CSC487: Data Mining - Homework #3

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1. Suppose that we have age data including the following numbers in sorted order. ***(25 points total)***

[13, 15, 16, 16, 19, 20, 20, 21, 22, 22, 25, 25, 25, 25, 30, 33, 33, 35, 35, 35, 35, 36, 40, 45, 46, 52, 70]

Let us first load in the data…

```python
# load in the data...
nums = [13, 15, 16, 16, 19, 20, 20, 21, 22, 22, 25, 25, 25,
        25, 30, 33, 33, 35, 35, 35, 35, 36, 40, 45, 46, 52, 70]
df1 = pd.DataFrame()
df1['nums'] = nums

# preview the data...
df1
```

```
##     nums
## 0     13
## 1     15
## 2     16
## 3     16
## 4     19
## 5     20
## 6     20
## 7     21
## 8     22
## 9     22
## 10    25
## 11    25
## 12    25
## 13    25
## 14    30
## 15    33
## 16    33
## 17    35
## 18    35
## 19    35
## 20    35
## 21    36
## 22    40
## 23    45
## 24    46
## 25    52
## 26    70
```

a.) Use smoothing by bin means to smooth the above data, using a bin depth of 3. Illustrate your steps. Comment on the effect of this technique for the given data. *(5 points)*

```
# length of data.
l = df1.size
l
```

```
## 27
```

```
# cut idx.
q = int(l/3)
q
```

```
## 9
```

```
# binning & averaging.
df1['3bin_mean'] = 0
df1['3bin_mean'].iloc[0:q] = df1['nums'].iloc[0:q].mean()
df1['3bin_mean'].iloc[q:2*q] = df1['nums'].iloc[q:2*q].mean()
df1['3bin_mean'].iloc[2*q:l] = df1['nums'].iloc[2*q:l].mean()

df1
```

```
##     nums  3bin_mean
## 0     13  18.000000
## 1     15  18.000000
## 2     16  18.000000
## 3     16  18.000000
## 4     19  18.000000
## 5     20  18.000000
## 6     20  18.000000
## 7     21  18.000000
## 8     22  18.000000
## 9     22  28.111111
## 10    25  28.111111
## 11    25  28.111111
## 12    25  28.111111
## 13    25  28.111111
## 14    30  28.111111
## 15    33  28.111111
## 16    33  28.111111
## 17    35  28.111111
## 18    35  43.777778
## 19    35  43.777778
## 20    35  43.777778
## 21    36  43.777778
## 22    40  43.777778
## 23    45  43.777778
## 24    46  43.777778
## 25    52  43.777778
```

```
## 26    70  43.777778
```

This technique generalizes our data into 3 groups, increasing our previous minimum and decreasing our previous maximum.

---

b.) How can you determine outliers in the data? *(5 points)*

Outliers are typically determines by the Interquartile Range (IQR). If a value is outside 1.5 times the IQR we call it an outlier.

```
# summary statistics.
df1.describe()
```

```
##             nums  3bin_mean
## count  27.000000  27.000000
## mean   29.962963  29.962963
## std    12.942124  10.806904
## min    13.000000  18.000000
## 25%    20.500000  18.000000
## 50%    25.000000  28.111111
## 75%    35.000000  43.777778
## max    70.000000  43.777778
```

```
# IQR.
q1 = df1.describe()['nums']['25%']
q2 = df1.describe()['nums']['75%']
```

```
# 1.5 IQR.
min_allowed = q1/1.5
min_allowed
```

```
## 13.666666666666666
```

```
# 1.5 IQR.
max_allowed = q2*1.5
max_allowed
```

```
## 52.5
```

```
# Mask the dataframe.
outliers = df1['nums'][(df1['nums'] < min_allowed) | (df1['nums'] > max_allowed)]
outliers
```

```
## 0     13
## 26    70
## Name: nums, dtype: int64
```

As seen in part a.) $l = 27$, thus our smallest value, idx 0, and our largest value, idx 27, are shown here. 13 & 17 would generally be accepted as outliers.

