CloudAEye Webinar series

How to become a data-driven enterprise with AI

Episode 3a: Classification models

Recap: Previous episode

Episode 1

Data-driven Enterprise, Introduction to AI concepts, Code examples

Episode 2

- Deep dive into supervised ML models
    - Regression and Classification/Train and Test split
- ML Model basics
    - Basic concepts: parameters, model fitting, bias and variance
    - Over and underfitting
    - Concepts of loss function and optimization
    - Regularization in ML models
- Code examples

Agenda for this episode

- Episode 3(a)
    - Introduction to classification
    - Logistic regression
        - Idea, model
- Episode 3(b)
    - A detailed worked out example of logistic regression
    - Code walkthrough and explanation
- Episode 3(c)
    - Practical aspects of logistic regression
    - How to understand a model
    - Evaluation of classification models

Supervised ML algorithms

Recap from last episode

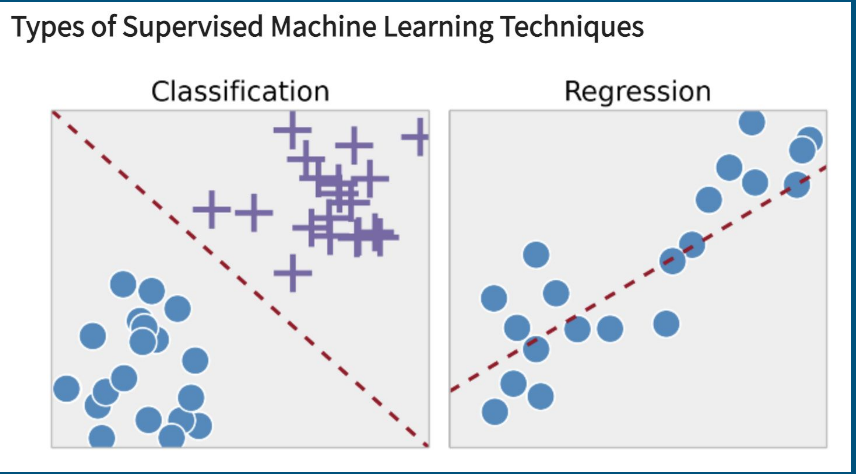
When the data is “labeled” or “tagged” for the correct outcome or value:

Input looks like (X, y)

Where X is the set of input features and y is the outcome variable that is provided

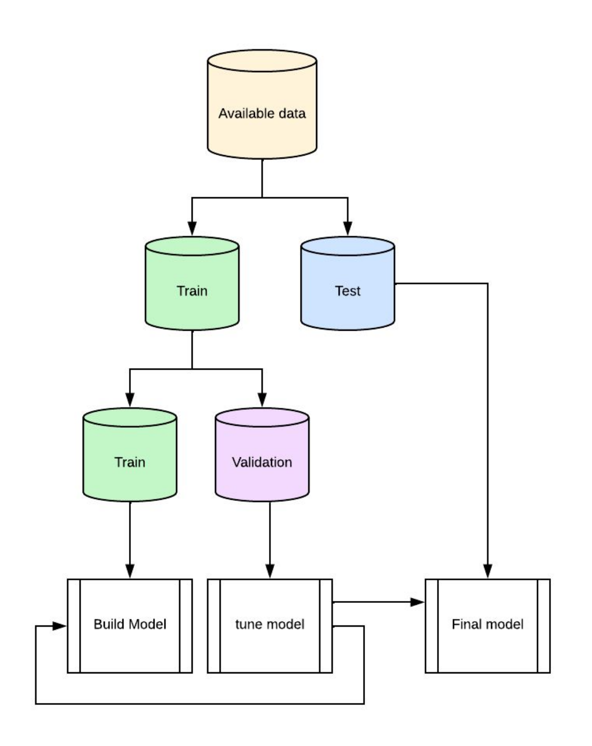
Based on y we have two classes of supervised learning:

1. Regression, where y is continuous ex: linear regression, tree-based regression, SVR
2. Classification, where y is discrete. ex: logistic regression, decision trees, SVM, KNN, deep networks



Model Building: Train-Test split

- Available data is divided into
  - Train (usually 80%)
  - Test (20%)
- Test data is kept aside (held out) and never seen by the algorithm during model building
- To build a better model we may need to tweak different settings (hyper parameters) so Train data is further divided into
  - Train (80%)
  - Validation (20%)



Supervised ML: Basics of Model Building

- What is a model? How is it different from algorithm?

