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Answer 1:

a)

wheel: want to own a balance wheel

^wheel: do not want to own a balance wheel

selfie: like selfie ^selfie: dislike selfie

| | wheel | selfie | ^wheel | ^selfie | <mark>wheel, selfie</mark> | wheel, ^selfie | ^wheel, selfie | ^wheel, ^selfie |
|----------|-------|--------|--------|---------|----------------------------|------------------|----------------|-----------------|
| license | 3250 | 3750 | 1750 | 1250 | <mark>2500</mark> | <mark>750</mark> | 1250 | 5 00 |
| ^license | 2750 | 4000 | 2250 | 1000 | 2250 | 500 | 1750 | 500 |
| sum | 6000 | 7750 | 4000 | 2250 | <mark>4750</mark> | 1250 | 3000 | 1000 |

Support >= 5% means >=500 records, because all counts of itemsets are more than 500, except some unmeaning items which have 0 counts, such as "wheel, ^wheel", we can draw the below strong association according rules above table:

| Rule | Confidence |
|---------------------------|-----------------------------|
| wheel, selfie → license | 2500/4750 ≈ 52.6% |
| ^wheel, ^selfie → license | 500/1000 = 50% |
| wheel, ^selfie → license | 750/1250 = 60% |
| ^wheel, selfie → license | 1250/3000 ≈ 41.7 |

Note: the confidence of last row is less than 50%, so remove it

b)

Interest(wheel, selfie
$$\rightarrow$$
 license) = conf(wheel, selfie \rightarrow license) * $\frac{1}{P(license)}$ = 0.526 * 2 = 1.052 Interest(^wheel, ^selfie \rightarrow license) = conf(^wheel, ^selfie \rightarrow license) * $\frac{1}{P(license)}$ = 0.5 * 2 = 1 Interest(wheel, ^selfie \rightarrow license) = conf(wheel, ^selfie \rightarrow license) * $\frac{1}{P(license)}$ = 0.6 * 2 = 1.2

c)

In part (a), we can find the confidence of "wheel, ^selfie \rightarrow license" is the biggest one, so "wheel, ^selfie \rightarrow license" is most interesting rule in part (a), which can be described that these participants who want to own balance wheels and dislike selfie perhaps have driver licenses.

d)

In part (b), we can find that "wheel, ^selfie → license" have the most lift ratio, because of this, we can consider this rule is most interesting.

Actually, it is obvious that this conclusion is same to **c**), because the left ratio is proportional to confidence value.

Answer 2:

a)

We use some simple marks instead of these stock names and operations:

| | Buy | Sell | No operation |
|-----------------|-----|------|--------------|
| HSBC | bHS | sHS | ^HS |
| BoEA | bBo | sBo | ^Bo |
| China_Mobile | bCM | sCM | ^CM |
| China_Petroleum | bCP | sCP | ^CP |

According to above table, we can improve Transaction Data to this:

| | HSBC | BoEA | China_Mobile | China_Petroleum |
|------|------|------|--------------|-----------------|
| # 1 | bHS | sBo | bCM | ^CP |
| # 2 | bHS | sBo | ^CM | ^CP |
| # 3 | ^HS | bBo | bCM | bCP |
| # 4 | bHS | ^Bo | bCM | ^CP |
| # 5 | bHS | ^Bo | sCM | sCP |
| # 6 | ^HS | sBo | bCM | bCP |
| # 7 | bHS | sBo | ^CM | ^CP |
| # 8 | bHS | bBo | ^CM | ^CP |
| # 9 | ^HS | ^Bo | bCM | sCP |
| # 10 | bHS | ^Bo | bCM | bCP |

Frequent itemsets:

min_sup = 20% means >=2 records

1-itemsets:

| 1-itemset | Count |
|-----------|-------|
| bHS | 7 |
| ^HS | 3 |
| sBo | 4 |
| bBo | 2 |
| ^Bo | 4 |
| bCM | 6 |
| sCM | 1 |
| ^CM | 3 |
| bCP | 3 |
| sCP | 2 |
| ^CP | 5 |

