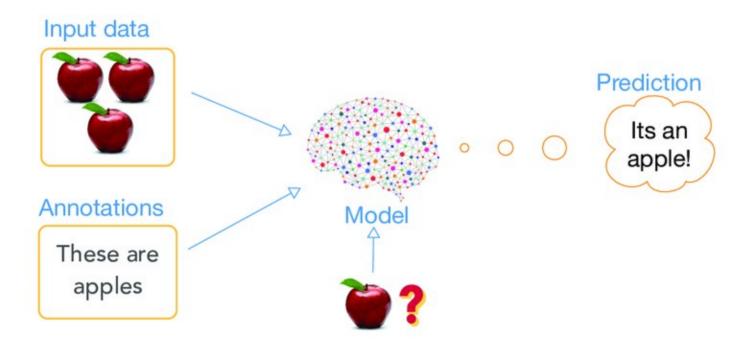
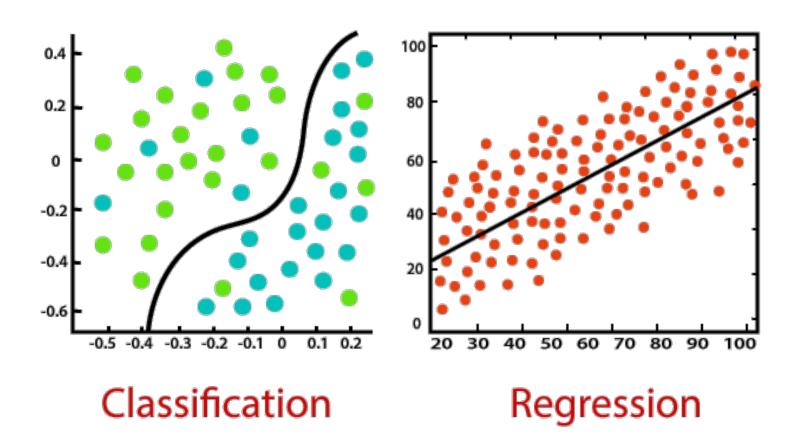
## Supervised learning – logistic regression

