

DUBLIN INSTITUTE OF TECHNOLOGY

DT228A/1 MSc. in Computing DT228B/1 MSc. in Computing DT228B/2 MSc. in Computing

SUMMER EXAMINATIONS 2017/2018

MACHINE LEARNING [SPEC9270]

Dr. John McAuley Professor Sarah Jane Delany Dr. Deirdre Lillis Dr. Georgiana Ifrim

Wednesday 16th May

 $2.00 \, \text{P.M.} - 4.00 \, \text{P.M.}$

Two Hours

Answer 2 questions.
All Questions carry equal marks.

	Mark	e Answer the	e following Question	ns. Each question	
	(i)	William in a Ci		1 0	[24 marks
	(i)	what is a C	ost Function? Give	an example of a c	ost function.
					[4 marks
	(ii)	In the followinformation	wing example, which for the purpose of c	h descriptive featu classification? Ple	are carries the least ase explain why.
		ID	Name	Age	Height
		1	John	10	6.2
		2	Jo	20	5.2
		3	Paula	30	5.8
			-		[4 marks
M Les s	(iii)		e difference in induc and information-ba		larity-based learning g ID3 [4 marks
	(iv)	I have the for similarity b	ollowing data, pleas ased learning and ju	e suggest a simila stify your decisio	rity measure for n.
		ID	Weight	Height	
		1	362	4.2	
		2	268	5.2	
		$\frac{2}{3}$	185	5.2	_
					[4 marks
	(v)	3	185	5.8	[4 marks
	(v)	What is the	185	5.8	and Sokal-Michener
	(vi)	What is the measure?	difference between	the Jaccard index	[4 marks] and Sokal-Michener [4 marks] can this present? And
		What is the measure?	difference between	the Jaccard index	and Sokal-Michener

1				16			11		200	3^{rd}		Std.
	Feature		Count	Miss.	Card.	Min.	Qrt.	Mean	Median	Qrt.	Max.	Dev.
	AGE		5,200	()	51	18	-22	41.59	47	50	80	15.66
	MOTORV	ALUE	5.200	17.25	3,934	4,352	15,089.5	23,479	24,853	32.078	166,993	11,121
	НЕМЕТН	DEPSADULTS	5,200	39.25	4	()	()	0.84	1	1	2	0.65
	НЕМЕТНІ	DEPSKIDS	5,200	39.25	5	()	0	1.77	2	3	3	1.11
											- wi	20/
				G.			N	lode	Mode	2^{nd}	2 nd Mode	2 nd Mode
	Feature	(Count	Miss.	Card.	Мо	de I	Freq.	%	Mode	Freq.	%
	GENDER		5.200	()	2	fem	ale 2	,626	50.5	male	2.574	49.5
	Loc		5,200	()	2	urb	an 2	948	56.69	rural	2,252	43.30
	Occ		5,200	37.71	1.828	Nur	rse	11	0.34	Sales	9	0.28
	MotorI	NS	5.200	0	2	ye	s 4	,303	82.75	no	897	17.25
	HEALTH	INS .	5,200	-0	2	ye	es 3	1,159	60.75	no	2,041	39.25
	HEALTH	TYPE	5,200	39.25	4	Pla	nB I	,596	50.52	PlanA	796	25.20
3	PREFCH	ANNEL	5,200	()	3	em	ail 2	2,296	44.15	phone	1.975	37.98
											[8]	Mark
	(i)	What p	roble	ms ex	ist in	the da	ata?					
											[4]	Mark
	(ii)	Llow w	ould v	(01) 0.0	ldross	those	nroh	lame?			fil	=
	(ii)	How w	ould y	ou ac	ldress	these	e prob	lems?	**		Til	E
	(ii)	How w	ould y	ou ac	ldress	these	e prob	lems?			[2]	Marl
	(ii)	How w								s situa	-	Marl
		How ca	an a m	issinş	g indic	cator	featur	e help	in this		tion?	
(c)			an a m	issinş	g indic	cator	featur	e help	in this		tion?	
(c)		How ca	an a m	follo	g indic	eator	featur	repres	enting	two cla	tion? [2] asses:	Marl Marl
(c)		How ex	ve the - (1, 1)	following following for the following following for the following	g indicates wing so 2), (2 the Eu	eator et of p	featur points nd Cla	repres	enting (3, 1), (two cla (3, 3), e, plea	[2] asses: (3, 4) ase class	Marl
(c)		You ha	ve the l - (1, 1) KNN, ng que	followand to and the region of the regions of the r	wing s 2), (2 the Eustance	et of p	points nd Cla n Dist with	represass 2 -	enting to (3, 1), (Measurabourho	two classifications (3, 3), re, plead of	[2] asses: (3, 4) ase class 1 (k=1)	Marl sify 1
(c)		You hat Class 1 Using following	ve the l - (1, 1) KNN, ng que	follow follow 1), (1, and the erry instance)	wing s 2), (2 the Eustance	et of p	points nd Cla n Dist with	represass 2 -	enting to (3, 1), (Measurabourho	two classifications (3, 3), re, plead of	[2] asses: (3, 4) ase class 1 (k=1) coint an	Marl sify 1
(c)		You hat Class 1 Using following Please After you. The testing of testing of testing the street of t	ve the l - (1, 1 KNN, ang que show the bad at has be position in general to the show the show that has be position in general to the show that has be position in general to the show that has be position in general to the show that has be position in the show that has be possition in the show that has be possible to the show that has be possible to the show that has been shown that has b	following following following following following following for the following followin	wing s 2), (2 the Eustance working theck- is that hown en you when	eator et of p clidea (3, 2) ags, ea up, the t you to be a have you d	points nd Cla nn Dist with a ach ca e docte tested 99% a e the dilon't h	repress ass 2 - tance la neight or has positive ccurat isease ave the	enting (3, 1), (Measurabourho	two classifications (3, 3), ree, pleadood of each pleadood was and a seriouthe property (as is to see). The	tion? [2] asses: (3, 4) ase class 1 (k=1) boint and [8] agood raise disease bability the problem of the problem	Marl sify to hews se on y of babili news

