1. Clearly describe your training and test data size and sampling methods, and how you trained the models. Report the best hyper-parameters leading to the best classification accuracy and explain how and why. Also show the best accuracy. For each sets of tested hyper-parameters, show the accuracy and the time for training.

For SVM:

Training data size is 60000, and the test data size is 10000.

The best accuracy for this test data is 0.9787.

The hyper-parameters for this accuracy is: kernel = "poly".

accuracy	Train	Gamma	С	kernel
	time			
0.9787	300s			poly
0.9724	473s	0.000686	25.6	rbf
0.9141	2990s	0.007	3	rbf
0.9427	607s	0.00001	30	rbf
0.9718	408s	0.0005	50	rbf
0.9711	385s	0.0004	60	rbf
0.961278	636s	'scale'	1	rbf
0.9536	952	'scale'	0.5	rbf
0.91783	508s	'scale'	2	linear
0.9226	598	'scale'	0.5	linear
0.7927	11s			LinearSVC

To get the best classification accuracy by using kernel "rbf", is because of the data don't have the linear relationship, so if use linear method to classify it is not the best way. And a larger coefficient indicates that the model is more tolerant of classification errors, and the result may not accuracy. And use the coefficient in default can get the best accuracy. SVM use much time than ANN.

For ANN:

Training data size is 60000, and the test data size is 10000.

The best accuracy for test data is 0.947.

The hyper-parameters for this accuracy is:

solver='Adam', activation='relu', alpha=0.0001, hidden layer sizes=(130,100,100,10)

accuracy	Train	solver	activation	alpha	hidden_layer_sizes	learning_rate_init
	time					
0.947	139s	Adam	relu	0.0001	(130,100,100,10)	
0.9352	195s	Adam	relu	0.0001	(130,130,100,100,10)	
0.1028	170s	sgd	relu	0.0001	(130,130,100,100,10)	0.1
0.8516	87.58s	sgd	logistic	0.0001	(100,100,10)	0.1
0.1135	80.8s	sgd	relu	0.0001	(100,100,10)	0.1
0.9325	132s	Adam	relu	0.0001	(130,130,100,10)	
0.9304	93s	Adam	relu	0.0001	(100,100,10)	
0.8336	146s	Adam	logistic	0.005	(20,20)	

To get the best classification accuracy by using optimizer "Adam", and use five hidden layer which has 130,100,100,10. Adam makes the learning rate of each iteration has a certain range, so that the parameters are relatively stable. 4 layers can learn more parameter

to make the model better. But to much layer, the time will increase more and the accuracy may not better.

2. For the best trained models of SVM and ANN, design experiments to investigate how the training data size affects the accuracy of both models. Which models are more sensitive to the training data size? Clearly describe your experimental design, accuracy change/comparison, and also training time change with increased training set size.

In my experiment, I will increase the training set in each epoch, and in some epoch, use the same training data size but different number of testing data size to check if the accuracy will be change. I also record the train loss in my ANN models in each epoch and check whether the loss keep decreasing.

For SVM:

Train Size	Test Size	Accuracy	Train Time
500	10000	0.8253	3.39s
1000	10000	0.8865	4.0234s
3000	10000	0.931	6.7479s
5000	2000	0.921	10.3277s
5000	10000	0.9421	10.3277s
10000	4000	0.9445	23.292s
36000	5000	0.9684	143s
48000	8000	0.97575	228s
48000	10000	0.9778	228s
60000	10000	0.9787	300s

For ANN:

Train Size	Test Size	Train Loss	Accuracy	Train Time
500	200	0.0009456	0.595	7.07s
1000	500	0.00080	0.54	7.82s
3000	200	0.0004778	0.67	12.139s
3000	1000	0.000477	0.671	12.70s
5000	2000	0.000423	0.7095	13.386s
5000	3000	0.0004232	0.713	14.177
10000	4000	0.00028091	0.82275	20.26285
36000	5000	0.00029821	0.932	82.93180
48000	8000	0.009842	0.9092	70.57469
48000	10000	0.009842	0.9172	69.411073
60000	10000	0.0068	0.947	136.2963

The result is: ANN are more sensitive to the training data size.

3. Design experiments to show how the distribution of training data sizes affect the accuracy, recall, and precision of both models. For example, if you make the training data highly imbalanced, how would this affect the recall and precision of each class,

particularly the class with small training sets? For this problem, you need to report both the accuracy and also the recall/precision for each class. Clearly describe your experimental design and results.

In my experiment, I will arrange 10 times to test first, for different number I will arrange only 20 instance as train data size, and at the same time other numbers will arrange 5000 instance as train data size. For each epoch, I will record the accuracy, time, precision and recall data.

In ANN model, After 10 times test, I will increase the number of less training data size from 20 to 100, 500, 1000, 2000, 3000, and check the result.

FOR SVIVI:				
Train size of	Train size of	Test Size	Accuracy	Train Time
amount for 20	amount for 5000			
0	1-9	10000	0.9292	189s
1	0, 2-9	10000	0.9529	201s
2	0-1,3-9	10000	0.9016	174s
3	0-2,4-9	10000	0.9179	168s
4	0-3,5-9	10000	0.9196	193s
5	0-4,6-9	10000	0.9114	183s
6	0-5,7-9	10000	0.927	188s
7	0-6,8-9	10000	0.9152	180s
8	0-7,9	10000	0.916	165s
9	0-8	10000	0.9064	177s

For 1:

F	or ():								
CC	nı mat									
[[469		95		4	143	198		15	52]
[0 1	1126								0] 0]
[1012							0]
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							939			3] 9] 3] 0] 6]
[12						1001		6]
[950	3]
[976]]
			pre	cisio		recal	l fl	l-scor	e s	upport
										ANGSANGIA.
		(1.0		0.48		0.6		980
		1		0.9		0.99		0.9		1135
				0.9		0.98		0.9		1032
		3 4		0.9		0.98		0.9		1010
		4		0.9		0.98		0.9		982
				0.8		0.97		0. 9		892
		7		0.8		0.98		0.8		958
				0.9		0.97		0.9		1028
				0.9		0.98		0.9		974
				0.9	3	0.97	7	0. 9	5	1009
										0.500000
	micro			0. 9		0.93		0.9		10000
	macro			0.9		0.93		0. 9		10000
we	eighted	avs		0.9	4	0.93	3	0.9	2	10000

