Project Schedule

Date	L#	Topic	Goals
01-16 (T)	1	Introduction	Understand what is data science research
02-06 (T)	7	Proposal: Teaming and proposal	Submit your proposal paper: • What is your project topic/research problem? • How will you find your dataset? • What may be your proposed method?
03-08 (R)	15	Milestone	Submit your milestone paper: • Your topic, dataset, and method • Milestone progress: Some preliminary results • Challenges and proposed solutions • Plan for the next two months
04-26 (R)	26	Oral 1 (up to 20% additional credits)	Every team gives an oral presentation. Classmates, instructor, and invited faculty will evaluate your presentation.
05-01 (T)	27	Oral 2	
05-03 (R)		Paper due	Project final paper due: You have to submit your code package, data, and term paper at 11:59PM this date.

Project Evaluation

- Proposal paper (10 points)
- Milestone presentation/paper (15 points)

- **Final term oral presentation (25 points)**
  - **04/26 and 05/01**
  - **Graded by classmates, invited faculty, and instructor**
- **Final term paper (25 points)**
  - **05/03**
  - **Graded by instructor**
- **Code package and data (25 points)**
  - **05/03**
  - **Graded by instructor and TA**

Dr. Taeho Jung

Data Security and Privacy Lab (DSP-Lab)
CSE 20110 Discrete Mathematics (Fall 2017)
CSE 40622 Cryptography (Spring 2018)

Grading Code Package and Data

- README.md (20%: 5 points)
- Runnable? (40%: 10 points)
- Reproducible? (40%: 10 points)
- Jupyter Notebook is encouraged as supplementary materials. (+2 points)

- Example:
  - REAME.md and makefile: https://github.com/shangjingbo1226/AutoPhrase
  - Jupyter for word2vec: http://nbviewer.jupyter.org/github/danielfrg/word2vec/blob/master/examples/word2vec.ipynb

Grading Final Term Paper

Introduction:	15%	Provide context and motivation. What questions are being addressed? Why are these questions interesting or important?
Related Work:	10%	What other methods have addressed these or similar questions? How do these methods differ from your method?
Solution/Method:	25%	What did you do? What tools and techniques did you use? Was any innovation attempted?
Data and Experiments:	10%	What data did you use? Are your experimental methods reliable? What preprocessing was done the data?
Evaluation and Results:	25%	Did you properly evaluate your experiments? Did you test for statistical significance? Do your conclusions match your results?
Writing Quality:	15%	Clarity of writing (5%), organization (5%), and grammar (5%).

Grading Oral Presentation

Introduction:	15%	Provide context. What questions are being addressed?
Solution/Method:	30%	What did you do? Why did you choose this method? What tools and techniques did you use?
Data and Experiments:	10%	What data did you use? Are your experimental methods reliable?
Evaluation and Results:	30%	What evaluation did you do? Do your conclusions match your results?
Presentation Quality:	15%	Clarity of speaking (5%), organization (5%), and visuals (5%).

Grading Form

- Students (anonymized; skip your own team): 60%
- Invited faculty: 30%
- Instructor: 10%

	Intro (15)	Solution, method (30)	Data and experiments (10)	Evaluation, analysis, results (30)	Presentation quality (15)	Sum (100)
NPM						
ACC						
MLB						
MML						
EBM						
POW						
PBC						
DPH						
AFG						
MPT						

How to Have Grade A?

- Calculated score >= 94
  - **HW1*5% + HW2*5% + HW3*5% + HW4*5%**
  - **Mid exam*20%** (at most 100*20% though honor code bonus)
  - **<u>Final exam*30%</u>** (no honor code bonus)
  - Course project
    - **Proposal*3% + Milestone*4.5%**
    - Presentation (at most 100*7.5%, up to +20% for early-bird: Apr. 26)
      83.333 → 100 (may happen)
      - **<u>Students*4.5%</u>**
      - **<u>Invited faculty*2.25%</u>**
      - **<u>Instructor*0.75%</u>**
    - **<u>Final project paper*7.5%</u>**
      - Usually proportional to the presentation
    - **<u>Code/data package*7.5%</u>**

