional Programming



Machine Learning



Types of Machine Learning

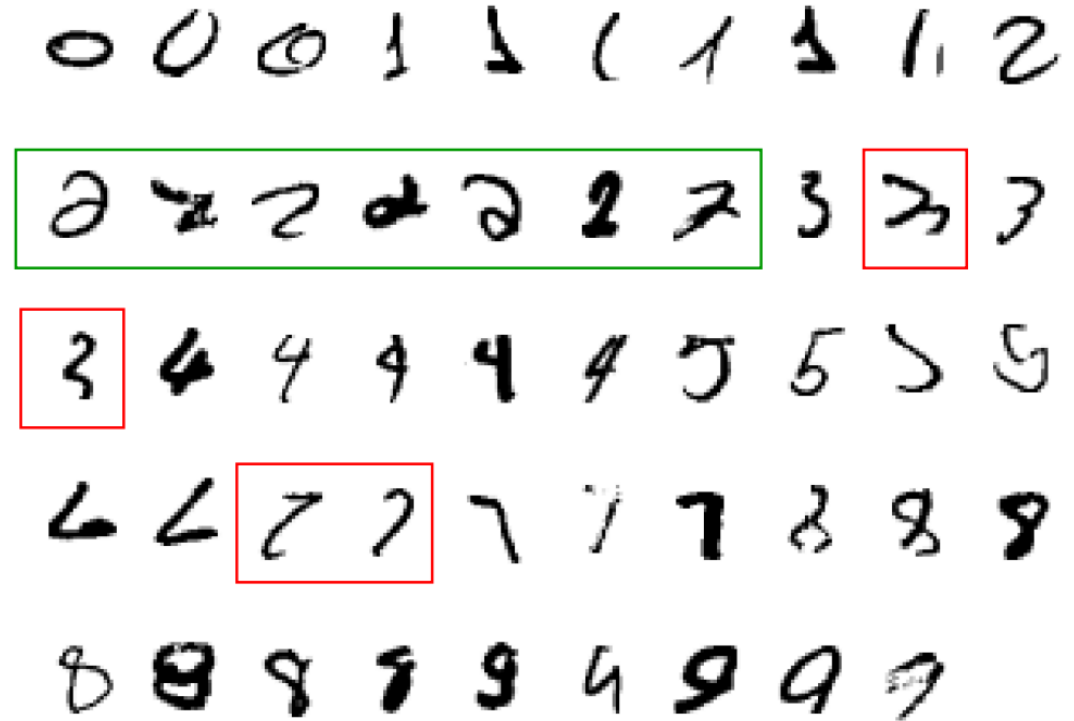


Classification Problem

- Assigns an instance to one of the predefined category or class.
- Model learning on labelled data.
- Unseen data given to learned model.
- Output provided either in terms of class labels or probabilities.
- Performance evaluation metric for a model is chosen based upon problem statement, dataset and type of output.