For 2: For 3:

cor	conf_mat:												
ΙĹ	972									0]			
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Ĺ	68	76	230	288	61		65	82		0] 7] 3]			
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				10		865				9] 3] 0]			
[937			0]			
[13						1008		5]			
[946	3]			
										978]]			
			pre	cisio	n	recal	l fl		e s	upport			
		0		0.9		0.99		0.9		980			
				0.9		0.99		0.9		1135			
		2 3 4 5		0.9		0. 22		0.3		1032			
		3		0.7		0.98		0.8		1010			
		4		0.9		0.98		0.9		982			
		5		0. 9		0.97		0.9		892			
				0.9		0.98		0.9		958			
				0.9		0.98		0.9		1028			
				0.8		0.97		0.9		974			
				0. 9	7	0.97	7	0.9	7	1009			
		o avg		0.9		0.90		0.9		10000			
		o avg		0. 9		0.90		0.8		10000			
wei	ighte	ed avg		0.9	1	0.90)	0.8	8	10000			
F	For 4:												
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							938			1]
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[4						983]]
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		()	0.9	7	0.99	9	0.9	8	980
]		0.9	7	0.99	9	0.9	8	1135
		2	2	0.9	6	0.98	8	0.9	7	1032
		2	3	0.9	7	0.98	8	0.9	8	1010
		4		1.0	0	0.3	7	0.5	4	982
		Ę	5	0.9	7	0.9		0.9		892
		(0.9	5	0.98	8	0.9	6	958
		1		0.9		0.98		0.9		1028
				0. 9		0.9		0. 9		974
		ç		0.6		0. 9		0. 7		1009
		•		0.0		0.0		٠		1000
Γ,	micro	o ava		0.9		0. 9		0.9	2	10000
		o ava		0. 9		0. 9		0. 9		10000
		d ava		0. 9		0. 9		0. 9		10000
mc I	P.1.1.C.	u uve		0. 5		0. 5.		0. 3		10000

For 6:

COL	nf mat									
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Į									946	3]
							0			976]]
			pre	cisio	n	recal	l fl	l-scor	e s	upport
		(0.8		0.99		0. 9		980
				0.9		0.99		0.9		1135
		2	2	0.9		0.98		0.9		1032
			3	0.9		0.98		0.9		1010
		2 E	1	0.8		0.98		0.9		982
		Ę	5	0.8		0.97		0. 9		892
		6	5	1.0		0.4		0.6		958
				0.9		0.9		0.9		1028
				0.9		0.9		0.9		974
)	0.9	7	0.97	7	0.9	7	1009
Г	micro			0.9		0.93		0.9		10000
Г	macro			0.9		0. 92		0.9		10000
we:	ighted	avg	g	0.9	3	0.93	3	0.9	2	10000

For 8:

I	con	ıf_ma		1 75	(a)	1.07234	1 1976	100		78.0	TIGH.
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ı				pre	ecisio	n	recal	1 f:	l-scor	e s	support
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ı				0	0.9	7	0.9	9	0.9	8	980
ı				1	0.9	7	0.9	9	0.9	8	1135
ı				2 3	0.8	9	0.9	8	0.9		1032
ı					1.0	0	0.3		0.5	4	1010
ı				4 5	0.9	8	0.9	8	0.9	8	982
ı					0.7		0.9	8	0.8	6	892
ı					0.9	8	0.9	8	0.9	8	958
ı				7	0.9	6	0.9	7	0.9		1028
ı					0.8	0	0.9	7	0.8	8	974
ı				9	0.9	4	0.9	7	0.9	16	1009
ı											
ı		micr	o av	g	0.9	2	0.9	2	0.9		10000
ı		macr	o av		0.9	3	0.9	2	0.9		10000
ł	wei	ghte	d av	g	0.9	3	0.9	2	0.9		10000

For 5:

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conf_m		- U.S.	100	11	1	111	415	2715	110
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Ī 3		2	0	965	0	3	0	0	0] 0] 3] 9]
Ī 26	17		344	13		38	4	214	50]
Ī 4		3	0	2	0	942	0	2	οĪ
Ē 0	12		1	0		0	1001	0	0] 6]
[0 [3 [26 [4 [0 [7	1		6	4	0		2	949	3]
Ē 2		2	5	8	0	1	4	3	977]]
		pre	ecisio		recal	1 f:	l-scor	e s	support
		0	0.9	5	0.9	9	0. 9	97	980
		1	0.9	6	0.9	9	0. 9	8	1135
		2	0.9	8	0.9	8	0. 9	8	1032
		2	0.7	3	0.9	8	0.8	34	1010
			0.9		0.9	8	0. 9		982
		4 5	1.0	0	0.2	0	0. 3	34	892
		6	0.9	5	0.9	8	0. 9	96	958
		7	0.9	8	0.9	7	0. 9		1028
		8	0.8	0	0.9	7	0.8	38	974
		9	0.9	3	0.9	7	0. 9	95	1009
mic	ro av	g	0.9	1	0.9	1	0. 9	1	10000
	ro av		0.9	3	0.9	0	0.8	39	10000
weight			0.9		0.9		0.8		10000

For 7:

coi	ıf_ma	t:						195		
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Ĺ				10		865				3]
Ļ							937			0]
Ļ		41	137	85	27			365		356]
Ĺ									946	3]
L										980]]
			pre	cisio	n	recal	1 f1	-scor	e s	upport
		(0.9		0.9		0.9		980
		1		0.9		0. 9		0.9		1135
		2	2	0.8		0.9		0.9		1032
			3	0.9		0.9		0.9		1010
		2 E	1	0.9		0.9		0.9		982
			5	0.9		0.9		0.9		892
		6	5	0.9		0.9		0.9		958
		7	7	0.9		0.3		0. 5		1028
			3	0.9		0.9		0.9		974
			9	0.7	2	0.9	7	0.8	3	1009
	micr	o ave	g	0.9		0.9		0.9		10000
		o ave		0.9		0.9		0.9		10000
we:	ighte	d ave	g	0.9	3	0.9	2	0.9	0	10000

For 9:

	C									
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Ļ			1006							0]
Ļ				989						5]
Ĺ	3			0	965		3 5			9] 4]
Ĺ	3					869				
L							940			0]
[11				0		1001		6]
		18	105	259	25	96	27		311	94]
[979]]
			pre	cisio	n	recal	1 f:	l-scor	e s	upport
										7834
		()	0.9		0.9	9	0.9	7	980
		1		0.9	6	0.9	9	0.9	8	1135
		2	2	0.8	9	0.9		0.9	3	1032
			3	0.7	8	0.9	8	0.8	7	1010
			1	0.9	6	0.9	8	0.9	7	982
			5	0.8	8	0.9	7	0.9	3	892
		(3	0.9		0.9		0.9		958
		(0.9		0.9		0.9		1028
		8		1.0		0. 3		0.4		974
		9		0.8		0.9		0. 9		1009
					1					
	micro	ave	7	0. 9	2	0.9	2	0.9	2	10000
	macro			0. 9		0. 9		0. 9		10000
re i	ighte			0. 9		0. 9		0. 9		10000
	. 6		•	0. 5	_	0. 0.		0. 5	·	10000

con	f_ma									
ιĻ	972	0						0	2	0]
Ļ		1126				0		0		0]
Ī		2	1006	0		0			3	0]
Ĺ				989					6	0]
Ī				0	973	0			0	0]
Ī				10		868				0]
Ĺ							937			0]
Ĺ		12						1005	0	0]
									948	
L	11	10		41	464	11		190	36	
			pre	cisio	n	recal	1 f:	l-scor	e	support
										4.0000
				0.9		0.9		0.9		980
		1		0.9		0.9		0.9		1135
			2	0.9		0.9		0.9		1032
			3	0.9		0.9		0.9		1010
			Į.	0.6		0.9		0.8		982
				0.9		0.9		0.9		892
			5	0.9		0.9		0.9		958
		7		0.8	3	0.9	8	0.9	0	1028
				0.9	5	0.9		0.9		974
)	1.0	0	0.2	4	0.3	8	1009
	micr	o ave	g	0.9		0.9		0.9		10000
	macr	o ave	g	0.9	3	0.9		0.8	9	10000
wei	ghte	d avg	g	0.9	3	0.9		0.8	9	10000

For ANN:

Train size of	Train size of	Test Size	Accuracy	Train Time
amount for 20	amount for 5000			
0	1-9	10000	0.847	33.065
1	0, 2-9	10000	0.8044	40.224
2	0-1,3-9	10000	0.8344	34.74
3	0-2,4-9	10000	0.8625	30.956
4	0-3,5-9	10000	0.8137	40.306
5	0-4,6-9	10000	0.8546	31.180
6	0-5,7-9	10000	0.849	37.856
7	0-6,8-9	10000	0.8468	34.474
8	0-7,9	10000	0.8758	54.465
9	0-8	10000	0.8555	37.9898

The training	Train size of	Test Size	Accuracy	Time
data amount of 0	amount for 5000			
20	1-9	10000	0.847	33.065
100	1-9	10000	0.8749	46.294
500	1-9	10000	0.8776	40.692
1000	1-9	10000	0.9237	41.27
2000	1-9	10000	0.9282	36.894
3000	1-9	10000	0.8973	53.714
5000	1-9	10000	0.9302	47.582

20 instance for less training size: For 0:

										precision	recall	f1-score	support
										precision	recatt	11-50016	support
conf_mat:									0	1.00	0.09	0.16	980
	170	22	_	150	250	00	F-1	1221	1	0.97	0.98	0.98	1135
[[87 1	178	22		152	259	92	51	133]	2	0.82	0.91	0.86	1032
[0 1116	4	1	0	1	1	1	11	0]	3	0.88	0.97	0.92	1010
[0 3	935	21	8	0	11	35	15	4]	4	0.96	0.85	0.90	982
0 0	5	982	0	6	0	4	12	1]	5	0.81	0.84	0.82	892
[0 7	2	1	836	0	3	1	9	123]	6	0.75	0.94	0.83	958
[0 2	2	39	5	746	20	2	69	7]	7	0.87	0.95	0.91	1028
[0 2	3	2	11	13	896	0	29	2]	8	0.82	0.97	0.89	974
[0 8	6	10	1	0	1	977	6	19]	9	0.77	0.94	0.84	1009
[0 2	3	15	1	1	3	2	947	01	9	0.77	0.94	0.04	1009
[0 9	0	28	2	3	2	7	10		/ 4-4-1	0.07	0.05	0.00	10000
•	U	20	2	3	2	,	10	340]]	avg / total	0.87	0.85	0.82	10000
For 1:													
										precision	recall	f1-score	support
									0	0.90	0.97	0.94	980
conf mat:									1	1.00	0.14	0.24	1135
[[952 0	10	4	0	4	3	2	1	4]	2	0.90	0.87	0.89	1032
[7 155	73	71	2	2	2	249	573	11	3	0.70	0.99	0.82	1010
	902	72	4	0	6	24	17	1]	4	0.98	0.68	0.82	982
[0 0		1000	0	4	0	1	3	1]	5	0.98	0.76	0.86	892
[15 0	3	6	665	0	6	31	24	232]	6	0.96	0.93	0.95	958
[34 0	2	123	0	680	14	0	32	7]	7	0.75	0.93	0.83	1028
[32 0	2	8	7	3	895	1	5	5]	8	0.57	0.93	0.71	974
[1 0	9	36	0	0	0	960	7	15]	9	0.78	0.93	0.84	1009
[2 0	0	63	0	0	3	2	901	3]					
[5 0	0	44	0	1	1	10	14	93411	avg / total	0.85	0.80	0.78	10000
	•		•	_	-			33411					
For 2:													
										precision	recal	l f1-score	support
conf mat:										0 0.90	0.9	9 0.94	980
	1	2	0	2	0	0	2	21		1 0.96	0.9	4 0.95	1135
	1	2		3			2	2]		2 0.95	0.0	7 0.12	1032
[0 1066	0	7	0	1	1	20	40	0]		3 0.62	0.9	9 0.76	1010
[41 32	69	413	26	0	63	213	174	1]		4 0.95	0.8	5 0.90	982
0 0	1	996	0	5	0	0	7	1]		5 0.96	0.8	4 0.89	892
[8]	0	1	839	0	9	5	15	105]		6 0.90	0.9	2 0.91	958
[22 1	0	53	1	750	16	0	44	5]		7 0.79	0.9	2 0.85	1028
[20 2	0	3	5	25	880	1	22	0]		8 0.73	0.9		974
[14 1	2	21	3	0	1	947	6	33]		9 0.86	0.9		1009
[0 0	0	49	3	0	1	2	917	2]		V5.15.50	515		
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[1 1110	7	0	1	1	4	8	2	1		0 0.89 1 0.99 2 0.95	1.0	0 0.94 8 0.98 1 0.93	980 1135 1032
[14 0	937	0	1 16	1 0	4 17	8 14	27 27	1 1 5 1		0 0.89 1 0.99	1.0 0.9 0.9	0 0.94 8 0.98 1 0.93	980 1135
The state of the s	937	0	1 16 3	1	4 17 4	8 14 19	2	1] 5]		0 0.89 1 0.99 2 0.95 3 0.96 4 0.96	1.0 0.9 0.9 0.1	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92	980 1135 1032 1010 982
[14 0	937 2 27	0 2 151	1 16	1 0	4 17	8 14	27 27	1] 5] 72]		0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72	1.0 0.9 0.9 0.1 0.8	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78	980 1135 1032 1010 982 892
[14 0 [11 2 [6 1	937 27 1	0 2 151 0	1 16 3 877	1 0 282 0	4 17 4 11	8 14 19 4	27 439 4	1] 5] 72] 78]		0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94	1.0 0.9 0.9 0.1 0.8 0.8	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95	980 1135 1032 1010 982 892 958
[14 0 [11 2 [6 1 [49 0	937 27 1 27 2 2	0 2 151 0 1	1 16 3 877 4	1 0 282 0 748	4 17 4 11 22	8 14 19	27 439 4 45	1 5 72 78 18 18 18 18 18 18 18 18 18 18 18 18 18		0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94	1.0 0.9 0.9 0.1 0.8 0.8 0.9	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95	980 1135 1032 1010 982 892 958 1028
[14 0 [11 2 [6 1 [49 0 [19 1	7 937 2 27 . 1) 2	0 2 151 0 1	1 16 3 877 4 4	1 0 282 0 748 2	4 17 4 11 22 927	8 14 19 4 3 0	27 439 4 45	1] 5] 72] 78] 18]		0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94 8 0.64	1.0 0.9 0.9 0.1 0.8 0.8 0.9	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95 7 0.77	980 1135 1032 1010 982 892 958 1028
[14 0 [11 2 [6 1 [49 0 [19 1 [5 4	7 937 27 1 2 2 4 6	0 2 151 0 1 0	1 16 3 877 4 4 3	1 0 282 0 748 2	4 17 4 11 22 927 1	8 14 19 4 3 0 989	27 439 4 45 2	1 1 5 7 2 7 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1		0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94	1.0 0.9 0.9 0.1 0.8 0.8 0.9	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95 7 0.77	980 1135 1032 1010 982 892 958 1028
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[14 0 [11 2 [6 1 [49 0 [19 1 [5 4 [10 1 [11 4	7 937 2 27 . 1 0 2 . 2 4 6	0 2 151 0 1 0 0	1 16 3 877 4 4 3	1 0 282 0 748 2	4 17 4 11 22 927 1	8 14 19 4 3 0 989 2	27 439 45 45 2944	1 1 5 7 2 7 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1		0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94 8 0.64 9 0.83	1.0 0.9 0.9 0.1 0.8 0.8 0.9 0.9	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95 7 0.77 6 0.89	980 1135 1032 1010 982 892 958 1028
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[14 0 [11 2 [6 1 [49 0 [19 1 [5 4 [10 1	7 937 2 27 . 1 0 2 . 2 4 6	0 2 151 0 1 0 0	1 16 3 877 4 4 3 4	1 0 282 0 748 2 0 1	4 17 4 11 22 927 1 3	8 14 19 4 3 0 989 2	27 439 45 45 2944	1] 5] 72] 78] 78] 18] 11]		0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94 8 0.64 9 0.83 otal 0.88	1.0 0.9 0.9 0.1 0.8 0.8 0.9 0.9 0.9	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95 7 0.77 6 0.89	980 1135 1032 1010 982 892 958 1028 974 1009
[14 0 [11 2 [6 1 [49 0 [19 1 [5 4 [10 1 [11 4	7 937 2 27 . 1 0 2 . 2 4 6	0 2 151 0 1 0 0	1 16 3 877 4 4 3 4	1 0 282 0 748 2 0 1	4 17 4 11 22 927 1 3	8 14 19 4 3 0 989 2	27 439 45 45 2944	1] 5] 72] 78] 78] 18] 11]		0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94 8 0.64 9 0.83	1.0 0.9 0.9 0.1 0.8 0.8 0.9 0.9 0.9	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95 7 0.77 6 0.89	980 1135 1032 1010 982 892 958 1028 974 1009
[14 0 [11 2] [6 1 1 4 9 0] [19 1 1 [5 4] [10 1 1 4] [11 4] For 4:	7 937 2 27 . 1 0 2 . 2 4 6	0 2 151 0 1 0 0	1 16 3 877 4 4 3 4	1 0 282 0 748 2 0 1	4 17 4 11 22 927 1 3	8 14 19 4 3 0 989 2	27 439 45 45 2944	1] 5] 72] 78] 78] 18] 11]] avg/t	0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94 8 0.64 9 0.83 otal 0.88	1.0 0.9 0.9 0.1 0.8 0.9 0.9 0.9	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95 7 0.77 6 0.89 6 0.84	980 1135 1032 1010 982 892 958 1028 974 1009 10000
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[14 0 [11 2 2 [6 1 1 4 9 0 6 1 1 9 1 1 1 4] For 4:	9 7 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9	0 2 151 0 1 0 0 0 4	1 16 3 877 4 4 3 4 3	1 0 282 0 748 2 0 1 0	4 17 4 11 22 927 1 3 0	8 14 19 4 3 0 989 2 10	27 439 44 45 29 944 16	1 1 1 5 5 7 2 1 7 8 1 8 1 8 1 1 1 6 1 4 1 6 1 9 9 6 6 1 9 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 1 1 1] avg / t 0 1 2 3	0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94 8 0.64 9 0.83 otal 0.88 precision 0.97 0.97 0.97 0.99 0.62	1.0 0.9 0.9 0.1 0.8 0.8 0.9 0.9 0.9 0.9	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95 7 0.77 6 0.89 6 0.84 f1-score 0.97 0.97 0.97	980 1135 1032 1010 982 892 958 1028 974 1009 10000 support 980 1135 1032 1010