Letter Grades

- A: 93-100
- A-: 90, 91, 92
- B+: 87, 88, 89
- B: 84, 85, 86
- B-: 81, 82, 83
- C+: 78, 79, 90
- C: 75, 76, 77

Final Exam

- Time: May 8 (Tuesday) 10:30 am – 12:30 pm
- Location: 117 DeBartolo

- Write down your answers/solutions on the blue book.
- Return your exam paper after the exam.
- You can have a double-sided letter-size reference paper.

- You must bring a pen/pencil/writing tool.
- You had better bring a calculator.
- You are not allowed to use laptop/computer/cellphone!
- You are not allowed to bring text book.

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

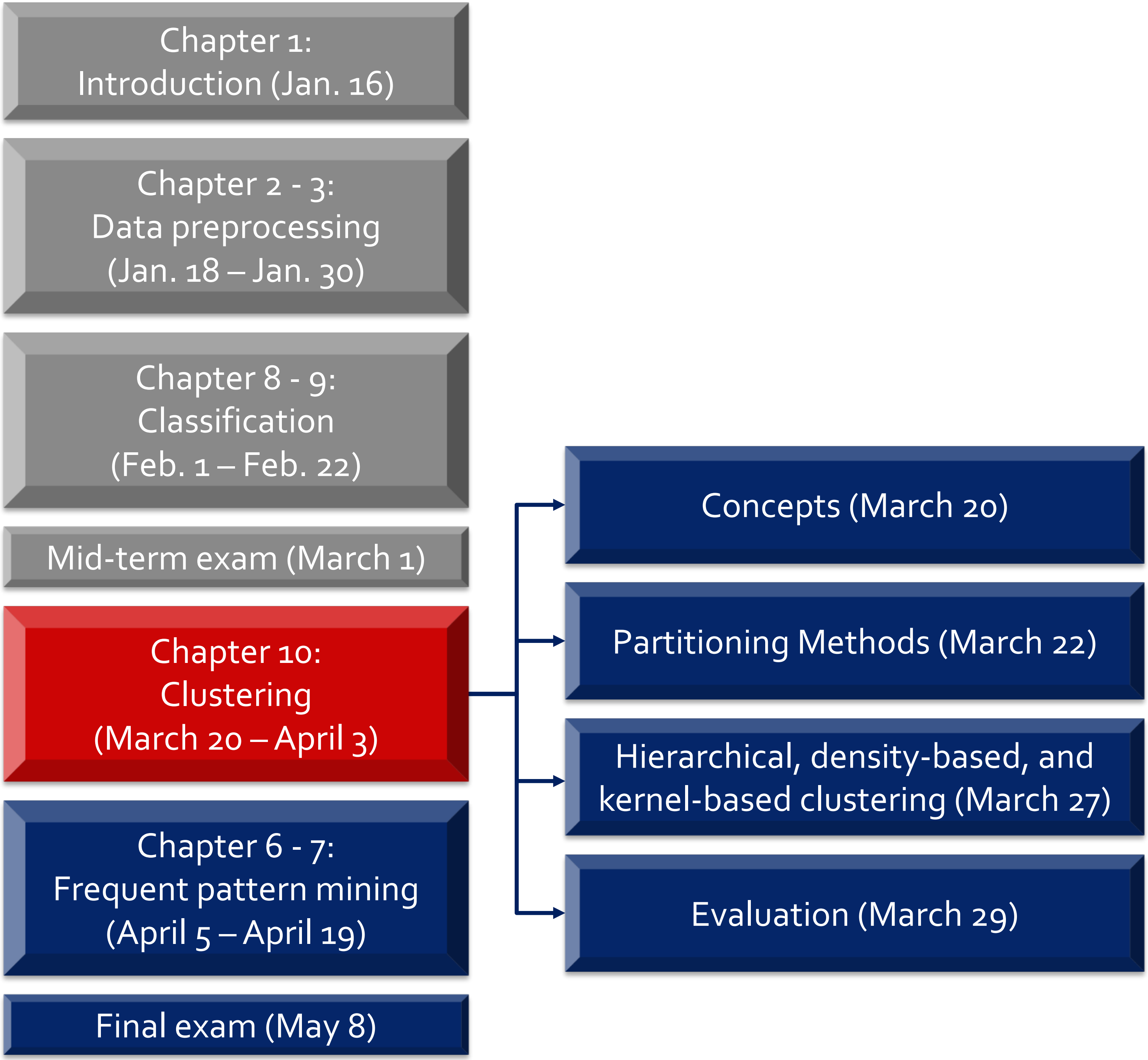
Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)