		(i)	Why is it particularly good news	that the disease is	s rare?						
					[5 Marks						
	=	(ii)	What is the probability that you	actually have the	disease?						
					[5 Marks						
2.	(a)	(i)	A challenge when working with textual data is the decision on the representation to use. Describe a suitable representation for a collection of tweets, some examples of which are included below. Justify your choice of feature and feature values.								
			We've no bread but plenty of ice cre-	am #sneachta	,						
			I'm snowed in with NO BREAD.								
			Coldness level: teenager actually v								
			全盆盆 Ireland is bedding down for	or the next few days	#BeastFrom TheEast						
					[5 marks						
		(ii)	Show the actual feature vector for assumptions made.	the first tweet ab	ove indicating any						
			assumptions made.		12						
		/!!!N	[3 marks								
		(iii)	Discuss two challenges with deali with them.	ng with textual da	ta and how to deal						
		(*)			[4 marks						
		(iv)	Explain the difference between reconfusion matrix below. In your appropriate scenario of use on text explaining why it is appropriate:	answer give an ex	ample of an						
				Predicted	Predicted						
				Class 1	Class 2						
			Actual Class 1	720	80						
			Actual Class 2	180	20						
					[13 marks						
	(b)		have been hired by the European S		uild a model that						
			icts the amount of oxygen that an as								
			minutes of intense physical work. The the age of the astronaut and their								
		1 14/111	be the age of the astronaut and then	average heart rat	e through out the						

