	12	/ 20
ultiple Choice		
Each correctly answered multiple choice question gives 1 point.  Each incorrect answer results in -1 point.  However, the minimum scores in each of the four groups are 0 point.	ts.	/5
ta processing and feature spaces		
emperature in Celsius is of 🌠 interval scale 🗌 ratio scale.		
he idea of TF-IDF text representation is that globally frequent terms are		X
less fraguent terms.		
	nary leatures.	0
↑ True ☐ False	+han Euclidea	n (L2)
True ☐ False  Nanhattan (L1) distance between two points is always smaller or equal	tilali Luciidea	0
istance between the same two points.		
	C	
True Paise  When the mean is larger than the median, the underlying distribution is larger than the median.		1
☑ positively skewed □ negatively skewed.		
☑ positively skewed □ negatively skewed.		4 /5
☑ positively skewed □ negatively skewed.		4 /5
☑ positively skewed □ negatively skewed.  ssociation Rule Mining		4 /5
ssociation Rule Mining  while this the cize of the itemset generated from the transaction		4 /5
Ssociation Rule Mining  What is the size of the itemset generated from the transaction		
ssociation Rule Mining  What is the size of the itemset generated from the transaction  {bread, butter, beer, milk, butter, beer}? □ 2 ☑4 □ 6	nen all other re	
ssociation Rule Mining  What is the size of the itemset generated from the transaction  {bread, butter, beer, milk, butter, beer}? □ 2 ☑4 □ 6	nen all other re	
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ssociation Rule Mining  What is the size of the itemset generated from the transaction {bread, butter, beer, milk, butter, beer}? □ 2	hen all other rid as well.	ules
Ssociation Rule Mining  What is the size of the itemset generated from the transaction  {bread, butter, beer, milk, butter, beer}? □ 2 ☑4 □ 6  If confidence of the rule A->BCD is below the confidence threshold the created from the itemset {ABCD} are necessarily below the threshold of the rule ☑ False  Which algorithm requires that the items are sorted by frequency?	nen all other rid as well.	ules

pervised task  a supervised task.  e of the □ lazy  eager learning type.  raining examples have different values is □ problematic es based on information gain in terms of generalization error.  evaluation metric is robust with respect to class imbalance.  n, each data point belongs to the test set exactly  n, each data point belongs to the test set exactly  fervised task □ a supervised task.  sis  sensitive to outliers □ not sensitive to outliers.  ing-based clustering  a density-based clustering approach.	Decision tree classifiers are of the An attribute, in which all training  If helpful for decision trees based The accuracy / error rate evaluati  If True If False	□ lazy ☑ eager learning type.  examples have different values is □ on information gain in terms of ge	eneralization error	×
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pervised task □ a supervised task.  is ☑ sensitive to outliers □ not sensitive to outliers.  ing-based clustering ☑ a density-based clustering approach.	In a k-fold cross validation, each o	ata point belongs to the test set ex	xactiy	X
pervised task □ a supervised task.  is ☑ sensitive to outliers □ not sensitive to outliers.  ing-based clustering ☑ a density-based clustering approach.	□ once ☑ k times.			
pervised task □ a supervised task.  is ☑ sensitive to outliers □ not sensitive to outliers.  ing-based clustering ☑ a density-based clustering approach.				
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is   ✓ sensitive to outliers   not sensitive to outliers.  ing-based clustering   ✓ a density-based clustering approach.				
is   ✓ sensitive to outliers   not sensitive to outliers.  ing-based clustering   ✓ a density-based clustering approach.	Clustering is an unsupervised	task □ a supervised task.		-
ing-based clustering 🗹 a density-based clustering approach.	The k-Means algorithm is $\square$ ser	sitive to outliers 🗌 not sensitive to	o outliers.	C
to duis another point Conly if	DRCCAN is □ a partitioning-bas	ed clustering 🛮 a density-based clu	ustering approach	. (
density-connected via another point Comy in	Tarainte A and B are density-	connected via another point Conin	y II	
ints C is a core point A, B, and C are core points.	A and B are a core points	C is a core point \( \subseteq A, B, and C a	are core points.	
	Agnes and Diana both refer to h	ierarchical clustering approaches.		1
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efer to hierarchical clustering approaches.				
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efer to hierarchical clustering approaches.				

The following table shows a list of transactions:

T1	Burger, Wrap
T2	Burger, Coke, Fries
T3	Burger, Coke, Fries
T4	Burger, Fries, Wrap
T5	Burger, Coke, Wrap
T6	Coke, Fries

a) Apply the Apriori algorithm with a minimum support of 0.5. Construct for each step the candidate set  $\mathcal{C}_k$  and the frequent itemset list  $L_k$  starting with k=1 until all frequent itemsets are generated. For each step, also list the itemsets that are pruned based on the apriori property and list the itemsets that are pruned due to the application of the minimum support threshold.

minimum support = 0.5 x 6 = 3

C1 = Burger (6) Exa Coke? Fries (4), Lotal Wrap (3) V

L1 = Burger (6), Coke (4), Fries (41, Wrap (3) V

no itemsets one primed in this step V

C2 = {Burger, Coke? (3), {Burger, Fries} (3), {Burger, Wrap? (3)}

{ECoke, Fries? (3), {Coke, Wrap? (1), {Fries, Wrap? (1) V

{ECoke, Wrap? and {Fries, Wrap? should be primed due to minim

{Coke, Wrap? and {Fries, Wrap! should be primed due to minim

Eg = & Burger, Coke (3), {Burger, Fries ? (3), {Burger, Wrap ? (3), {coke, fries } (3)}

C3 = { Burger, Coke, Fries ? (2), {Burger, Coke, Wrap ? (1), }

& Burger, Fries, Wrap ? (1) | A W Wrap & will be pruced based

& Burger, tries, wrap? and & Burger, Fries, wrap? will be prived based & Burger, Cake, wrap? and & Burger, Fries, wrap? will be prived based on apriori property; and all the the 3 item sets are prived based on the minim support threshold. (1)

b) Generate all possible rules from the frequent itemsets and calculate their confidence.