Chapter 1: Introduction (Jan. 16)
Chapter 2 - 3: Data preprocessing (Jan. 18 – Jan. 30)
Chapter 8 - 9: Classification (Feb. 1 – Feb. 22)
Mid-term exam (March 1)
Chapter 10: Clustering (March 20 – April 3)
Chapter 6 - 7: Frequent pattern mining (April 5 – April 19)
Final exam (May 8)
Concepts (March 20)
Partitioning Methods (March 22)
Hierarchical, density-based, and kernel-based clustering (March 27)
Evaluation (March 29)

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

- Concepts and Apriori (April 5)
- FP-Growth (April 10)
- Evaluation (April 12)
- Beyond Itemsets (April 17)

Final exam (May 8)


Review


Everybody 100 points if I got in Playoffs...
questions to answer...
Are you ready?
NUGGETS
15

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q1: Who is the instructor of Data Science Spring'18?

A) 

B) 

C) 

D) 

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q2:

What is cluster?
What is cluster analysis/clustering?
What is the difference between ***classification*** and ***clustering***?

What are the two **properties** of a good cluster?

List at least three **applications** of cluster analysis.

List at least four types of **data sets** for cluster analysis.

What are the three pairs of clustering **task types** (e.g., partitional vs hierarchical)?

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q3:

What is the **objective function** of K partitioning methods?

What is the **centroid** of a group of data points?

What is the **medoid** of the group?

What is the major difference between ***centroid*** and ***medoid***?

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q4: **K-Means Clustering**

Given *K*, the number of clusters, the *K-Means* clustering algorithm is outlined as follows

Select *K* points as initial centroids

Repeat

Form K clusters by assigning each data object to its nearest centroid using a distance metric

Move each centroid to the mean of its assigned data objects (i.e., re-compute the centroid of each cluster)

Until convergence

Change in cluster assignment less than a threshold

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q5: Pros and Cons of K-Means Clustering

Pro:

What is the complexity?

Cons:

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q5: Pros and Cons of K-Means Clustering

Pro:
What is the complexity?

Cons:
Specify K: run a range of values and select the best (min SSE); use rule of thumb or "elbow" method
Local optimum - sensitive to initialization: heuristics to choose initialization, for example, the farthest points
Sensitive to noise and outliers: use K-Medoids or K-Medians
Only applicable for numerical data: use K-Modes for categorical data
Unable to discover clusters with non-convex shapes: use density-based clustering (DBSCAN) or Kernel K-Means

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q6: **Kernel K-Means**

What is the objective function?

What is Kernel Matrix?

List two common kernel functions.

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q6: **Kernel K-Means**

What is the objective function?

$$\underset{\mathcal{J}_1,\ldots,\mathcal{J}_k}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{j\in\mathcal{J}_i} \left\| \mathbf{a}_j - \frac{1}{|\mathcal{J}_i|} \sum_{l\in\mathcal{J}_i} \mathbf{a}_l \right\|_2^2.$$

$$\Downarrow$$

$$\underset{\mathcal{J}_1,\ldots,\mathcal{J}_k}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{j\in\mathcal{J}_i} \left\| \phi(\mathbf{a}_j) - \frac{1}{|\mathcal{J}_i|} \sum_{l\in\mathcal{J}_i} \phi(\mathbf{a}_l) \right\|_2^2.$$

What is Kernel Matrix?

$$\kappa(\mathbf{a}_i, \mathbf{a}_j) = \langle \phi(\mathbf{a}_i), \phi(\mathbf{a}_j) \rangle.$$

List two common kernel functions.

