Department of Informatics, King's College London Data Mining(7CCSMDM1) Answer of Assignment 1

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Part 1 Classification

1.1

Number of instances	48842
Number of missing values	6465
Fraction of missing values over all attribute values	0.95%
Number of instances with missing value	3620
Fraction of instances with missing values over all instances	7.41%

1.2

Attributes	Encoded value
age	$[2\ 3\ 1\ 0\ 4]$
workclass	$[7\;6\;4\;1\;2\;0\;5\;8\;3]$
education	$[\ 9\ 11\ 1\ 12\ 6\ 15\ 7\ 8\ 5\ 10\ 14\ 4\ 0\ 3\ 13\ 2]$
education-num	$[12\ 8\ 6\ 13\ 4\ 9\ 11\ 10\ 3\ 15\ 14\ 2\ 5\ 1\ 0\ 7]$
marital-status	$[4\ 2\ 0\ 3\ 5\ 1\ 6]$
occupation	$[\ 1\ 4\ 6\ 10\ 8\ 12\ 3\ 14\ 5\ 7\ 13\ 0\ 11\ 2\ 9]$
relationship	$[1\ 0\ 5\ 3\ 4\ 2]$
race	$[4\ 2\ 1\ 0\ 3]$
sex	[1 0]
capitalgain	$[1\ 0\ 4\ 2\ 3]$
capitalloss	$[0\ 3\ 1\ 2\ 4]$
hoursperweek	$[2\ 0\ 3\ 4\ 1]$
native-country	[39 5 23 19 0 26 35 33 16 9 2 11 20 30 22 31 4 1 37 7 25 36
	14 32 6 8 10 13 3 24 41 29 28 34 38 12 27 40 17 21 18 15]

1.3

Error rate when just ignoring instances with missing values: 17.26%.

1.4

Both decision tree are tested based on the same test set split from D.

Error rate when building decision tree with D1: 18.03%.

Error rate when building decision tree with D2: 8.34%.

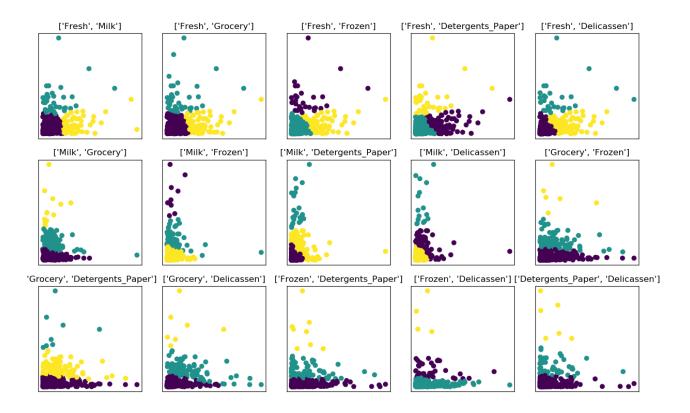
It is clear that error rate is lower when building decision tree based on D2. It suggests that filling missing values with most common value performs better than just giving missing value a new value 'missing value'.

Part 2 Clustrering

2.1

j	$\mu = \sum_{i=1}^{m} x_{i,j}$	$[x_{j,min}, x_{j,max}]$
Fresh	12000.30	[3,112151]
Milk	5796.27	[55,73498]
Grocery	7951.28	[3,92780]
Frozen	3071.93	[25,60896]
Detergents_Paper	2881.49	[3,40827]
Delicassen	1524.87	[3,47943]

2.2



2.3

	k=3	k=5	k=10
BC	$3.1820e^{+09}$	$2.7368e^{+10}$	$1.7359e^{+11}$
WC	$8.0333e^{+10}$	$5.3106e^{+10}$	$3.0377e^{+10}$
BC/WC	0.039610	0.515350	5.714309