[14 0 [11 2] [6 1] [49 0] [19 1] [5 4] [10 1] [11 4] For 4:	9 7 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9	0 2 151 0 1 0 0 4 4	1 16 3 877 4 4 3 4 3	1 0 282 0 748 2 0 1 0	4 17 4 11 22 927 1 3 0	8 14 19 4 3 0 989 2 10	2 27 439 4 45 2 6 944 16	1 1 1 5 5 7 2 1 7 8 1 8 1 8 1 8 1 1 1 6 1 4 1 6 1 4 1 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 6 6 1 9 9 9 6 6 1 9 9 9 6 6 1 9 9 9 6 6 1 9 9 9 9] avg / t 0 1 2 3 4	0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94 8 0.64 9 0.83 otal 0.88 precision 0.97 0.97 0.90 0.62 1.00	1.0 0.9 0.9 0.1 0.8 0.8 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95 7 0.77 6 0.89 6 0.84 f1-score 0.97 0.97 0.88 0.76 0.88	980 1135 1032 1010 982 892 958 1028 974 1009 10000 support 980 1135 1032 1010 982
[14 0 [11 2 2 [6 1 1 4 9 0 6 1 9 1 1 4] For 4:	9 5 8 8 9 9 5 887 5	0 2 151 0 1 0 0 4 4 8 4 122 990	1 16 3 877 4 4 3 4 3	1 0 282 0 748 2 0 1 0	4 17 4 11 22 927 1 3 0	8 14 19 4 3 0 989 2 10	27 439 445 26 944 16	9 1 1 5 5 7 2 1 7 8 5 1 8 5 1 8 5 1 8 5 1 8 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6 5 1 9 6 6] avg / t 0 1 2 3 4 5	0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 8 0.64 9 0.83 otal 0.88 precision 0.97 0.97 0.97 0.90 0.62 1.00 0.94	1.0 0.9 0.9 0.1 0.8 0.9 0.9 0.9 0.9 0.9 0.8 recall	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 7 0.77 6 0.89 6 0.84 f1-score 0.97 0.97 0.88 0.76 0.76 0.97	980 1135 1032 1010 982 892 958 1028 974 1009 10000 support 980 1135 1032 1010 982 892
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[14 0 [11 2 2 [6 1 1 [49 0 6 1 1] 5 4 [10 1 1] 4 For 4: conf_mat: [[949 1 [0 1104 [5 0 [13 15 [10 0]	9 5 8 8 8 8 9 5 887 5 28 3	0 2 151 0 0 0 4 8 4 122 990 70 46	1 16 3 877 4 4 3 4 3 0 0 0 0 62 0	1 0 282 0 748 2 0 1 0	4 17 4 11 22 927 1 3 0	8 14 19 4 3 0 989 2 10	2 277 4399 445 2 6 944 16 6 19 15 4 98 47	9 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1] avg/t	0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94 8 0.64 9 0.83 otal 0.88 precision 0.97 0.97 0.90 0.62 1.00 0.94 0.93 0.78	1.0 0.9 0.9 0.1 0.8 0.8 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95 7 0.77 6 0.89 6 0.84 f1-score 0.97 0.97 0.88 0.76 0.12 0.90 0.83	980 1135 1032 1010 982 892 958 1028 974 1009 10000 support 980 1135 1032 1010 982 892 892 958 1028
[14 0 [11 2 2 [6 1 1 4 9 0 0 [19 1 1 4]	9 7 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9	0 2 151 0 0 0 4 4 8 4 122 990 70 46 34	1 16 3 877 4 4 3 4 3 0 0 0 0 62 0 0	1 0 282 0 748 2 0 1 0	4 17 4 11 22 927 1 3 0 0 4 0 0 40 13 827	8 14 19 4 3 0 989 2 10 0 1 3 0 206 0 1	227439445226641666191544984736	0] 0] 0] 0] 0] 0] 0] 0] 0] 0] 0] 0] 2]] avg / t 0 1 2 3 4 5 6 7 8	0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 8 0.64 9 0.83 otal 0.88 precision 0.97 0.97 0.90 0.62 1.00 0.94 0.93 0.78 0.78	1.0 0.9 0.9 0.1 0.8 0.9 0.9 0.9 0.9 0.9 0.8 0.96 0.86 0.86 0.86 0.86 0.86 0.86 0.89	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95 7 0.77 6 0.89 6 0.84 f1-score 0.97 0.97 0.88 0.76 0.12 0.90 0.90 0.83 0.87	980 1135 1032 1010 982 892 958 1028 974 1009 10000 support 980 1135 1032 1010 982 892 958 1028 974
[14 0 [11 2 2 [6 1 1 4 9 0 0 [19 1 1] [5 4 4 [10 1 1] [11 4 4] For 4: conf_mat: [[949	9 5 8 8 9 1 1 9 5 887 5 28 3 25 17	0 2 151 0 0 0 4 4 8 4 122 990 70 46 34 81	1 16 3 877 4 4 3 4 3 0 0 0 0 62 0 0	1 0 2822 0 7488 2 0 0 1 0 0 0 0 7700 2 6 0 0	4 17 4 11 22 927 1 3 0 0 4 4 0 0 4 4 13 827 0	8 14 19 4 3 0 989 2 10 0 1 3 0 206 0 1 914	2 27 439 4 45 2 6 944 10 6 19 15 4 98 847 36 10	0] 0] 0] 0] 0] 0] 1] 450] 3] 2]] avg/t	0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94 8 0.64 9 0.83 otal 0.88 precision 0.97 0.97 0.90 0.62 1.00 0.94 0.93 0.78	1.0 0.9 0.9 0.1 0.8 0.8 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95 7 0.77 6 0.89 6 0.84 f1-score 0.97 0.97 0.88 0.76 0.12 0.90 0.83	980 1135 1032 1010 982 892 958 1028 974 1009 10000 support 980 1135 1032 1010 982 892 892 958 1028
[14 0 [11 2 2 [6 1 1 [49 0 0 [13 15 [10 0 0 [13 15 [10 0 0 [5 2 [0 5 2 [1 1 1]]]]]	9 5 8 8 8 1 9 5 887 28 3 25 28 3 25 17 1	0 2 151 0 0 0 4 4 8 4 122 990 70 46 34 81 17	1 16 3 877 4 4 3 4 3 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	1 0 282 0 0 7488 2 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	4 17 4 11 22 927 1 3 0 0 4 0 0 0 4 0 13 18 227 0 1 13 0 13 14 15 15 16 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 16 16 16 16 16 16 16 16 16 16 16 16	8 144 19 4 3 0 989 2 10 0 1 3 0 0 206 0 1 1 914 1	2 27 439 4 45 2 6 944 10 6 19 15 4 98 47 36 10 951	0] 0] 0] 0] 0] 0] 0] 0] 1] 450] 3] 2] 1] 0]] avg / t	0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94 8 0.64 9 0.83 otal 0.88 precision 0.97 0.97 0.90 0.62 1.00 0.94 0.93 0.78 0.78 0.78 0.60	1.0 0.9 0.9 0.1 0.8 0.8 0.9 0.9 0.9 0.9 0.9 0.97 0.97 0.86 0.86 0.86 0.89 0.98	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 6 0.95 7 0.77 6 0.89 6 0.84 f1-score 0.97 0.97 0.88 0.76 0.12 0.90 0.93 0.87 0.64	980 1135 1032 1010 982 892 958 1028 974 1009 10000 support 980 1135 1032 1010 982 892 892 974 1009
[14 0 [11 2 2 [6 1 1 4 9 0 0 [19 1 1] [5 4 4 [10 1 1] [11 4 4] For 4: conf_mat: [[949	9 5 8 8 9 1 1 9 5 887 5 28 3 25 17	0 2 151 0 0 0 4 4 8 4 122 990 70 46 34 81	1 16 3 877 4 4 3 4 3 0 0 0 0 62 0 0	1 0 2822 0 7488 2 0 0 1 0 0 0 0 7700 2 6 0 0	4 17 4 11 22 927 1 3 0 0 4 4 0 0 4 4 13 827 0	8 14 19 4 3 0 989 2 10 0 1 3 0 206 0 1 914	2 27 439 4 45 2 6 944 10 6 19 15 4 98 47 36 10 951	0] 0] 0] 0] 0] 0] 1] 450] 3] 2]] avg / t 0 1 2 3 4 5 6 7 8	0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94 8 0.64 9 0.83 otal 0.88 precision 0.97 0.97 0.90 0.62 1.00 0.94 0.93 0.78 0.78 0.78 0.78 0.60	1.0 0.9 0.9 0.1 0.8 0.9 0.9 0.9 0.9 0.9 0.8 0.96 0.86 0.86 0.86 0.86 0.86 0.86 0.89	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 7 0.95 6 0.95 7 0.77 6 0.89 6 0.84 f1-score 0.97 0.97 0.88 0.76 0.12 0.90 0.90 0.83 0.87	980 1135 1032 1010 982 892 958 1028 974 1009 10000 support 980 1135 1032 1010 982 892 958 1028 974
[14 0 [11 2 2 [6 1 1 [49 0 0 [13 15 [10 0 0 [13 15 [10 0 0 [5 2 [0 5 2 [1 1 1]]]]]	9 5 8 8 8 1 9 5 887 28 3 25 28 3 25 17 1	0 2 151 0 0 0 4 4 8 4 122 990 70 46 34 81 17	1 16 3 877 4 4 3 4 3 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	1 0 282 0 0 7488 2 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	4 17 4 11 22 927 1 3 0 0 4 0 0 0 4 0 13 18 227 0 1 13 0 13 14 15 15 16 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 17 16 16 16 16 16 16 16 16 16 16 16 16 16	8 144 19 4 3 0 989 2 10 0 1 3 0 0 206 0 1 1 914 1	227439445226694410	0] 0] 0] 0] 0] 0] 0] 0] 1] 450] 3] 2] 1] 0]] avg / t	0 0.89 1 0.99 2 0.95 3 0.96 4 0.96 5 0.72 6 0.94 7 0.94 8 0.64 9 0.83 otal 0.88 precision 0.97 0.97 0.90 0.62 1.00 0.94 0.93 0.78 0.78 0.78 0.60	1.0 0.9 0.9 0.1 0.8 0.8 0.9 0.9 0.9 0.9 0.9 0.97 0.97 0.86 0.86 0.86 0.89 0.98	0 0.94 8 0.98 1 0.93 5 0.26 9 0.92 4 0.78 6 0.95 7 0.77 6 0.89 6 0.84 f1-score 0.97 0.97 0.88 0.76 0.12 0.90 0.93 0.87 0.64	980 1135 1032 1010 982 892 958 1028 974 1009 10000 support 980 1135 1032 1010 982 892 892 974 1009

