# Machine Learning Review

Naïve Bayes

#### Bayes' rule applied to documents and classes

• For a document d and a class c

$$P(c \mid d) = \frac{P(d \mid c) P(c)}{P(d)}$$

$$C_{map} = argmax P (c | d)$$

$$= argmax \frac{P(d | c) P(c)}{P(d)}$$

$$= argmax P (d | c) P (c)$$

## Bayes classifier

$$C_{map} = argmax P (d | c) P (c)$$
$$= argmax P (x_1, x_2, \dots, x_n, | c) P (c)$$

Documents represented as features

- Bag of words assumption: assume position doesn't matter.
- Conditional independence: assume feature probabilities  $P\left(x_i|c_j\right)$  are independent given class c.

$$P(x_1, x_2, ..., x_n | c) = P(x_1 | c) * P(x_2 | c) .... P(x_n | c)$$

### Bayes classifier

Positions = all words positions in the document

$$C_{NB} = argmax P(c_j) \prod_{i \in positions} P(x_i | c_j)$$

because log(ab) = log(a) + log(b)

$$C_{NB} = argmax \left[ \log P \left( c_j \right) + \sum_{i \in positions} \log P \left( x_i \mid c_j \right) \right]$$

#### Learning the Multinomial Naive Bayes Model

Maximum likelihood estimates

• Simply use the frequencies in the data

$$\widehat{P}(c_j) = \frac{doccount(C=c_j)}{N_{doc}}$$

$$\widehat{P}(w_i \mid c_j) = \frac{count(w_i, c_j)}{\sum_{w \in V} count(w, c_j)}$$

fraction of times word  $w_i$  appears among all words in documents of topic  $c_i$ 

#### **Smoothing Naive Bayes**

What if your test data contains a word that is not in your training data?

$$\widehat{P}(w_i \mid c_j) = \frac{count(w_i, c_j) + 1}{\sum_{w \in V}(count(w, c_j) + 1)}$$

$$= \frac{count(w_i, c_j) + 1}{\left(\sum_{w \in V} count(w, c_j)\right) + |V|}$$

Default probability of every word is 1 over vocabulary