  An ML algorithm is the particular method, and the model is the result of applying that method

  $\mathbf{Y} = f(X)$ here **f** is the model

  Example: a linear regression model, a decision tree model

- Parametric vs non-parametric models
  - A parametric model uses a set of parameters to represent the learning of the algorithms e.g., coefficients of regression or weights of neural networks etc
  - A nonpayment model doesn't explicitly use weights or parameters e.g., k-nearest neighbors

Linear Regression

- Most basic form of supervised ML model

Given a n-dimensional vectors of numeric input variables X_i (usually called “independent” or “explanatory” variables) and a numeric outcome variable y_i (usually called“the dependent variable”):

- Find a n-dimensional vector β such that $\beta.x_i$ is a good estimate of y_i.

$$\hat{Y} = \beta_0 + \beta_1 x_1 + \dots + \beta_n x_n$$

Linear Regression: Least Square Solution

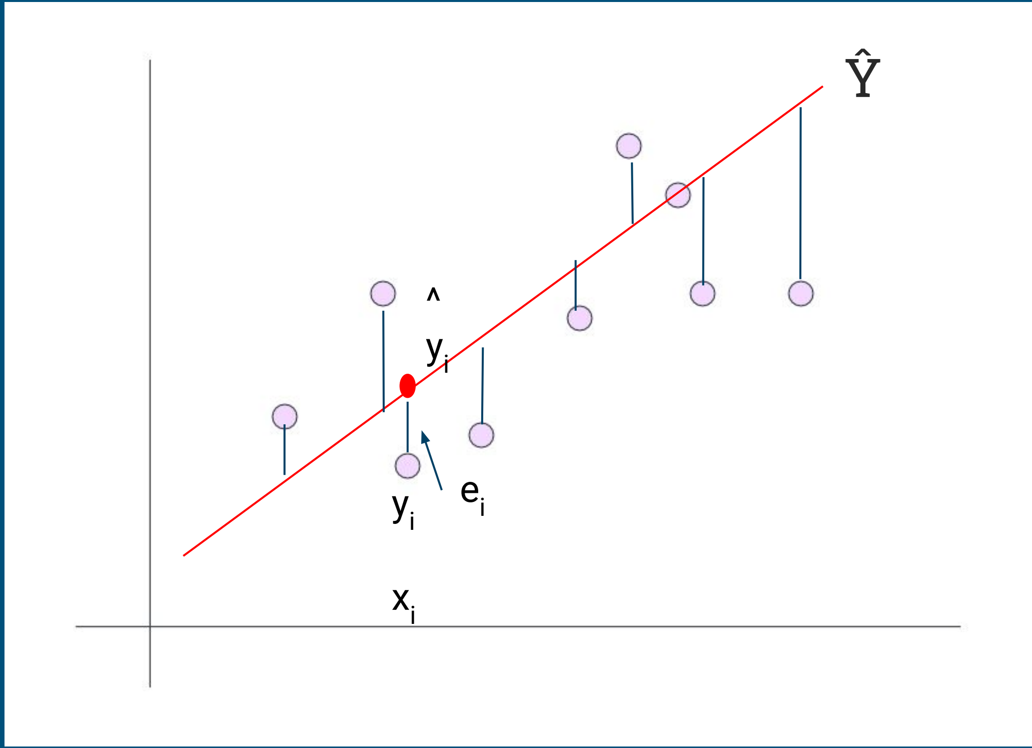
At each training point x_i, the actual output is y_i but the model predicts $\hat{y}_i$
So at each point the error ei = ŷi - y_i