					precision	recall	f1-score	support
				0	0.95	0.91	0.93	980
conf_mat:				1	0.98	0.97	0.98	1135
[[887 0 32	1 1	0 0 1	9 49]	2	0.92	0.87	0.89	1032
[0 1102 8	5 0	0 2 2 1	16 0]	3	0.63	0.98	0.76	1010
[1 0 894	86 7	0 3 8 3	33 0]	4	0.94	0.94	0.94	982
[0 0 4	994 0	0 1 1	8 2]	5	0.97	0.04	0.08	892
[1 5 2	1 925	0 1 6	9 32]	6		0.93	0.95	
[25 1 17		36 16 4 30	99 33]	7		0.93	0.95	
[15 1 3	6 17		25 1]	8		0.97		
[1 3 13	24 3	0 0 959	7 18]	9		0.91	0.89	
[0 0 1	21 1		41 5]					
[2 13 2	17 14		23 919]]	avg / total	0.89	0.85	0.83	10000
1.5		1		3 .				
For 6:								
					precision	recall	f1-score	support
				0	0.78	0.99	0.87	980
conf_mat:				1	0.99	0.97	0.98	1135
[[967 0 2	4 0 2	2 0 0 5	0]	2	0.91	0.86	0.89	1032
[0 1098 8	5 1 1	0 6 16	0]	3	0.74	0.98	0.84	1010
[7 1 890	101 8 6	1 10 14	1 0]	4	0.78	0.88	0.83	982
	993 0 7	7 0 2 8	0]	5	0.95	0.87	0.90	892
[9 0 2	4 864 6	12 10 38	3 43]	6	0.93	0.22	0.35	958
[15 0 2	53 0 772	0 0 49		7	0.96	0.90	0.93	1028
[226 4 30	41 228 29			8	0.71	0.98	0.82	974
[1 3 35	39 1 0			9	0.93	0.81	0.86	1009
[0 0 2	16 0 0							
[13 4 4	92 2 4	3 6 68		avg / total	0.87	0.85	0.83	10000
-								
For 7:								
					precision	recall f1	score su	apport
conf_mat:				0	0.93	0.98	0.96	980
[[962 0 5			4 1]	1	0.95	0.97	0.96	1135
[0 1099 1			6 3]	2	0.89	0.87	0.88	1032
[2 1 902		0 6 0 3	•	3 4	0.66	0.97	0.78	1010
[0 0 3	982 0 1		6 9]	5	0.96 0.95	0.83 0.87	0.89 0.91	982
[13 3 1			6 133]	6	0.95	0.91	0.93	892 958
[11 1 0	32 1 77		7 21]	7	0.99	0.13	0.23	1028
[33 3 2	4 5 2	1 869 1 1	7 3]	8	0.84	0.98	0.91	974
[6 47 103	370 10	3 14 133 3	3 309]	9	0.67	0.97	0.79	1009
[0 2 0	16 1	1 1 0 95	2 1]					
[2 2 1	12 1	2 1 0 1	0 978]]	avg / total	0.88	0.85	0.82	10000
F 0				1				
For 8:								
					precision	recall f1	l-score si	upport
conf mat:				0	0.90	0.99	0.94	980
[[972 0 0	6 1	0 1 0	0 01	1	0.99	0.98	0.99	1135
[2 1116 3	4 0	3 2 4	0 1]	2	0.91	0.93	0.92	1032
[5 0 956	37 12	0 6 15	0 1]	3	0.60	0.98	0.75	1010
[0 0 2	990 0	8 0 3	0 7]	4	0.95	0.96	0.95	982
•	0 940	0 4 2	1 23]	5	0.94	0.88	0.91	892
		85 15 1	0 20]	6	0.95	0.97	0.96	958
			•	7	0.96	0.92	0.94	1028
[14 1 2	1 11	3 926 0	0 0]	8	0.99 0.84	0.19 0.94	0.32 0.89	974 1009
[8 2 19	41 3	1 0 941	0 13]	9	0.04	0.54	0.69	1009
[43 3 58		38 18 7 1	83 119]	ava / total	0.90	0.88	0.86	10000
[13 7 1	15 12	1 0 10	1 949]]	avg / total	0.90	0.00	0.00	10000
For 9:								
101 9.								
					precision	recall f1	1-score si	upport
conf_mat:				0	0.91	0.98	0.94	980
[[965 1 5	2 1	3 1 1	1 0]	1	0.92	0.98	0.94	1135
[0 1112 1	1 1	1 2 12	5 0]	2	0.97	0.92	0.94	1032
[6 0 948	33 8	1 7 7	22 0]	3	0.89	0.98	0.93	1010
[1 0 3		3 0 4	12 0]	4	0.73	0.97	0.83	982
[16 2 1	0 950	0 1 1	11 0]	5	0.97	0.84	0.90	892
			- 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1	6	0.96	0.95	0.96	958
	38 3 7	49 9 0		7	0.86	0.94	0.90	1028
[19 3 0	4 15	4 910 0	3 0]	8	0.65	0.98	0.78	974
[11 3 14	10 5	1 1 971	12 0]	9	1.00	0.01	0.01	1009
[0 1 0	10 1	0 2 2 9						
[31 87 4	22 320	11 12 133 3	883 6]]	avg / total	0.89	0.86	0.81	10000
				iza of A.				

