```
Problem 1
The tree before prune:
node 0
Top: 6,4, 0.97
Education Level gain = 0.125
Career gain = 0.125
Years of Experience gain = 0.020
Selected Attribute: Education
  node 1
  High School 4,1, 0.72
  Career gain = 0.171
  Years of Experience gain = 0.322
  Selected Attribute: Years of Experience
    node 3
    More than 10
    Career gain = 1.0
    Selected attribute Career
      node 8
      Management
      Class High
      node 9
      Service
       Class Low
    node 4
    Less than 3
    Class Low
    node 5
    3 to 10
    ClassLow
  node 2
  College 3,2, 0.97
  Career gain = 0.420
  Years of Experience gain = 0.171
  Selected Attribute: Career
```

```
node 6
    Management
    class High
    node 7
    Service 1,2, 0,91
    Years of Experience gain = 0.918
    selected attribute: Years of Experience
      node 10
      More than 10
      Class Low
      node 11
      Less than 3
      Class Low
      node 12
      3 to 10
      Class High
puring the tree
for the 1 iteration:
node num: sum_of_total_wrong:
                                 wrong_count:
12
           0
                                    1
           0
                                    0
11
10
                                    0
           0
           0
                                    0
           0
                                    0
                                    0
           1
pruning node 7
for the 2 iteration:
node num: sum_of_total_wrong:
                                 wrong_count:
                                    0
           0
           0
                                    0
           0
                                    0
```

9

8

7

9

8

7

6	0	1
5	0	0
4	0	0
3	0	0
2	1	2
1	0	1
0	1	1

The final tree

node 0
Top: 6,4, 0.97
Education Level gain = 0.125
Career gain = 0.125
Years of Experience gain = 0.020
Selected Attribute: Education

node 1
High School 4,1, 0.72
Career gain = 0.171
Years of Experience gain = 0.322
Selected Attribute: Years of Experience node 3
More than 10
Career gain = 1.0
Selected attribute Career

node 8 Management Class High node 9 Service

Class Low

node 4 Less than 3 Class Low

node 5 3 to 10

ClassLow

node 2
College 3,2, 0.97
Career gain = 0.420
Years of Experience gain = 0.171
Selected Attribute: Career

node 6 Management class High

node 7 Service 1,2, 0,91 Years of Experience gain = 0.918 selected attribute: Years of Experience Class Low