We define a Loss function, called the Sum of Squares Error as

$$L(Y, \beta) = \sum e_i^2 = \sum (\hat{y}_i - y_i)^2$$

Recall that $\hat{y}_i = \beta_0 + \beta_1 x_i$ So the loss function becomes

$$L(Y, \beta) = \sum (\beta_0 + \beta_1 x_i - y_i)^2$$



Fitting the model

In our Notebook we see that we can use scikit-learn package for fitting a linear regression model by calling:

```
regr = linear_model.LinearRegression()
# Train the model using the training sets
regr.fit(diabetes_X_train, diabetes_y_train)
```

Model.fit is a very important concept in scikit-learn as all models follow the same interface

What exactly is a model? How is it fitted?

From Linear regression to Logistic Regression

- Classification has discrete valued targets
  - Binary – {YES, NO}, {0, 1}, {Normal, abnormal}
  - Multi-valued – images classified into {Cats, Dogs, Birds, Horses, ..}
- Linear regression models that we have seen before are not suitable for this type of applications
- The output values are not guaranteed to

  Be bounded between [0,1]

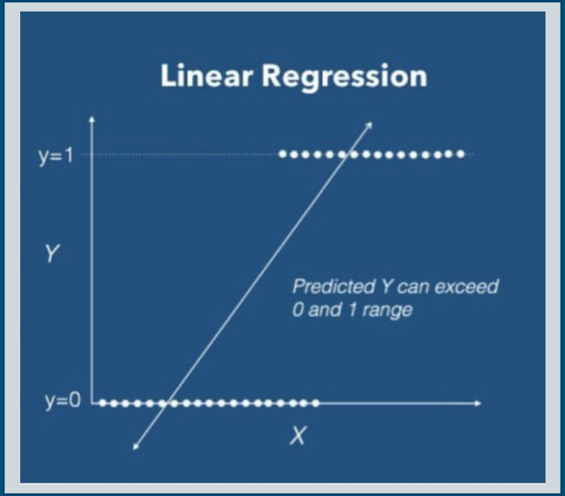


Image source:
https://medium.com/analytics-vidhya/a-comprehensive-guide-to-logistic-regression-e0cf04fe738c

From Linear regression to Logistic Regression

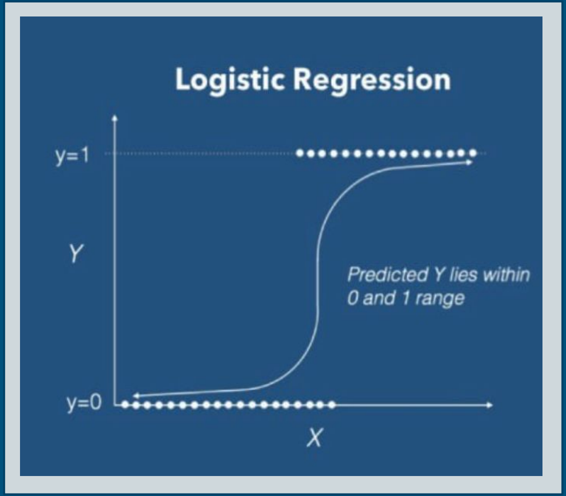
So we use a different type of model that takes the linear regression output and passes it through a squashing function

Called the “Sigmoid” or Logistic function

σ(z) = 1/(1 + e ^ (-z)) so, the model equation

becomes

$$y = \frac{1}{1+e^{-(w_0 + w_1 x)}}$$



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https://medium.com/analytics-vidhya/a-comprehensive-guide-to-logistic-regression-e0cf04fe738c

Converting the logistic function into classifier

The logistic or sigmoid function $\sigma(z)$ provides a score between 0 and 1

We can use the score to define a **threshold** value that corresponds to a “decision boundary” to perform the classification task

For instance if **threshold** = 0.5 then

We can assign

$y = 0$ if $\sigma(.) <= 0.5$ and

$y = 1$ if $\sigma(.) > 0.5$

Thus a threshold converts the output of the logistic function $\sigma()$ to a classifier

White board

The derivation of the equation

Log odds ratio

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