COMP9318 (18S1) Assignment 1

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Q1.

(1)

|  |  |  |  |
| --- | --- | --- | --- |
| Location | Time | Item | Quantity |
| Sydney | 2005 | PS2 | 1400 |
| Sydney | 2005 | ALL | 1400 |
| Sydney | 2006 | PS2 | 1500 |
| Sydney | 2006 | Wii | 500 |
| Sydney | 2006 | ALL | 2000 |
| Sydney | ALL | PS2 | 2900 |
| Sydney | ALL | Wii | 500 |
| Sydney | ALL | ALL | 3400 |
| Melbourne | 2005 | XBox 360 | 1700 |
| Melbourne | 2005 | ALL | 1700 |
| Melbourne | ALL | XBox 360 | 1700 |
| Melbourne | ALL | ALL | 1700 |
| ALL | 2005 | PS2 | 1400 |
| ALL | 2005 | XBox 360 | 1700 |
| ALL | 2005 | ALL | 3100 |
| ALL | 2006 | PS2 | 1500 |
| ALL | 2006 | Wii | 500 |
| ALL | 2006 | ALL | 2000 |
| ALL | ALL | PS2 | 2900 |
| ALL | ALL | Wii | 500 |
| ALL | ALL | XBox 360 | 1700 |
| ALL | ALL | ALL | 5100 |

(2)

SELECT \* FROM Sales

UNION

SELECT Location, Time, “ALL”, SUM(Quantity)

FROM Sales

GROUP BY Location, Time

UNION

SELECT Location, “ALL”, Item, SUM(Quantity)

FROM Sales

GROUP BY Location, Item

UNION

SELECT “ALL”, Time, Item, SUM(Quantity)

FROM Sales

GROUP BY Time, Item

UNION

SELECT Location, “ALL”, “ALL”, SUM(Quantity)

FROM Sales

GROUP BY Location

UNION

SELECT “ALL”, Time, “ALL”, SUM(Quantity)

FROM Sales

GROUP BY Time

UNION

SELECT “ALL”, “ALL”, Item, SUM(Quantity)

FROM Sales

GROUP BY Item

UNION

SELECT “ALL”, “ALL”, “ALL”, SUM(Quantity)

FROM Sales;

(3)

|  |  |  |  |
| --- | --- | --- | --- |
| Location | Time | Item | Quantity |
| Sydney | 2006 | ALL | 2000 |
| Sydney | ALL | PS2 | 2900 |
| Sydney | ALL | ALL | 3400 |
| ALL | 2006 | ALL | 2000 |
| ALL | 2005 | ALL | 3100 |
| ALL | ALL | PS2 | 2900 |
| ALL | ALL | ALL | 5100 |

(4)

Step 1: mappings

1 if x = `Sydney'; 2 if x = `Melbourne'; 0 if x = ALL:

1 if x = 2005; 2 if x = 2006; 0 if x = ALL:

1 if x = `PS2'; 2 if x = `XBox 360'; 3 if x = `Wii'; 0 if x = ALL:

|  |  |  |  |
| --- | --- | --- | --- |
| Location | Time | Item | Quantity |
| 1 | 1 | 1 | 1400 |
| 1 | 1 | 0 | 1400 |
| 1 | 2 | 1 | 1500 |
| 1 | 2 | 3 | 500 |
| 1 | 2 | 0 | 2000 |
| 1 | 0 | 1 | 2900 |
| 1 | 0 | 3 | 500 |
| 1 | 0 | 0 | 3400 |
| 2 | 1 | 2 | 1700 |
| 2 | 1 | 0 | 1700 |
| 2 | 0 | 2 | 1700 |
| 2 | 0 | 0 | 1700 |
| 0 | 1 | 1 | 1400 |
| 0 | 1 | 2 | 1700 |
| 0 | 1 | 0 | 3100 |
| 0 | 2 | 1 | 1500 |
| 0 | 2 | 3 | 500 |
| 0 | 2 | 0 | 2000 |
| 0 | 0 | 1 | 2900 |
| 0 | 0 | 3 | 500 |
| 0 | 0 | 2 | 1700 |
| 0 | 0 | 0 | 5100 |

Step 2: An injective map from cell to offset

f(location, time, item) = 16\*location + 4\*time + item

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Location | Time | Item | Quantity | Offset |
| 1 | 1 | 1 | 1400 | 21 |
| 1 | 1 | 0 | 1400 | 20 |
| 1 | 2 | 1 | 1500 | 25 |
| 1 | 2 | 3 | 500 | 27 |
| 1 | 2 | 0 | 2000 | 24 |
| 1 | 0 | 1 | 2900 | 17 |
| 1 | 0 | 3 | 500 | 19 |
| 1 | 0 | 0 | 3400 | 16 |
| 2 | 1 | 2 | 1700 | 38 |
| 2 | 1 | 0 | 1700 | 36 |
| 2 | 0 | 2 | 1700 | 34 |
| 2 | 0 | 0 | 1700 | 32 |
| 0 | 1 | 1 | 1400 | 5 |
| 0 | 1 | 2 | 1700 | 6 |
| 0 | 1 | 0 | 3100 | 4 |
| 0 | 2 | 1 | 1500 | 9 |
| 0 | 2 | 3 | 500 | 11 |
| 0 | 2 | 0 | 2000 | 8 |
| 0 | 0 | 1 | 2900 | 1 |
| 0 | 0 | 3 | 500 | 3 |
| 0 | 0 | 2 | 1700 | 2 |
| 0 | 0 | 0 | 5100 | 0 |

Step 3:

|  |  |
| --- | --- |
| ArrayIndex | Value |
| 0 | 5100 |
| 1 | 2900 |
| 2 | 1700 |
| 3 | 500 |
| 4 | 3100 |
| 5 | 1400 |
| 6 | 1700 |
| 8 | 2000 |
| 9 | 1500 |
| 11 | 500 |
| 16 | 3400 |
| 17 | 2900 |
| 19 | 500 |
| 20 | 1400 |
| 21 | 1400 |
| 24 | 2000 |
| 25 | 1500 |
| 27 | 500 |
| 32 | 1700 |
| 34 | 1700 |
| 36 | 1700 |
| 38 | 1700 |

Q2.

(1)

Suppose if feature vector =, then y=0. So, 

According to Bayesian Theorem, P(h|x)P(x)=P(x|h)P(h).

Then we get,, which can be simplified to

.

According to Naive Bayes Classifier, .

We get

.

Because the x is a binary vector, so x is either 0 or 1.

Assume that

,

So,

.

So,

,

Using log to simplify it,

so, we could suppose that  is b,  is , then we get ,so Naive Bayes Classifier is a linear classifier.

 is , where  is .

(2)

For logistic Regression, it only allocates the probabilities to the only cases it observed.

Naive Bayes Classifier is a generative classifiers which learn a model of joint probabilities p(x, y) and use Bayes rule to calculate p(x, y) to make a prediction. Logistic Regression is a discriminative models learn the posterior probability p(x, y) “directly”.

In discriminative models, you have “less assumptions”, when you have very little data that a generative model can beat a discriminative model.

Q3.

(1)

We know that,



So, we get,



Since it’s the log-likelihood which need to be maximized, so with the negative sign, it will need to be minimized which is actually a loss function.

So we get,



(2)