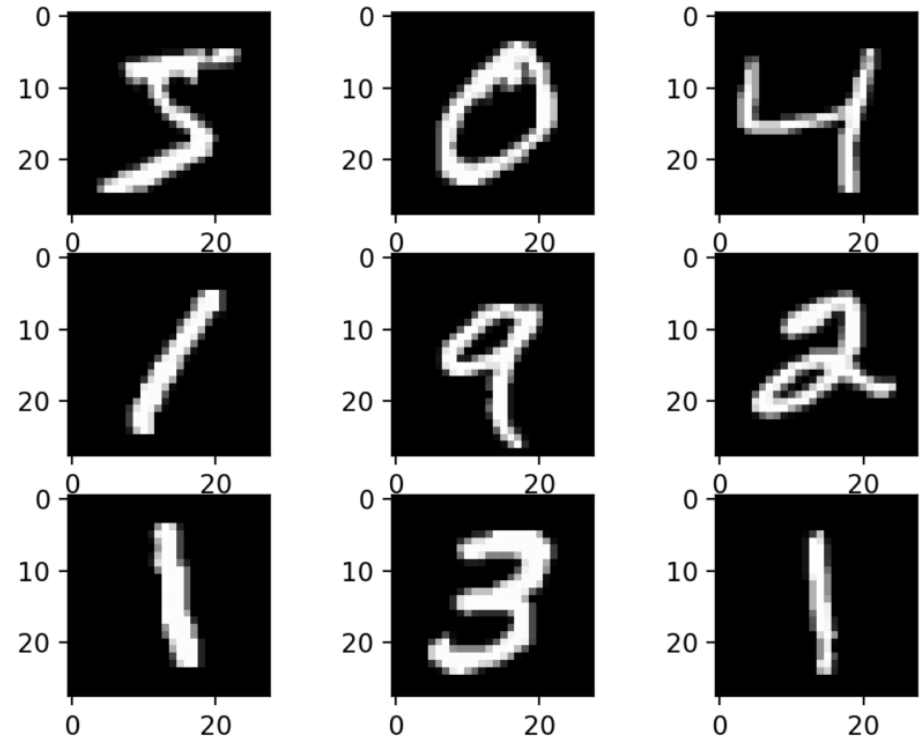
Handwritten Digit Recognition

- To recognize images of Handwritten digits based on classification methods for multivariate data.
- Optical Character Recognition (OCR)
 - Predict the label of each image using the classification function learned from training
- OCR is basically a classification task on multivariate data
 - Pixel Values -> Variables
 - Each type of character -> Class



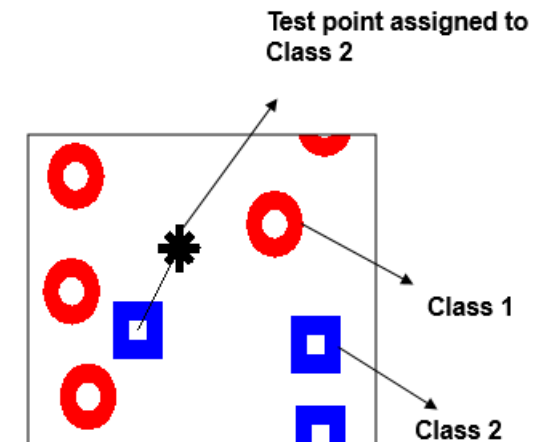
Dataset

- Challenges in processing of images due to differences in:
 - Size
 - Resolution
 - Line Thickness
 - Background and Digit Color
 - Shear etc..
- MINIST dataset:
 - Publicly available processed Dataset.
 - Created in 1994.
 - Originally contained 128*128 binary images, now available as 28*28 grayscale images.
 - Contains around 70000 images of 10 digits.



K-Nearest Neighbor (KNN)

- It is a supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point.
- Finds the nearest neighbors from the training set to test image and assigns its label to test image.
- No Assumption about the data.
- Euclidean Distance to find nearest neighbor.
- Compute the k nearest neighbors and assign the class by majority vote.
- K value can be changed, and the model accuracy varies for that.



Accuracy

- Simplest and Most commonly used approach.
- How many predictions made by the model are correct.

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions Made}}$$

- Error rate of a model is calculated from the accuracy as well.

$$\text{Error Rate} = 1 - \text{Accuracy}$$

- Works best for balanced dataset, i.e., when every class in the dataset is equally important.
- Not a reliable indicator of classifier's effectiveness in times of imbalanced dataset.



Issues of Accuracy metric

- Given an 8-year dataset of Stock market, labelling the days of Bank Nifty as bearish and bullish.
- Out of 2000 instances 1850 days are bullish, and 150 days are bearish.
- Train : Test split on 80:20.
- Dumb model learned each day is bullish.
- Testing Model on 400 instances (360 bullish, 40 bearish).
- $\text{Accuracy} = \frac{360}{400} = 90\%$
- Error Rate= 10%
- On deploying model fails miserably, when the bear market begins.