2-itemset:

| 2-itemset | Count | 2-itemset | Count | 2-itemset | Count |
|---------------------|-------|---------------------|-------|---------------------|-------|
| bHS, bBo | 1 | bBo, bCM | 1 | bCM, bCP | 3 |
| bHS, sBo | 3 | bBo, △CM | 1 | bCM, sCP | 1 |
| bHS, ^Bo | 3 | sBo, bCM | 2 | bCM, ^CP | 2 |
| △HS, bBo | 1 | sBo, ^CM | 2 | sCM, sCP | 1 |
| ∆HS, sBo | 1 | ^Bo, bCM | 3 | ^CM, ^CP | 3 |
| △HS, △Bo | 1 | △Bo, sCM | 1 | | |
| bHS, bCM | 3 | bBo, bCP | 1 | | |
| bHS, sCM | 1 | bBo, ^CP | 1 | | |
| bHS, ^CM | 3 | sBo, bCP | 1 | | |
| ^HS, bCM | 3 | sBo, ^CP | 3 | | |
| bHS, bCP | 1 | △Bo, bCP | 1 | | |
| bHS, sCP | 1 | △Bo, △CP | 1 | | |
| bHS, ^CP | 5 | ^Bo, sCP | 2 | | |
| ^HS, bCP | 2 | | | | |
| AHS, sCP | 1 | | | | |

3-itemset:

| 3-itemset | Count | 3-itemset | Count |
|--------------------------|-------|--------------------------|-------|
| bHS, sBo, bCM | 1 | bHS, ^CM, ^CP | 3 |
| bHS, sBo, ^CM | 2 | ^HS, bCM, bCP | 2 |
| bHS, sBo, ^CP | 3 | sBo, bCM, ^CP | 1 |
| bHS, ^Bo, bCM | 2 | sBo, ^CM, ^CP | 2 |
| bHS, ^Bo, ^CP | 1 | △Bo, bCM, sCP | 1 |
| bHS, bCM, ^CP | 2 | | |

4-itemset:

| 4-itemset | Count |
|--------------------|-------|
| bHS, sBo, ^CM, ^CP | 2 |

b) according 3-itemset of a), we can conclude: (min_conf=70%)

| Rule | Confidence | Rule | Confidence | Rule | Confidence |
|----------------|-----------------------|---------------------------|-----------------------|---------------------------|-----------------------|
| bHS, sBo → ^CM | 2/3 ≈ 0.67 | bHS, bCM → ^Bo | 2/3 ≈ 0.67 | ^CM, ^CP → bHS | 3/3 = 1 |
| bHS, ^CM → sBo | 2/3 ≈ 0.67 | ^Bo, bCM → bHS | 2/3 ≈ 0.67 | △HS, bCM → bCP | $2/3 \approx 0.67$ |
| sBo, ^CM → bHS | 2/2 = 1 | bHS, bCM → ^CP | 2/3 ≈ 0.67 | ^HS, bCP → bCM | 2/2 = 1 |
| bHS, sBo → ^CP | 3/3 = 1 | bHS, ^CP → bCM | $\frac{2/5}{} = 0.4$ | bCM, bCP → ^HS | $2/3 \approx 0.67$ |
| bHS, ^CP → sBo | 3/5 = 0.6 | bCM, ^CP → bHS | 2/2 = 1 | sBo, ^CM → ^CP | 2/2 = 1 |
| sBo, ^CP → bHS | 3/3 = 1 | bHS, ^CM → ^CP | 3/3 = 1 | sBo, ^CP → ^CM | 2/3 ≈ 0.67 |
| bHS, ^Bo → bCM | 2/3 ≈ 0.67 | bHS, ^CP → ^CM | 3/5 = 0.6 | △CM, △CP → sBo | 2/3 ≈ 0.67 |

Strong rules for conf>70%:

Answer 3:

c1:Up, c2:Down, c3:Level

$$I(c1, c2, c3) = I(3, 2, 2) = \frac{3}{7} * \log_2 \frac{3}{7} + \frac{2}{7} * \log_2 \frac{2}{7} + \frac{2}{7} * \log_2 \frac{2}{7} \approx 1.557$$

