



- Regular expressions
- TF-IDF such as word2vec
- ML techniques
- Networkx
- Neo4j
- Graph alogorithim centrality measure

- Graph data modeling

## Machine learning

### Supervised learning

### Unsupervised learning

05 February 2024

Supervised learning error metrics  
Supervised learning algorithms are trained labelled examples, such as input where desired output is known.

### Unsupervised learning error metrics

Unsupervised learning algorithms find structure in unlabeled, unclassified or uncategorized data.

Either correct or

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Commonly used for:

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Known inputs and outputs to train the algorithm, uses this to make predictions on new unseen data

Commonly used where historic data predicts future events

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Clustering

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Dimensionality reduction

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Data split 3 sets:

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Training data, Validation data, test data

- Two types of problems:

- Regression: mapping predictive relationship between labels and data points

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Classification: Predict correct label for input data

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Regression: linear regression

- Classification: K-NN, SVM, random forest, decision trees, naïve bayes, logistic regression



Classification error metrics

Regression error metrics

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Mean absolute error, mean of absolute value of error

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With classification the error can either be correct or incorrect

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Large errors not really punished

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Accuracy, number of correct prediction divide by overall predictions

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Mean square error, mean of squared error

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Large error punished more

Root meansquare error, root of MSE

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Pros: useful when classes are balanced

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Punishes large errors again

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Cons: not useful when classes are unbalanced

- **Recall:** to find all relevant cases within dataset, true positives divided by true positives + false negatives

- **Precision:** ability to identify only relevant data points, true positives divided by true positives + false positives

- Will have trade-off between recall and precision

- F1 score takes harmonic mean of precision vs recall



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- A document represented as a vector of word counts is called a "Bag of Words"
  - "Blue House" -> (red,blue,house) -> (0,1,1)
  - "Red House" -> (red,blue,house) -> (1,0,1)
- You can use cosine similarity on the vectors made to determine similarity:

$$\text{sim}(A, B) = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$



PIERIAN DATA



- Term Frequency - Importance of the term within that document
  - $TF(d,t)$  = Number of occurrences of term  $t$  in document  $d$
- Inverse Document Frequency - Importance of the term in the corpus
  - $IDF(t) = \log(D/t)$  where
    - $D$  = total number of documents
    - $t$  = number of documents with the term

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- We can improve on Bag of Words by adjusting word counts based on their frequency in corpus (the group of all the documents)
- We can use TF-IDF (Term Frequency - Inverse Document Frequency)

## Vectorization:

- Convert each message represented as a list of tokens (lemmas), into a vector that machine learning models can understand
- Do that in 3 steps with bag of words model:
  - Count how many times does a word occur in each message (term frequency)
  - Weight the counts, so that frequent tokens get lower weight (inverse document frequency)
  - Normalize vectors to unit length, to abstract from original text length

Use pipeline?

# Deep learning

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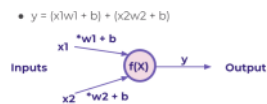
## Steps:

1. Single biological neuron
2. Perceptron
3. Multi-layer perceptron model
4. Deep learning neural network

## Other concepts:

1. Activation functions
2. Gradient descent
3. Back propagation

## Perceptron model:



- We've been able to model a biological neuron as a simple perceptron! Mathematically our generalization was:

$$\hat{y} = \sum_{i=1}^n x_i w_i + b_i$$

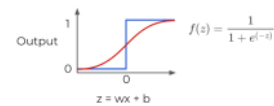
## Neural network:

- Can expand on idea of single perceptron, to create a multi-layer perceptron model
- Outputs of one perceptron act as inputs to another perceptron
- **Hidden layers:** layers in-between input and output layers
- **Deep neural networks:** contain 2 or more hidden layers

## Activation functions:

- $Z = x^*w + b$
- Pass  $z$  through activation function to limit its value

- Lucky for us, this is the sigmoid function!



- Wiki to see other activation functions

## Multi class classification problems:

2 types of situations:

- Non - exclusive classes
  - Data point to which multiple classes/categories assigned to it
- Mutually exclusive classes
  - Only one class per data point
  - e.g photo can either be colour or grayscale

## Organizing multiple classes:

- Have 1 output node per class
- Use one hot encoding (dummy variables)
- After data organised correctly, choose correct classification function for output layer
- Non-exclusive: sigmoid function
- Mutually exclusive: softmax function

$$\sigma(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad \text{for } i = 1, \dots, K$$

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## Cost functions:

- Output  $y$  models estimation of what it predicts the label to be. How do we evaluate it?
- Need to take estimated outputs and compare with real values of the label
- Cost function is an average
- Calculate difference between actual and predicted values

$$C = \frac{1}{2n} \sum_x [y(x) - a^L(x)]^2$$

- Want to minimise cost function, what value of  $w$  results in minimum of  $c(w)$
- Use gradient descent to solve problem
- Step size is learning rate
- For classification problems use *cross entropy loss function*

## Backpropagation:

- Want to know how cost function changes with respect to weights in the network, so can update weights to minimize cost func
- How sensitive cost function to changes in  $w$

$$\frac{\partial C_0}{\partial w^L} = \frac{\partial z^L}{\partial w^L} \frac{\partial a^L}{\partial z^L} \frac{\partial C_0}{\partial a^L}$$

- Lots of maths steps?

# models

12 February 2024 15:08

## K means clustering:

- Unsupervised algorithm which will attempt to group similar clusters together in your data
- Typical clustering problems:
  - Clustering similar documents
  - Cluster customers based on features
  - Identify similar physical groups
- Divide data into distinct groups
- Choose number of clusters "k", randomly assign each point to cluster. Keep repeating until clusters stop changing

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# OOP

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