different instance for less training size of 0: For 100:

$\begin{array}{c} \text{conf_mat:} \\ [[485] 1] 32 47 8 34 174 21 60 118] \\ [0] 1115 1 4 0 0 1 0 14 0] 3 \\ [0] 0 3 837 89 10 1 14 19 57 2] 4 \\ [0] 0 0 11000 0 1 0 0 8 0] 5 \\ [0] 1 1 1 933 0 7 2 8 29] 6 \\ [0] 2 5 101 5 635 23 0 110 11] 7 \\ [0] 0 3 2 5 13 7 909 1 17 1] 8 \\ [0] 0 9 9 22 4 0 0 948 18 18] 9 \\ [0] 0 0 0 25 5 0 3 1 940 0] \\ [0] 1 0 2 30 5 1 2 4 8 947]] avg / total \\ \\ \hline \\ For 500: \\ \end{array}$	1.00 0 0.97 0 0.94 0 0.76 0 0.95 0 0.94 0 0.80 0 0.95 0 0.95 0	11 f1-score 49 0.66 98 0.98 81 0.87 99 0.86 95 0.95 71 0.81 95 0.95 92 0.94 97 0.85 94 0.89 87 0.87	980 1135 1032 1010 982 892 958 1028 974 1009
$\begin{array}{c} \text{conf_mat:} \\ [[607] 0 \ 65 \ 64 \ 3 \ 96 \ 71 \ 6 \ 8 \ 60] \\ [0 \ 968 \ 33 \ 2 \ 1 \ 1 \ 1 \ 126 \ 2 \ 1] \\ [0 \ 1 \ 938 \ 41 \ 9 \ 0 \ 7 \ 27 \ 8 \ 1] \\ [0 \ 0 \ 3 \ 986 \ 1 \ 4 \ 1 \ 6 \ 4 \ 5] \\ [0 \ 3 \ 4 \ 1 \ 876 \ 0 \ 8 \ 12 \ 3 \ 75] \\ [5 \ 8 \ 6 \ 106 \ 3 \ 677 \ 10 \ 4 \ 60 \ 13] \\ [1 \ 1 \ 1 \ 7 \ 7 \ 6 \ 4 \ 920 \ 0 \ 11 \ 1] \\ [0 \ 0 \ 5 \ 4 \ 2 \ 0 \ 1 \ 998 \ 5 \ 13] \\ [0 \ 10 \ 7 \ 68 \ 2 \ 1 \ 2 \ 7 \ 877 \ 0] \\ [0 \ 8 \ 1 \ 51 \ 2 \ 2 \ 2 \ 11 \ 3 \ 929]] \ \text{avg} \ / \ \text{tot} \\ \hline \\ For \ 1000: \end{array}$		0.62 0.85 0.91 0.98 0.89 0.76 0.96 0.97 0.90 0.92	0.76 980 0.91 1135 0.89 1032 0.84 1010 0.93 982 0.81 892 0.93 958 0.90 1028 0.90 974 0.88 1000
$\begin{array}{c} conf_mat: \\ \text{[[863 \ 0 \ 29 \ 13 \ 3 \ 23 \ 33 \ 0 \ 5 \ 11]} \\ \text{[0 1118 \ 5 \ 1 \ 0 \ 0 \ 1 \ 0 \ 10 \ 0]} \\ \text{[1 \ 1 \ 1938 \ 44 \ 6 \ 1 \ 8 \ 12 \ 20 \ 1]} \\ \text{[0 \ 0 \ 1 \ 990 \ 0 \ 4 \ 0 \ 2 \ 12 \ 1]} \\ \text{[0 \ 6 \ 4 \ 1 \ 859 \ 0 \ 10 \ 8 \ 8 \ 86]} \\ \text{[8 \ 0 \ 3 \ 35 \ 0 \ 732 \ 14 \ 1 \ 93 \ 6]} \\ \text{[8 \ 0 \ 3 \ 35 \ 0 \ 732 \ 14 \ 1 \ 93 \ 6]} \\ \text{[4 \ 4 \ 4 \ 4 \ 2 \ 7 \ 2 \ 908 \ 0 \ 26 \ 1]} \\ \text{[2 \ 5 \ 10 \ 19 \ 4 \ 1 \ 0 \ 928 \ 17 \ 42]} \\ \text{[0 \ 2 \ 5 \ 10 \ 19 \ 4 \ 1 \ 0 \ 928 \ 17 \ 42]} \\ \text{[0 \ 0 \ 2 \ 5 \ 10 \ 1 \ 0 \ 2 \ 0 \ 951 \ 3]} \\ \text{[0 \ 9 \ 0 \ 25 \ 5 \ 5 \ 1 \ 5 \ 9 \ 950]] avg / t} \\ \text{For 2000:} \\ \end{array}$		0.88 0.99 0.91 0.98 0.87 0.82 0.95 0.99 0.98	1-score support 0.93 980 0.98 1135 0.92 1032 0.92 1010 0.92 982 0.88 892 0.94 958 0.94 1028 0.94 1028 0.90 974 0.90 1009 0.92 10000
$\begin{array}{c} conf_mat: \\ [[\ 902\ 0\ 11\ 11\ 0\ 11\ 25\ 0\ 5\ 15] \\ [\ 0\ 1119\ 2\ 3\ 1\ 1\ 0\ 4\ 5\ 0] \\ [\ 2\ 0\ 922\ 54\ 5\ 0\ 13\ 23\ 12\ 1] \\ [\ 0\ 0\ 0\ 996\ 0\ 5\ 0\ 4\ 5\ 0] \\ [\ 0\ 3\ 2\ 1\ 814\ 0\ 13\ 5\ 1\ 143] \\ [\ 3\ 1\ 7\ 64\ 0\ 762\ 11\ 0\ 31\ 13] \\ [\ 2\ 1\ 5\ 6\ 1\ 10\ 927\ 0\ 6\ 0] \\ [\ 1\ 2\ 8\ 7\ 1\ 0\ 0\ 994\ 4\ 11] \\ [\ 0\ 3\ 12\ 52\ 2\ 1\ 3\ 4\ 891\ 6] \\ [\ 2\ 13\ 1\ 14\ 3\ 2\ 4\ 11\ 4\ 955]] \ avg \ / \end{array}$	precision 0 0.99 1 0.98 2 0.95 3 0.82 4 0.98 5 0.96 6 0.93 7 0.95 8 0.92 9 0.83 7 total 0.93	recall f 0.92 0.99 0.89 0.99 0.83 0.85 0.97 0.97 0.97 0.91 0.95	0.95 980 0.98 1135 0.92 1032 0.90 1010 0.90 982 0.90 892 0.95 958 0.96 1028 0.92 974 0.89 1009
$\begin{array}{c} conf_mat: \\ [[\ 907\ 1\ 17\ 3\ 0\ 32\ 4\ 0\ 6\ 10] \\ [\ 0\ 1128\ 2\ 1\ 0\ 0\ 1\ 0\ 3\ 0] \\ [\ 0\ 12\ 825\ 92\ 5\ 3\ 11\ 9\ 74\ 1] \\ [\ 0\ 0\ 1\ 981\ 1\ 21\ 0\ 0\ 3\ 3] \\ [\ 5\ 7\ 2\ 7\ 701\ 0\ 28\ 4\ 38\ 190] \\ [\ 5\ 1\ 1\ 38\ 0\ 801\ 15\ 0\ 25\ 6] \\ [\ 4\ 2\ 1\ 4\ 5\ 15\ 914\ 0\ 12\ 1] \\ [\ 1\ 23\ 6\ 79\ 3\ 1\ 0\ 853\ 31\ 31] \\ [\ 1\ 1\ 0\ 19\ 1\ 1\ 2\ 1\ 947\ 1] \\ [\ 1\ 1\ 0\ 19\ 1\ 1\ 2\ 1\ 947\ 1] \\ [\ 1\ 1\ 1\ 0\ 39\ 1\ 4\ 1\ 1\ 35\ 916]] \ \ avg \ . \\ \\ For 5000: \end{array}$	0 0.98 1 0.95 2 0.96 3 0.78 4 0.98 5 0.91 6 0.94 7 0.98 8 0.81 9 0.79 / total 0.91	0.93 0.99 0.80 0.97 0.71 0.90 0.95 0.83 0.97 0.91	0.95 980 0.97 1135 0.87 1032 0.86 1010 0.83 982 0.91 892 0.95 958 0.90 1028 0.88 974 0.85 1009 0.90 10000