---

c.) Use min-max normalization to transform the value 35 for age onto the range [0.0, 1.0]. ***(5 points)***

```python
# Create min max scaling function.
def min_max_scaler(val):
    r = df1['nums'].max() - df1['nums'].min()
    return (val - df1['nums'].min()) / r

# Scale 35.
min_max_scaler(35)
```

```
## 0.38596491228070173
```

We can see min-max normalization transforms 35 into 0.386 .

---

d.) Use z-score normalization to transform the value 35 for age? ***(5 points)***

```python
# Create z score scaling function.
def z_score_scaler(val):
    return (val - df1['nums'].mean()) / df1['nums'].std()

# Scale 35.
z_score_scaler(35)
```

```
## 0.3891970907527787
```

We can see z-score normalization transforms 35 into 0.389 .

---

e.) Use normalization by decimal scaling to transform the value 35 for age. ***(5 points)***

```python
# Create decimal scaling function.
def decimal_scaler(val):
    return val/100

# Scale 35.
decimal_scaler(35)
```

```
## 0.35
```

We can see normalization transforms by decimal scaling 35 into 0.35 .

---

2. Write a function in your preferred language which can take a data vector and do min-max normalization by transforming data onto a desired range. ***(25 points)***

```
# Use data from q1 as example.
a = np.array(nums)

# preview the data...
a
```

```
## array([13, 15, 16, 16, 19, 20, 20, 21, 22, 22, 25, 25, 25, 25, 30, 33, 33,
##        35, 35, 35, 35, 36, 40, 45, 46, 52, 70])
```

```
# Define variable min max scaler.
def min_max_mapper(np_array, new_min, new_max):
    mn = np_array.min()
    mx = np_array.max()
    r = mx - mn
    a = (np_array - mn) / r
    new_r = new_max - new_min
    return (a * new_r) + new_min

# Test with data.
min_max_mapper(a, -10, 10)
```

```
## array([-10.        ,  -9.29824561,  -8.94736842,  -8.94736842,
##         -7.89473684,  -7.54385965,  -7.54385965,  -7.19298246,
##         -6.84210526,  -6.84210526,  -5.78947368,  -5.78947368,
##         -5.78947368,  -5.78947368,  -4.03508772,  -2.98245614,
##         -2.98245614,  -2.28070175,  -2.28070175,  -2.28070175,
##         -2.28070175,  -1.92982456,  -0.52631579,   1.22807018,
##          1.57894737,   3.68421053,  10.        ])
```

Solution writted in python dependent on numpy .