( ) Generate all possible rules from the frequent itemsets and calculate their confidence.

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( ) Generate all possible rules from the frequent itemsets and calculate their confidence.

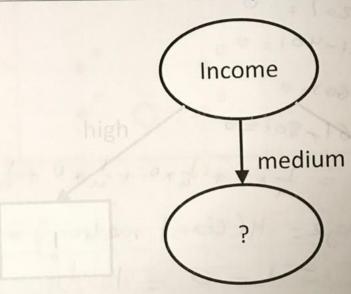
( ) Generate all possible rules from the frequent itemsets and calculate their confidence.

( ) Generate all possible rules from the frequent itemsets and calculate their confidence.

( ) Generate all possib

Given the following dataset and partial decision tree:

Age	Car	Income	Class
0-20	no	high	
0-20	no	medium	II
21-40	yes	medium	1
21-40	no -	low	
41-60	yes	low	
41-60	no .	medium	1.
61-80	yes	high	
61-80	yes	medium	<b>)</b> "



Calculate the information gain for the remaining attributes (car, age) to complete the decision tree for the medium branch. Decide which attribute should be used for the next split.

H(class) = 1, H(class) car)?

H(classicar) = -2 log = -2 log = -2 (-1) - 2 (-1) = 1 H(classicar) = -2 log = -2 log = -2 (-1) - 2 (-1) = 1 H(classicar) = -2 log = -2 log = -2 (-1) - 2 (-1) = 1 H(classicar) = 4 x1 + 4 x1 = 1, H(classicar) = 1 H(classicar) = Melinicar

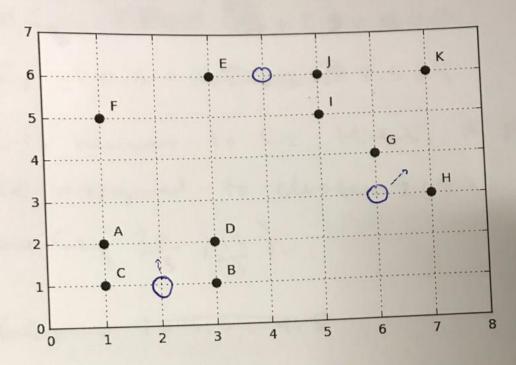
for age: 1 (21-40) 2 2 class 1 18 (41-60) 7 3 dail 1 (61-80) > 1 das " de production ? & H (class) medin, 0.20) 2 H (class) median, 21-401=0 H (dors) neation, 41-60)=0 H (dass [medium, 61,801=0 H (class medium, Age) = + x0+ 1x0+ 1x0+ 1x0 = 0 16 of authribuste Age: H(class) medime.) = H(class medimens) = 1 - 0 = 1 V 16 of Age larger than 10 of Car, then the attribute that should be used on next

Split is Age-

## 4) Clustering:k-Means

5/20

The following datapoints are given:



									1.	1	K
	1.	10	TC	ID	E	F	G	H	1	J	17
	Α	В		-	12	1	6	7	5	5	/
v	1	3	1	3	3	1	-	2	5	6	6
^	2	0 1	0 1	2	6	5	4	3	1 -		
IV	1 2	140	14								

Cluster the datapoints with k-Means using Manhattan distance. The initial centroids for k-Means are (2,1), (6,3), and (4,6), i.e. the parameter k=3. Specify for each iteration, to which centroids each point got assigned to and the calculation of the new centroids.

Iteration 1:

C1 = (2,1): assigned objects = {

C, H VI C2 (132

C2 = (6,3): assigned objects = {

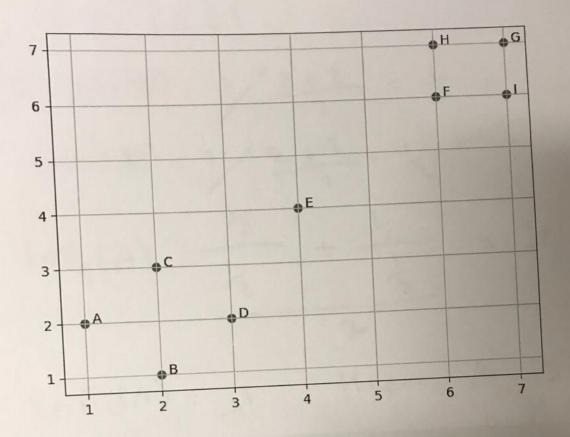
C3 = (4,6): assigned objects = {

Iteration 2:

## 5) Outlier Detection: Local Outlier Factor

18/20

The following dataset is given. Use Manhattan distance for your calculations.



Use the local outlier factor method ( $LOF_2$ ) to calculate the scores and decide whether the points

A and E are outliers given a threshold of 1.

N2(E) = {C,D}

N2(C) = SA, D3

N2 (D) = { \$ (B)

water.

(rdy()=1/3+3

lrd2(0)=1/2+2=1

しのら、他= 当十字

= 32+32 = 33

2

LOFICEI 2 >1 -> E is outlier

## 5) Outlier Detection: Local Outlier Factor