		The ta	ible belo	w shows a	a histoi	ricai data	iset th	at nas bee	ii coile	cted 101	r this task.
						HEART				HEART	
			ID	OXYCON	AGE	RATE	ID	OXYCON	AGE	RATE	
			1	37.99	41 42	138 153	7	44.72 36.42	43	158 143	
			2	47.34 44.38	37	151	9	31.21	37	138	
1			4	28.17	46	133	10	54.85	38	158	
			5	27.07	48	126	11	39.84	43	143	
			6	37.85	44	145	12	30.83	43	138	
										[20 marks
		(i)	Assumir	ig that the	current	weights i	n a mu	ltivariate li	near reg	ression	
				re $\mathbf{w}[0] =$ on for each					= 0.00,	make a	
	200	EL 2014 No.	2.45 1440 250								[6 marks
		(::)	G 1 1	te the sun	- C		ora fo	the get o	fnradi	otions c	vanarated
227	6 × 5	(ii)			1 01 54	uared err	015 10	i the set o	n preun	Ctions E	Scheratea
			in part i	1)							
										7	[6 marks
	•	(iii)	Assumi						the we	eights a	[6 marks t the next
		(iii)	Assumi	ing a learr					e the we	eights a	t the next
		(iii)	Assumi iteration	ing a learn of the grant descent	radient	descent	algori chniqu	thm. ie used in	Machi	ne Lear	[3 marks
			Assumi iteration	ing a learn of the grant descent	radient	descent	algori chniqu	thm. ie used in	Machi	ne Lear	[3 marks
	(c)	(iv)	Assumi iteration Gradier explain Regress	ing a learn of the grant descent how grad sion.	is a polient de	ppular te	algori chniqu in be u	thm. se used in sed in Mu	Machi ulti Var	ne Lear riable L	t the next [3 marks rning,
	(c)	(iv)	Assumi iteration Gradier explain Regress	ing a learn n of the grant of the grant nt descent n how grant sion.	is a polient de	ppular te	algori chniqu in be u	thm. se used in sed in Mu	Machi ulti Var	ne Lear riable L	[3 marks ming, inear
	(c)	(iv) Wha	Assumi iteration Gradier explain Regress	ing a learn of the grant descent how grad sion.	is a policent de lient de lien	ppular te escent ca	algori chniqu in be u	thm. le used in Mused in Mu	Machi ulti Var	ne Lear riable L	[3 marks ming, inear
	(c)	(iv) What give	Assumi iteration Gradier explain Regress an exam	ing a learn n of the grant descent how gradsion.	is a policent de between betwe	opular teescent ca	algori chniqu in be u	thm. le used in Mused in Mu	Machi ulti Var	ne Lear riable L	[3 marks ming, inear [5 marks marks]
		(iv) What give	Assumi iteration iteration Gradier explain Regress an exam	ing a learn of the grant descent how grad sion. difference apple of each you use the discress variations.	is a policent de between ch.	opular te escent ca	algori chniqu in be u	thm. le used in Mused in Mu	Machi ulti Var	ne Lear riable L	[3 marks ming, inear [5 marks
		(iv) What give	Assumi iteration distribution of the control of the	ing a learn of the grant descent how grad sion. difference apple of each you use the decross value one out	between.	en super	algori chniqu in be u	thm. le used in Mused in Mu	Machi ulti Var	ne Lear riable L	[3 marks ming, inear [5 mark
		(iv) What give	Assumi iteration distribution of the control of the	ing a learn of the grant descent how grad sion. difference apple of each you use the discress variations.	between.	en super	algori chniqu in be u	thm. le used in Mused in Mu	Machi ulti Var	ne Lear riable L	[3 mark ming, inear [5 mark mark mark mark mark mark mark mark

(a)	informa learning approac	ution-ba g and sin h, using	sed learn nilarity-l either res		-based lea ning. Provi is or prefer	rning, pro ide an exar ence bias t	bability- mple of ea to assist y	based
								[8 marks]
(b)	online rebehavio	etail stor	e that has lividuals	job of buil s a stock of is captured	over 100,0	000 items.	In this do	omain the
	domain cell mar	for a sub	oset of the	cates that the	sale. The d	lata in this	table is b	inary and a
	m	Item		Item	Item	Item	Item	Item
	A	107	498 0	5645 ×	7256	1762 ·	28063	75328 * ()
	В	1	0	0	1	0	0	1
	marked	with a 1	indicate	commenda s that the p				
	marked	with a 1		s that the p not.				
	marked indicate	with a 1 es that th	indicate ey have r Item 498	s that the p not.	erson has b	oought an i	Item, whill	le a 0
	marked indicate	with a 1 les that the Items 107%	indicates ey have r Item 498 0	s that the phot. Item. 5645 1	Item 7256 1	Itan 1762 0	Item, while 28063.	Item 75328
	marked indicate	with a less that the less that	indicates ey have r Item 498 0	s that the proof. Item. 5645 1 are over 1 odels of sim	Item 7256 1	Itan 1762 0	Item, while 28063.	Item 75328 0 [14 marks]
	marked indicate	with a less that the less that	indicates ey have r (198) 0 that there owing mo	s that the proof. Item 5645 1 are over 1 odels of sim	Item 7256 1	Itan 1762 0	Item, while 28063.	Item 75328 0 [14 marks]
	marked indicate	with a les that the sthat the sthat the sthat the sthat the strain of follows.	indicates ey have r 100 100 100 100 100 100 100 1	s that the proof. Item 5645 1 are over 1 odels of sim	Item 7256 1	Itan 1762 0	Item, while 28063.	Item 75328 0 [14 marks]
	marked indicate	Given of follo	that there owing mo	s that the proof. Item 5645 1 are over 1 odels of sim	Item 7256 1 00,000 iten illarity is n	Itan 1762 0	Item, while 28063.	Items 75328 0 [14 marks]
	marked indicate	Given of follo	that there owing mo	s that the phot. Item 5645 1 are over 1 odels of simulation	Item 7256 1 00,000 iten illarity is n	Itan 1762 0	Item, while 28063.	Items 75328 0 [14 marks]

Part (i).