#### What is supervised learning?

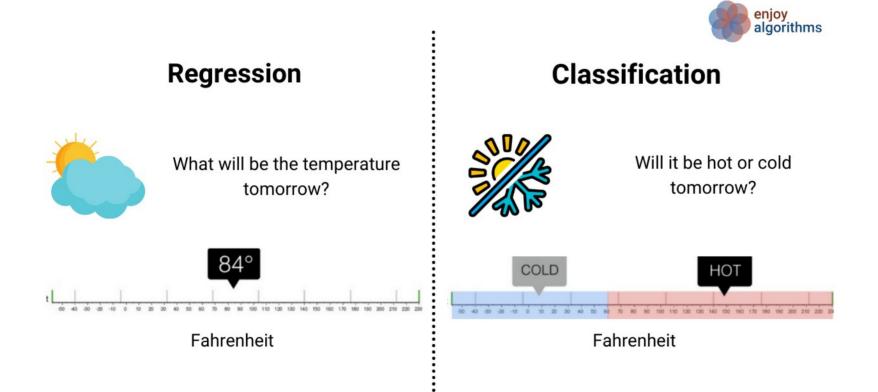
supervised learning



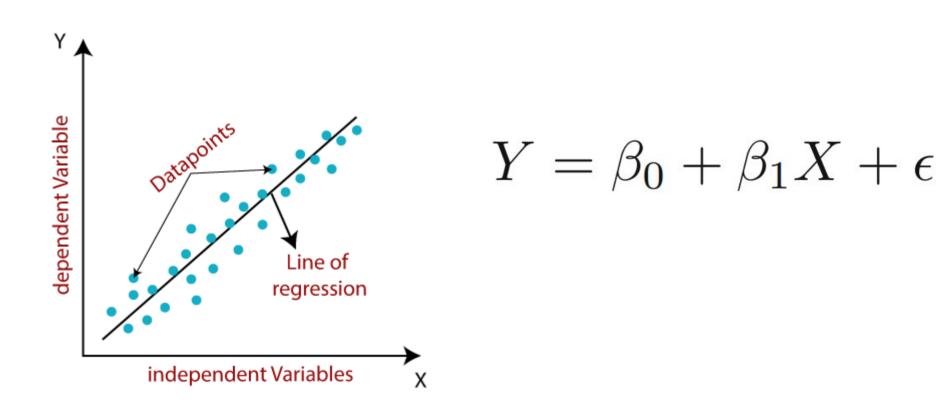
#### **Regression vs Classification**



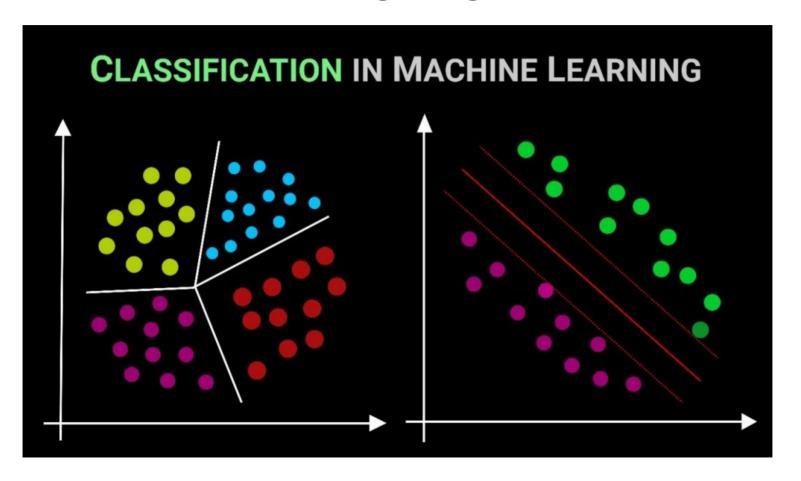
#### **Regression vs Classification**



#### Regression – most well known case:)



#### **Classification – assigning labels**



#### Classification: What about qualitative outcomes?

 Consider an outcome measuring if a person voted in the latest election.

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### Classification: What about qualitative outcomes?

- Consider an outcome measuring if a person voted in the latest election.
  - We want to see if age is a factor in voting?
  - Can we use the simple linear regression framework?

$$Y = \beta_0 + \beta_1 X + \epsilon$$

Y = 1 if person voted, 0 if not

X = age

- Let us extend the voting scenario a bit further.
  - Consider three outcomes for the persons vote republican, democrat or independent.

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    - How would you code this?

```
Republican 1
```

Democrats 2

Independent 3

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  - Consider three outcomes for the persons vote republican, democrat or independent.
    - How would you code this?

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Republican 1
```

Democrats 2

Independent 3

 What does this coding assume? What happens if we change the coding?

- Let us look at another aspect of the simple voting scenario (voted/not voted : Y=1/0).
  - Consider a linear model of this against age

$$Y = \beta_0 + \beta_1 X + \epsilon$$

- Can Y be fit as anything other than 0 and 1?
  - How would you transform a fitted Y to 0 or 1?
  - What about less than 0 or more than 1?

#### Classification: So what can we use?

- Think of the dichotomous voting case (Y=1/0)
  - What should we be fitting?
    - The probability of an outcome
      - Disease
      - Voting
    - What function can we use?

#### Classification: Logistic regression

One way to model the relationship between p(X) = P(Y=1 | X)

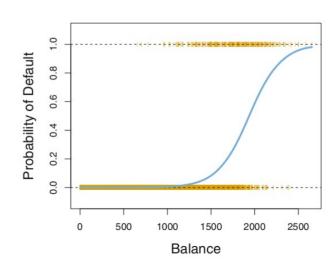
$$p(X) = P(Y = 1|X) = \frac{e^{\beta_0 + \beta_1 X}}{1 + e^{\beta_0 + \beta_1 X}}$$

#### Classification: Logistic regression

One way to model the relationship between p(X) = P(Y=1 | X)

$$p(X) = P(Y = 1|X) = \frac{e^{\beta_0 + \beta_1 X}}{1 + e^{\beta_0 + \beta_1 X}}$$

What is this monstrosity?

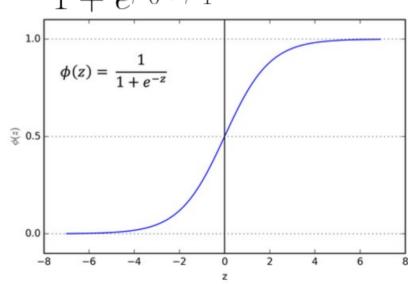


#### Classification: Logistic regression

One way to model the relationship between p(X) = P(Y=1 | X)

$$p(X) = P(Y = 1|X) = \frac{e^{\beta_0 + \beta_1 X}}{1 + e^{\beta_0 + \beta_1 X}}$$

- What is this monstrosity?
  - Sigmoid curve



### Logistic regression

• Why is it still a linear model?

$$p(X) = P(Y = 1|X) = \frac{e^{\beta_0 + \beta_1 X}}{1 + e^{\beta_0 + \beta_1 X}}$$

$$\frac{p(X)}{1 - p(X)} = e^{\beta_0 + \beta_1 X}$$

$$\log(\frac{p(X)}{1 - p(X)}) = \beta_0 + \beta_1 X$$

Link function: Links Y to the linear predictor Log-odds or logit

Linear predictor: Linear function of X

# Logistic regression: What do the coefficients mean?

Here is the model again:

$$log(\frac{p(X)}{1 - p(X)}) = \beta_0 + \beta_1 X$$

- $\beta_0$ : Intercept log-odds when X=0
- $\beta_1$ : Slope Increase in log-odds with unit increase in X or  $\exp(\beta_1)$  is the increase in odds for unit increase in X.

#### Logistic regression: Estimating the coefficients

- We can use a likelihood framework (cost function)
  - The likelihood formula is not analytically solvable
  - Use a numerical solver to estimate the coefficients
    - gradient descent
  - Use inbuilt methods in python

#### **Logistic regression: More topics**

- Multiple logistic regression
- Polytomous regression

#### **Exercise Time**