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3. Using information gain on the data in Table 1, do calculations for two levels of a decision tree which decides whether a person is senior or junior. ***(25 points)***

```python
# load in the data...
table1 = {
    'department' : ['sales', 'sales', 'sales', 'systems',
                    'systems', 'systems', 'systems', 'marketing',
                    'marketing', 'secretary', 'secretary'],
    'age' : ['31_35', '26_30', '31_35', '21_25',
             '31_35', '26_30', '41_45', '36_40',
             '31_35', '46_50', '26_30'],
    'salary' : ['46K_50K', '26K_30K', '31K_35K', '46K_50K',
                '66K_70K', '46K_50K', '66K_70K', '46K_50K',
                '41K_45K', '36K_40K', '26K_30K'],
    'status' : ['senior', 'junior', 'junior', 'junior',
                'senior', 'junior', 'senior', 'senior',
                'junior', 'senior', 'junior'],
    'count' : [30, 40, 40, 20, 5, 3, 3, 10, 4, 4, 6]
}
df2 = pd.DataFrame(table1)

# preview the data...
df2
```

```
##    department    age   salary  status  count
## 0       sales  31_35  46K_50K  senior     30
## 1       sales  26_30  26K_30K  junior     40
## 2       sales  31_35  31K_35K  junior     40
## 3     systems  21_25  46K_50K  junior     20
## 4     systems  31_35  66K_70K  senior      5
## 5     systems  26_30  46K_50K  junior      3
## 6     systems  41_45  66K_70K  senior      3
## 7   marketing  36_40  46K_50K  senior     10
## 8   marketing  31_35  41K_45K  junior      4
## 9   secretary  46_50  36K_40K  senior      4
## 10  secretary  26_30  26K_30K  junior      6
```

```python
# Create information gain function.
def gainer(df, label, counts):
    # Create DataFrame for storing gain.
    gainz = pd.DataFrame(index=['entropy', 'gain'])

    # Find total observations.
    total = df[counts].sum()
    print('{} total observations'.format(total))
    print()

    # Find total observations per label.
    sum0 = pd.DataFrame(
```

```
        df.groupby(by=label)[counts].apply(
            lambda x: x.sum()
        ))
    print('observations per label')
    print(sum0)
    print()

    # Find label probabilities.
    p_label = sum0 / total
    print('label probabilities')
    print(p_label)
    print()

    # Find total entropy.
    total_entrop = float((-p_label * np.log2(p_label)).sum())
    print('total entropy')
    print(total_entrop)
    print()

    # Find attribute columns.
    cols = df.columns.drop(label)
    cols = cols.drop(counts)
    print('attribute columns')
    print(cols)
    print()

    for col in cols:
        # Find total observations per bin.
        sum1 = pd.DataFrame(
            df.groupby(by=col)[counts].apply(
                lambda x: x.sum()
            ))

        # Find label totals per bin.
        sum2 = pd.DataFrame(
            df.groupby(by=[col, label])[counts].apply(
                lambda x: x.sum()
            ))

        # Solve for entropy per class
        p_label_class = sum2 / sum1
        H = -p_label_class * np.log2(p_label_class)

        # Solve for expected entropy per class
        entrop = pd.DataFrame(
            H.unstack().apply('sum', axis=1), columns=['H']
            )
        entrop['P[class]'] = sum1 / total
```

```
        entrop['E[H]'] = entrop['H'] * entrop['P[class]']
        entropy = entrop['E[H]'].sum()

        gain = total_entrop - entropy
        gainz[col] = [entropy, gain]

    return gainz

# calculate information gain on status at level 1.
g1 = gainer(df2, 'status', 'count')
```

```
## 165 total observations
##
## observations per label
##         count
## status
## junior    113
## senior     52
##
## label probabilities
##            count
## status
## junior  0.684848
## senior  0.315152
##
## total entropy
## 0.899030771238222
##
## attribute columns
## Index(['department', 'age', 'salary'], dtype='object')
```

```
g1.T
```

```
##              entropy      gain
## department  0.850424  0.048607
## age         0.474296  0.424735
## salary      0.361513  0.537518
```

As salary has the most information gain we will use it for the level 1 split.

```python
g2 = df2.groupby('salary').apply(
    lambda x: gainer(x.drop('salary', axis=1), 'status', 'count')
)
```

```python
g2
```

```
##                     department       age
## salary
## 26K_30K entropy    0.000000  0.000000
##         gain       0.000000  0.000000
## 31K_35K entropy    0.000000  0.000000
##         gain       0.000000  0.000000
## 36K_40K entropy    0.000000  0.000000
##         gain       0.000000  0.000000
## 41K_45K entropy    0.000000  0.000000
##         gain       0.000000  0.000000
## 46K_50K entropy    0.000000  0.000000
##         gain       0.946819  0.946819
## 66K_70K entropy    0.000000  0.000000
##         gain       0.000000  0.000000
```

As department and age have equal information gain we can use either for the level 2 split.