Confusion Matrix

- A visual representation of model performance.
- Shows a more detailed breakdown of correct and incorrect classification for each class.
- General idea is to count the number of times instances of one class are classified as other.
- Provides model performance for each class.
- Rows of the matrix represents actual class.
- Columns represents predicted class.
- Call `confusion_matrix` function on test dataset.

Predicted→ Actual↓	YES	NO
YES	Correctly Predicted Yes	Incorrectly Predicted No
NO	Incorrectly Predicted Yes	Correctly Predicted No

Confusion Matrix

- A confusion matrix for two classes (+, -).
- There are four quadrants in the confusion matrix, which are symbolized as below:
- **True Positive (TP)** : The number of instances that were positive (+) and correctly classified as positive (+v).
- **False Negative (FN)**: The number of instances that were positive (+) and incorrectly classified as negative (-). It is also known as **Type 2 Error**.
- **False Positive (FP)**: The number of instances that were negative (-) and incorrectly classified as (+). This also known as **Type 1 Error**.
- **True Negative (TN)**: The number of instances that were negative (-) and correctly classified as (-).

	C ₁	C ₂
C ₁	True positive	False negative
C ₂	False positive	True negative

	+	-
+	++	+-
-	-+	--

Confusion Matrix

Bullish	360	0
Bearish	40	0
	Bullish	Bearish

- Perfect classifier have only true positives and true negatives.
- Non-diagonal values should be minimum or zero(perfect classifier).
- Accuracy can be calculated from Confusion matrix.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$$

- Color coded matrix help visualization of model performance.
- Drawback: not understandable by layman.
- Concise Results serve better for non-technical persons.
- Many concise results can be drawn from confusion matrix.

Precision- Recall

Precision:

- How many predicted positive values are actually positive.
- It is defined as the fraction of the positive examples classified as positive that are really positive.

$$Precision = \frac{TP}{TP + FP}$$

- It is also known as Positive Prediction Value(PPV).

Recall:

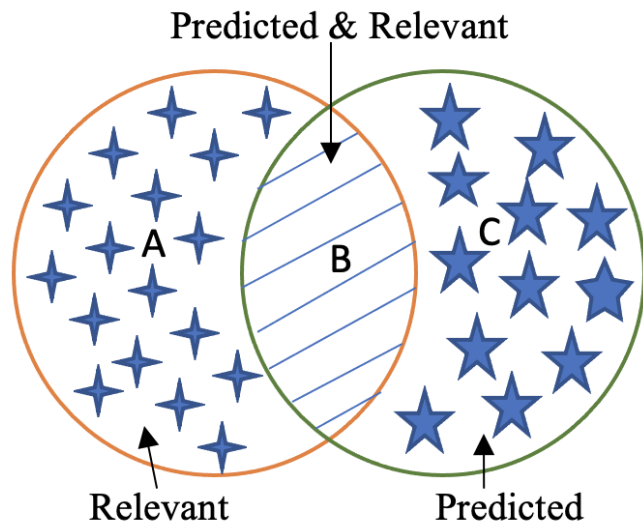
- Out of total actual positive values, how many positives did model predict.

$$TPR = \frac{TP}{TP + FN}$$

- Also known as TPR.



Precision- Recall



Precision answers:

“Out of the items that the classifier predicted to be relevant how many are truly relevant?”

Recall Answers:

“Out of all the items that are truly relevant, how many are identified by the classifier?”

F-1 Score

- When both Precision and Recall have importance for the problem statement.
- Harmonic Mean of Precision and Recall.

$$\text{F-1 Score} = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2 * TP}{2 * TP + FP + FN}$$

- Regular mean treats all the value equally.
- Harmonic mean gives more weightage to low values.
- A classifier will get a high F-1 Score if both Recall and Precision are high.



THANK YOU