

# COMP4388: MACHINE LEARNING

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Naive Bayes

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## Probabilistic Models

- 80% chance of rain
  - 90% chance the tumor is benign
  - 88% the email is spam
  - 90% chance of winning the elections
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- These are probabilistic estimates that show the probability of an event to occur

## Probabilistic Models (2)

- Estimates based on probabilistic methods
- Methods concerned with describing uncertainty
- These methods use data on past events to predict future events

## Probabilistic Models (3)

- For instance, the weather forecasting of 80% describes that the proportion of days from the past data with similar properties (conditions, attributes) , an 80% chance it will rain which means with similar conditions, 8 times out of 10 times it did rain with similar patters of weather attributes

## Probabilistic Models (4)

- 90% chance that the tumor is benign means that based on previously collected data and medical records, analysis of biopsies of similar tissues showed that 9 out of 10 times the tumors were benign (not malignant)

## Probabilistic Models (5)

- 88% of previously collected emails showed that based on the pattern of the current email, 8.8 out of 10 times in which emails with similar patterns and/or words were spam

## Naive Bayes

- Naive Bayes classifier is a generative probabilistic model that based on Bayes Theorem
- It assumes that all features are conditionally independent of one another given the target class
- Naive Bayes classifier also assumes that all assumptions are explicitly built using a set of input feature vectors

## Naive Bayes (2)

- Naive Bayes classifier is based on Bayes theorem and it calculates the probability of each target class  $y \in Y$  given a feature vector  $f \in F$

$$p(y|f) = \frac{p(y) p(f|y)}{p(f)}$$

## Naive Bayes (3)

$$p(y|f) = \frac{p(y) p(f|y)}{p(f)}$$

- where  $p(f|y)$  is the unknown probability estimation of the joint distribution of the feature vector  $f$  and the target class  $y$ ;  $p(y)$  is the class prior and is estimated from the training data

## Naive Bayes (4)

$$P(\text{spam}|\text{Prince}) = \frac{P(\text{Prince}|\text{spam})P(\text{spam})}{P(\text{Prince})}$$

- $P(\text{spam}|\text{Prince})$  is the posterior probability which measures how likely this message spam
- $P(\text{Prince}|\text{spam})$  is the likelihood which is the probability that word 'Prince' was used in previous '**spam**' messages
- $P(\text{spam})$  which is the probability that any prior message was spam
- $P(\text{Prince})$  is the marginal likelihood which is the probability that the word 'Prince' appeared in any message

## Naive Bayes (5)

- $p(f|y)$  is estimated by following Bayes theorem, which assumes that the attributes are independent given the target class

$$p(f_1, f_2, \dots, f_n | y) = p(f_1|y) p(f_2|y) \dots p(f_n|y)$$

- where  $f_i$  is the  $i^{\text{th}}$  dimension of the feature vector

## Naive Bayes (6)

- Though this can be seen as a naive independence assumption, naive Bayes has shown to be a strong classifier in many areas such as Spam email filters
- Moreover, this independence assumption is feasible with the datasets in which the features may not be strongly correlated (as if they are independent)

## Naive Bayes (7)

- Naive Bayes classifier can be then written as

$$p(y | f) = p(y) \prod_{m=1}^N p(f_m | y)$$

- and the classification rule of a new input feature vector  $f_{new}$  becomes

$$y^* = \arg \max_{y \in \mathcal{S}} p(y) \prod_{m=1}^N p(f_m^{new} | y)$$

## Naive Bayes (8)

- Using this classifier, the classification rule becomes as given a new input feature vector, classify it with the target class that of the highest probability

## Feature discretisation

- If the classification task involves continuous (quantitative) attributes, they have to be discretised so that the Bayesian classifier can calculate the prior-probability of the target classes
- Algorithms to discretise continuous attributes include Entropy Minimisation Discretisation (EMD), Kernel estimation,...

## Strengths of Naive Bayes

- Simple, fast, and quite effective
- Performs well on missing and noisy data
- Does not require many training examples through the training process
- Works well with large number of training examples
- Easy to obtain the estimated probability for a prediction



## Weaknesses of Naive Bayes

- Relies on an often faulty assumption of equally important and independent features
- Not the best choice of data with large number of numeric features
- Since the output is estimated probability, target class outputs are more reliable than probabilistic estimations