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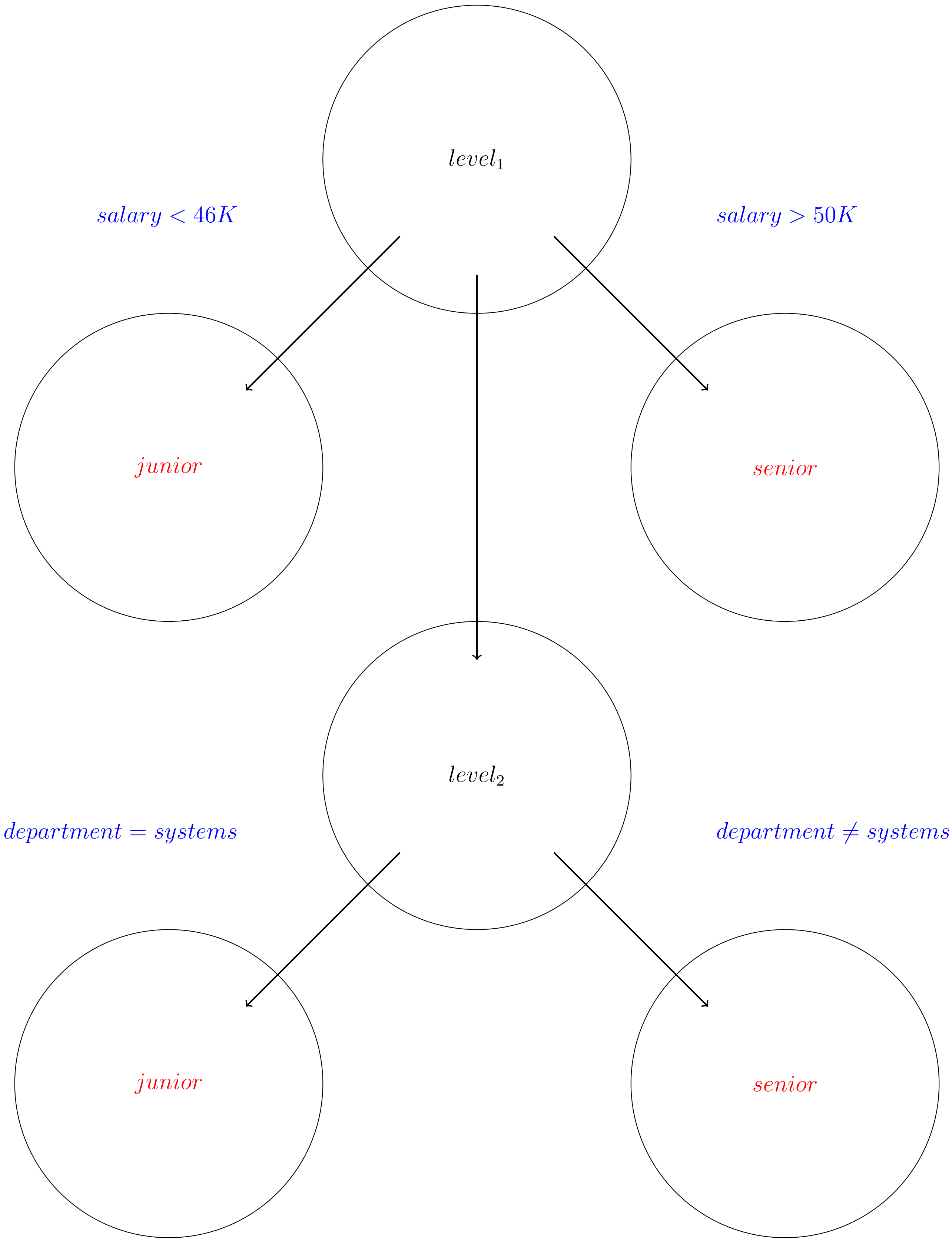
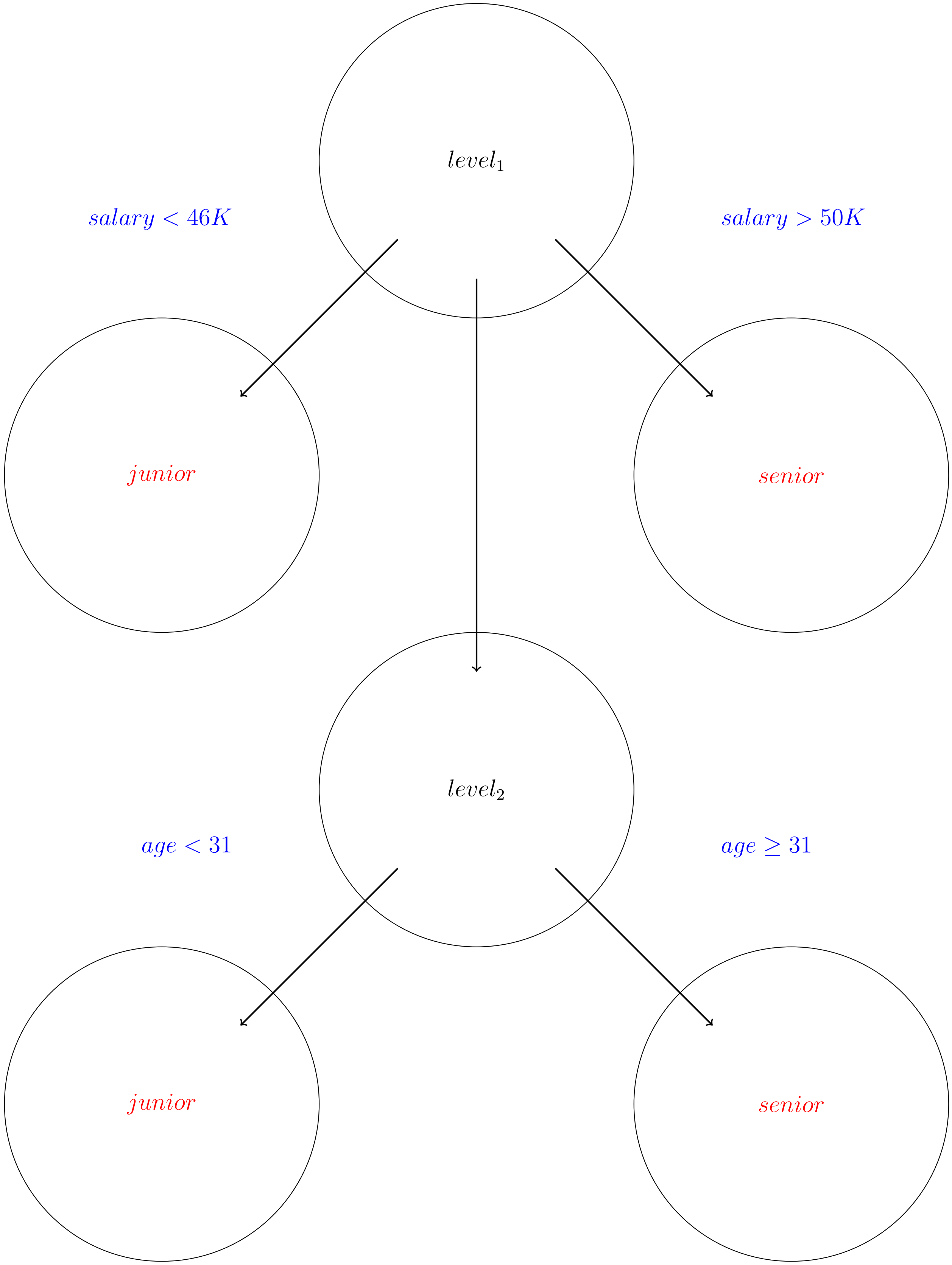
4. Using the decision tree, generate if-then rules. ***(25 points)***



Tree 1: Level 2 Split on Department



Tree 2: Level 2 Split on Age

For both tress we have $level_1$ if-then rules as follows ...

- $If \quad salary < 46K \quad then \quad label = junior$
- $If \quad salary > 50K \quad then \quad label = senior$
- $Else \quad continue$

For Tree 1 we have $level_2$ if-then rules as follows ...

- $If \quad department = systems \quad then \quad label = junior$
- $Else \quad then \quad label = senior$

For Tree 2 we have $level_2$ if-then rules as follows ...

- $If \quad age < 31 \quad then \quad label = junior$
- $Else \quad then \quad label = senior$