Entropy for 2TDB:

| 2TDB | c1 | c2 | c3 | I(c1, c2, c3) |
|-------|----|----|----|---------------|
| Up | 1 | 1 | 2 | 1.5 |
| Down | 1 | 0 | 0 | 0 |
| Level | 1 | 1 | 0 | 1 |

$$E(2TDB) = \frac{4}{7} * 1.5 + \frac{1}{7} * 0 + \frac{2}{7} * 1 \approx 1.14$$

Information_Gain (2TDB) = 1.557 - 1.14 = 0.417

Entropy for 1TDB:

| 1TDB | c1 | c2 | сЗ | I(c1, c2, c3) |
|-------|----|----|----|---------------|
| Up | 0 | 2 | 1 | 0.918 |
| Down | 2 | 0 | 0 | 0 |
| Level | 1 | 0 | 1 | 1 |

$$E(1TDB) = \frac{3}{7} * 0.918 + \frac{2}{7} * 0 + \frac{2}{7} * 1 = 0.6791$$

Information_Gain (1TDB) = 1.557 - 0.6791 = 0.878

Entropy for TD:

| 2TDB | c1 | c2 | c3 | I(c1, c2, c3) |
|-------|----|----|----|---------------|
| Up | 1 | 1 | 0 | 1 |
| Down | 0 | 0 | 2 | 0 |
| Level | 2 | 1 | 0 | 0.918 |

$$E(TD) = \frac{2}{7} * 1 + \frac{2}{7} * 0 + \frac{3}{7} * 0.918 = 0.6791$$

Information_Gain (TD) = 1.557 - 0.6791 = 0.878

According above tables, we can find that the information gains for TD and 1TDB are equal, and bigger than the 2TDB, so we choose TD as root node. And we can find if TD is down, the all results of NTD are level, so we decide this one branch of root node. Then, we need to decide child nodes and branches.

If TD is level:

$$I(c1, c2, c3) = I(2, 1, 0) = \frac{2}{3} * log_2 \frac{1}{3} + \frac{2}{3} * log_2 \frac{2}{3} + 0 \approx 0.918$$

Entropy for 1TDB:

| 1TDB | c1 | c2 | c3 | I(c1, c2, c3) |
|-------|----|----|----|---------------|
| Up | 0 | 1 | 0 | 0 |
| Down | 2 | 0 | 0 | 0 |
| Level | 0 | 0 | 0 | 0 |

$$E(1TDB) = \frac{1}{3} * 0 + \frac{2}{3} * 0 + \frac{0}{3} * 0 = 0$$

Information_Gain (1TDB) = 0.918 - 0 = 0.918

Entropy for 2TDB:

| 2TDB | c1 | c2 | c3 | I(c1, c2, c3) |
|-------|----|----|----|---------------|
| Up | 1 | 1 | 0 | 1 |
| Down | 0 | 0 | 0 | 0 |
| Level | 1 | 0 | 0 | 0 |

$$E(2TDB) = \frac{2}{3} * 1 + 0 + 0 \approx 0.667$$

Information_Gain (2TDB) = 0.918 - 0.667 = 0.251

Obviously, the information gain of 1TDB is bigger, so we can choose 1TDB as the child node of root node when TD is level. But we also need to check the other situation if TD is up.

Now, the only branch is when TD is up, we can calculate entropy in this situation: Entropy for 1TDB:

| 1TDB | c1 | c2 | c3 | I(c1, c2, c3) |
|-------|----|----|----|---------------|
| Up | 0 | 1 | 0 | 0 |
| Down | 0 | 0 | 0 | 0 |
| Level | 1 | 0 | 0 | 0 |

E(1TDB) = 0 + 0 + 0 = 0

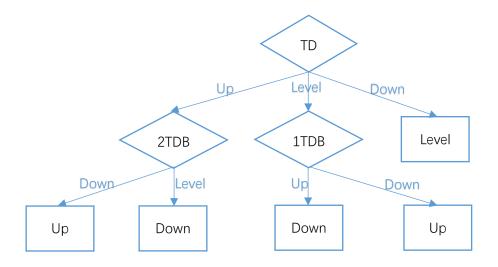
Entropy for 2TDB:

| 2TDB | c1 | c2 | c3 | I(c1, c2, c3) |
|-------|----|----|----|---------------|
| Up | 0 | 0 | 0 | 0 |
| Down | 1 | 0 | 0 | 0 |
| Level | 0 | 1 | 0 | 0 |

E(2TDB) = 0

Because entropy of both of these two attributes is zero, any one of them can be as the child node when TD is up. Then we choose 2TDB as the child node when TD is up.

According to above analysis, we can get this decision tree:



12 Sep: IF TD = Level AND 1TDB = Up THEN NTD = Down

13 Sep: IF TD = Down THEN NTD = Level