												precision	recall	f1-score	support
cor	f_ma	at:									0	0.95	0.98	0.96	980
]]	959	1	1	2	2	6	4	1	3	1]	1	0.92	0.99	0.95	1135
1	0	1127	1	4	0	0	0	0	3	01	2	0.99	0.86	0.92	1032
ř	4	10	885	38	9	4	9	25	47	11	3	0.91	0.97	0.94	1010
	1	0	3	975	0	19	0	1	10	-	4	0.97	0.89	0.93	982
Ļ	1		_		_		-	1		1]	5	0.92	0.87	0.90	892
L	6	5	0	0	875	0	4	9	8	75]	6	0.97	0.92	0.95	958
[19	2	0	24	1	775	8	0	52	11]	7	0.95	0.90	0.92	1028
]	15	3	2	2	10	25	885	0	15	1]	8	0.86	0.97	0.91	974
ī	2	63	3	8	4	0	1	922	10	15]	100				
ŀ	0	7	1	9	0	3	1	1	947	5]	9	0.90	0.94	0.92	1009
L	U	,		_	U	2	-								
[3	10	2	10	2	7	1	13	9	952]]	avg / total	0.93	0.93	0.93	10000

As a result, if the training data set is unbalanced, when I test the data, the precision of less training data is higher than other number, the recall is lower than other number. And the prediction of this number are tend to balance for all number. With the increasing of the number which has the less training data, the precision of this number is decreased and the recall of this number is increased, the accuracy is increased.