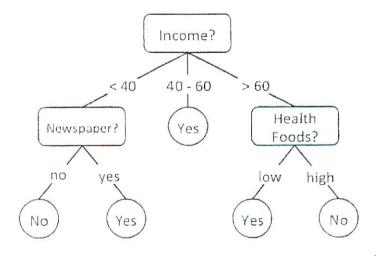
[8 marks]

(b)

The following table lists a dataset collected by a retail company capturing historical details of which of their customers have responded to promotions the company has run. The information captured covers customer income bracket, customer age, whether or not the customer regularly buys a newspaper, the proportion of health foods typically included in the customer's shopping, and, finally, whether or not they responded to previous promotional mailings.

	100			Health	
\mathbf{D}	‡Income⊭	Age	► Newspaper	Foods	Respond
C-01	<40	81	no	low	No
C-02	<40	76	no	high	No
C-03	40-60	86	no	low	Yes
C-04	>60	84	no	low	Yes
C-05	>60	45	yes	low	Yes
C-06	>60	66	yes	high	No
C-07	40-60	41	yes	high	Yes
C-08	<40	68	no	low	No
C-09	<40	32	yes	high	Yes
C-10	>60	56	yes	low	Yes
C-11	<40	58	yes	high	Yes
C-12	40-60	52	no	high	Yes
C-13	40-60	90	yes	low	Yes
C-14	>60	69	no	high	No

This dataset has been used to induce a **decision tree** that can predict whether or not new customers will respond to promotional mailings. This decision tree is shown below.



[24 marks]

		(i)	The information gain of the feature <i>Income</i> at the root node of the tree is 0.247. A colleague has suggested that <i>Newspaper</i> would be the best feature to query at the root node of the tree. Demonstrate whether or not this is the case. Please show all workings.
		(ii)	Another colleague has suggested that <i>Age</i> would be the best feature to query at the root node of the tree. Demonstrate whether or not this is the case. Please show all workings.
X	(c)-		In relation to the application of machine learning, describe what you understand by the following two terms: Domain Knowledge and Situational Fluency?
			[4 Marks]

Appendix A

Logistic function	$f(x) = \frac{1}{1 + \exp^{-x}}$
Euclidean distance	$d(x_1, x_2) = \sqrt{\sum_{r=1}^{n} (a_r(x_1) - a_r(x_2))^2}$
	cosine $(x_1, x_2) = \frac{x_1 \cdot x_2}{\ x_1\ \times \ x_2\ }$
Cosine similarity	cosine(x_1, x_2) = $\frac{\sum_{r=1}^{n} a_r(x_1) \times a_r(x_2)}{\sqrt{\sum_{r=1}^{n} a_r(x_1)^2} \times \sqrt{\sum_{r=1}^{n} a_r(x_2)^2}}$
Minkowski distance	$MD_{p}(x_{1},x_{2}) = \left(\sum_{r=1}^{n} \left a_{r}(x_{1}) - a_{r}(x_{2}) \right ^{p} \right)^{\frac{1}{p}}$
Entropy of the prior	$H(P(v_1),,P(v_n)) = \sum_{i=1}^{n} -P(v_i) \log_2 P(v_i)$
Bayes rule	$P(a \mid b) = \frac{P(b \mid a)P(a)}{P(b)}$

Appendix B

Table of Base 2 Logs for Different Fractions

log ₂ (a/b)					102 - VI 118	77		a							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
	1	0.00													
	2	-1.00	0.00												
	3	-1.58	-0.58	0.00											
	4	-2.00	-1.00	-0.42	0.00										
	5	-2.32	-1.32	-0.74	-0.32	0.00									
	6	-2.58	-1.58	-1.00	-0.58	-0.26	0.00								
	7	-2.81	-1.81	-1.22	-0.81	-0.49	-0.22	0.00							
b	8	-3.00	-2.00	-1.42	-1.00	-0.68	-0.42	-0.19	0.00						
	9	-3.17	-2.17	-1.58	-1.17	-0.85	-0.58	-0.36	-0.17	0.00					
	10	-3.32	-2.32	-1.74	-1.32	-1.00	-0.74	-0.51	-0.32	-0.15	0.00				
	11	-3.46	-2.46	-1.87	-1.46	-1.14	-0.87	-0.65	-0.46	-0.29	-0.14	0.00		-	
	12	-3.58	-2.58	-2.00	-1.58	-1.26	-1.00	-0.78	-0.58	-0.42	-0.26	-0.13	0.00		75
	13	-3.70	-2.70	-2.12	-1.70	-1.38	-1.12	-0.89	-0.70	-0.53	-0.38	-0.24	-0.12	0.00	
	14	-3.81	-2.81	-2.22	-1.81	-1.49	-1.22	-1.00	-0.81	-0.64	-0.49	-0.35	-0.22	-0.11	0.00