Polynomial kernel: $K(x_i,x_j) = (x_i^T x_j + c)^d$

RBF kernel: $K(x_i,x_j) = \exp(-\gamma|x_i-x_j|^2)$

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q7: **DBSCAN**

Specify ε and *MinPts*
Arbitrarily select a point *p*
Retrieve all points *density-reachable* from *p*
- If *p* is a core point, a cluster is formed
- If *p* is a border point, no points are density-reachable from *p*, and DBSCAN visits the next point of the database

Continue until *all* of the points have been processed

What are the Pros and Cons of DBSCAN?

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q7: **DBSCAN**

Specify *ε* and *MinPts*
Arbitrarily select a point *p*
Retrieve all points *density-reachable* from *p*
  If *p* is a core point, a cluster is formed
  If *p* is a border point, no points are density-reachable from *p*, and DBSCAN visits the next point of the database
Continue until *all* of the points have been processed

What are the Pros and Cons of DBSCAN?
Pro: Non-convex shape; partial clustering (outliers not in clusters); not have to specify K; O(n logn)
Con: Sensitive to the two parameters

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q8: **External Evaluation for Clustering**

Matching-based
- Purity (matching)
- Purity (maximum matching)
- Matching-based Precision, Recall, F1

Pairwise
- Confusion matrix (pairwise TP/FN/FP/TN)
- Jaccard coefficient
- Rand Statistic
- Pairwise precision, recall, and Fowlkes-Mallow Measure

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q9: **BetaCV Internal Evaluation for Clustering**

$$BetaCV = \frac{W_{in} / N_{in}}{W_{out} / N_{out}}$$

- The smaller, the better the clustering, when the weight is distance
- The bigger, the better the clustering, when the weight is similarity

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q10: Concepts

What is *k*-itemset?
What is *absolute support*?
What is *relative support*?
What is minimum support *min_sup*? And what is frequent itemset?

For an association rule X→Y,
what is *support*? Is it relative or absolute?
What is *confidence*?
Think about Y→X,
is *support* symmetric? Is *confidence* symmetric?

What is *closed pattern*? Is it lossless? (What does "lossless" mean?

What is *max pattern*? Is it lossless?

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q11: **Apriori**

What is Apriori property (or called the Downward Closure Property)?

Outline of Apriori (level-wise, candidate generation and test)

- Initially, scan DB once to get frequent 1-itemset
- **Repeat**
  - Generate length-(k+1) candidate itemsets from length-k frequent itemsets
  - Test the candidates against DB to find frequent (k+1)-itemsets
  - Set k := k +1
- **Until** no frequent or candidate set can be generated
- Return all the frequent itemsets derived

Apriori

Database TDB

Tid	Items
10	A, C, D
20	B, C, E
30	A, B, C, E
40	B, E

minsup = 2

1^{st} scan

C_1

Itemset	sup
{A}	2
{B}	3
{C}	3
{D}	1
{E}	3

F_1

Itemset	sup
{A}	2
{B}	3
{C}	3
{E}	3

C_2

Itemset
{A, B}
{A, C}
{A, E}
{B, C}
{B, E}
{C, E}

2^{nd} scan

C_2

Itemset	sup
{A, B}	1
{A, C}	2
{A, E}	1
{B, C}	2
{B, E}	3
{C, E}	2

F_2

Itemset	sup
{A, C}	2
{B, C}	2
{B, E}	3
{C, E}	2

C_3

Itemset
{B, C, E}

3^{rd} scan

F_3

Itemset	sup
{B, C, E}	2

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q12: Discussion on Apriori

What is the biggest weak point of the Apriori algorithm? Is it efficient?

Outline of Apriori (level-wise, candidate generation and test)

- Initially, scan DB once to get frequent 1-itemset
- **Repeat**
  - Generate length-(k+1) candidate itemsets from length-k frequent itemsets
  - Test the candidates against DB to find frequent (k+1)-itemsets
  - Set k := k +1
- **Until** no frequent or candidate set can be generated
- Return all the frequent itemsets derived

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q13: **FP-Growth**

- Find frequent single items and partition the database based on each such item
- Recursively grow frequent patterns by doing the above for each partitioned database (also called *conditional database*)
- To facilitate efficient processing, an efficient data structure, FP-tree, can be constructed

A database has 10 transactions. Let $min\_sup = 2$. Items are a, b, c, d, and e.

Trans. ID	Itemset
1	{a, b}
2	{b, c, d}
3	{a, c, d, e}
4	{a, d, e}
5	{a, b, c}
6	{a, b, c, d}
7	{a}
8	{a, b, c}
9	{a, b, d}
10	{b, c, e}

1. Use Python to implement Apriori to find all frequent patterns (i.e., frequent itemsets) and their counts from the transaction database. Please submit your code as **YourNetid-HW4-Q1.py**.
2. Draw the FP-tree on the PDF. Write down the reason that FP-Growth is often more efficient than Apriori on the PDF. You don't have to implement FP-Growth or use it to find the frequent patterns in this homework.

Find frequent patterns and closed patterns

Trans. ID	Items bought
1	ACFG
2	ABCF
3	ABCDF
4	BDE

If min_sup = 2, are they closed patterns?

- D
- ABCF
- BF
- BD
- ACF

Use Apriori to find all frequent patterns

Use FP-Growth to find all frequent patterns

Write down all closed patterns and their support

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q14: Association interestingness measures

What is null-invariance?

Give two null-variant measures.

Give five null-invariant measures and prove this property.

Measure	Definition	Range	Null-Invariant
$\chi^2(A, B)$	$\sum_{i,j=0,1} \frac{(e(a_i b_j) - o(a_i b_j))^2}{e(a_i b_j)}$	$[0, \infty]$	No
$Lift(A, B)$	$\frac{s(A \cup B)}{s(A) \times s(B)}$	$[0, \infty]$	No
$AllConf(A, B)$	$\frac{s(A \cup B)}{max\{s(A), s(B)\}}$	$[0, 1]$	Yes
$Jaccard(A, B)$	$\frac{s(A \cup B)}{s(A) + s(B) - s(A \cup B)}$	$[0, 1]$	Yes
$Cosine(A, B)$	$\frac{s(A \cup B)}{\sqrt{s(A) \times s(B)}}$	$[0, 1]$	Yes
$Kulczynski(A, B)$	$\frac{1}{2}(\frac{s(A \cup B)}{s(A)} + \frac{s(A \cup B)}{s(B)})$	$[0, 1]$	Yes
$MaxConf(A, B)$	$max\{\cancel{\frac{s(A)}{s(A \cup B)}, \frac{s(B)}{s(A \cup B)}}\}$	$[0, 1]$	Yes

max{ s(AUB) / s(A) , s(AUB) / s(B) }

Chapter 1:
Introduction (Jan. 16)

Chapter 2 - 3:
Data preprocessing
(Jan. 18 – Jan. 30)

Chapter 8 - 9:
Classification
(Feb. 1 – Feb. 22)

Mid-term exam (March 1)

Chapter 10:
Clustering
(March 20 – April 3)

Chapter 6 - 7:
Frequent pattern mining
(April 5 – April 19)

Final exam (May 8)

Q15: Sequential patterns

What is item, event, and sequence?
What is sequential pattern?

Seq. ID	Sequence
1	(AB)C(FG)G
2	(AD)CG(ABF)
3	AB(FG)

If min_sup = 2, are they sequential patterns?

- ACF
- (FG)B
- (FG)
- B(FG)
- GF

KEEP
CALM
AND
GOOD
LUCK!