Problem2

The answer of this problem is also stored in "prob2.csv" file in result directory.

```
6.7,3.1,4.4,1.4,x1,versicolor,versicolor,versicolor,versicolor
4.4,3.2,1.3,0.2,x2,setosa,setosa,setosa,setosa
5.3,3.7,1.5,0.2,x3,setosa,setosa,setosa,setosa
7.7,2.8,6.7,2.0,x10,virginica,virginica,virginica,virginica,
5.1,3.5,1.4,0.2,x11,setosa,setosa,setosa,setosa
6.5,3.0,5.2,2.0,x12,setosa,virginica,virginica,virginica
7.1,3.0,5.9,2.1,x13,virginica,virginica,virginica,virginica,
6.4,2.7,5.3,1.9,x14,virginica,virginica,virginica,virginica,
5.2,2.7,3.9,1.4,x15,versicolor,versicolor,versicolor,versicolor
7.0,3.2,4.7,1.4,x16,virginica,versicolor,versicolor,versicolor
7.2,3.2,6.0,1.8,x17,virginica,virginica,virginica,virginica
5.4,3.7,1.5,0.2,x19,setosa,setosa,setosa,setosa
5.6,3.0,4.5,1.5,x20,versicolor,versicolor,versicolor,versicolor
5.9,3.2,4.8,1.8,x21,versicolor,versicolor,versicolor,versicolor
5.1,3.4,1.5,0.2,x22,setosa,setosa,setosa,setosa
6.9,3.1,4.9,1.5,x23,versicolor,versicolor,versicolor,versicolor
6.0,2.2,4.0,1.0,x24,versicolor,versicolor,versicolor,versicolor,versicolor
4.7,3.2,1.6,0.2,x25,setosa,setosa,setosa,setosa
4.6,3.6,1.0,0.2,x27,setosa,setosa,setosa,setosa
5.6,3.0,4.1,1.3,x31,versicolor,versicolor,versicolor,versicolor
5.5,3.5,1.3,0.2,x33,setosa,setosa,setosa,setosa
5.5,2.4,3.8,1.1,x34,versicolor,versicolor,versicolor,versicolor
5.1,3.8,1.6,0.2,x35,setosa,setosa,setosa,setosa
6.3,3.3,4.7,1.6,x36,versicolor,versicolor,versicolor,versicolor
6.6,2.9,4.6,1.3,x100,versicolor,versicolor,versicolor,versicolor
7.7,3.0,6.1,2.3,x101,virginica,virginica,virginica,virginica,virginica
6.4,2.9,4.3,1.3,x102,versicolor,versicolor,versicolor,versicolor
6.9,3.1,5.1,2.3,x103,virginica,virginica,virginica,virginica,
6.7,3.0,5.0,1.7,x104,setosa,versicolor,versicolor,versicolor
4.3,3.0,1.1,0.1,x105,setosa,setosa,setosa,setosa
7.7,2.6,6.9,2.3,x106,virginica,virginica,virginica,virginica,
6.7,3.3,5.7,2.5,x107,virginica,virginica,virginica,virginica,
6.7,2.5,5.8,1.8,x108,virginica,virginica,virginica,virginica,
1.0,3.1,1.6,0.2,x109,setosa,setosa,setosa,setosa
5.7,4.4,1.5,0.4,x110,setosa,setosa,setosa,setosa
6.5,3.0,5.5,1.8,x111,setosa,virginica,virginica,virginica,
6.1,3.0,4.9,1.8,x112,versicolor,versicolor,versicolor,versicolor,versicolor
5.4,3.4,1.7,0.2,x113,setosa,setosa,setosa,setosa
```

```
6.5,3.2,5.1,2.0,x114,virginica,virginica,virginica,virginica,
5.2,3.4,1.4,0.2,x115,setosa,setosa,setosa,setosa
5.7,3.0,4.2,1.2,x116,versicolor,versicolor,versicolor,versicolor,versicolor
5.5,2.3,4.0,1.3,x117,versicolor,versicolor,versicolor,versicolor
5.0,3.4,1.6,0.4,x118,setosa,setosa,setosa,setosa
5.8,2.7,5.1,1.9,x119,virginica,virginica,virginica,virginica,virginica
6.1,2.8,4.0,1.3,x120,versicolor,versicolor,versicolor,versicolor
5.7,2.5,5.0,2.0,x121,virginica,virginica,virginica,virginica,virginica
6.3,2.9,5.6,1.8,x122,versicolor,virginica,virginica,virginica,virginica
4.9,3.1,1.5,0.1,x123,setosa,setosa,setosa,setosa
6.8,3.2,5.9,2.3,x124,virginica,virginica,virginica,virginica,
6.9,3.2,5.7,2.3,x125,virginica,virginica,virginica,virginica,
6.7,3.1,4.7,1.5,x126,versicolor,versicolor,versicolor,versicolor
5.7,2.8,4.1,1.3,x127,versicolor,versicolor,versicolor,versicolor
5.0,3.5,1.6,0.6,x128,setosa,setosa,setosa,setosa
5.4,3.9,1.7,0.4,x129,setosa,setosa,setosa,setosa
5.2,3.5,1.5,0.2,x130,setosa,setosa,setosa,setosa
6.1,2.8,4.7,1.2,x131,versicolor,versicolor,versicolor,versicolor
5.7,2.9,4.2,1.3,x132,versicolor,versicolor,versicolor,versicolor
5.8,2.7,3.9,1.2,x133,versicolor,versicolor,versicolor,versicolor
5.0,3.3,1.4,0.2,x134,setosa,setosa,setosa,setosa
6.8,2.8,4.8,1.4,x135,versicolor,versicolor,versicolor,versicolor,versicolor
6.3,2.8,5.1,1.5,x136,versicolor,versicolor,versicolor,versicolor
6.2,2.2,4.5,1.5,x137,virginica,versicolor,versicolor,versicolor
6.0,3.0,4.8,1.8,x138,versicolor,versicolor,versicolor,versicolor
5.1,3.5,1.4,0.3,x139,setosa,setosa,setosa,setosa
5.7,3.8,1.7,0.3,x140,setosa,setosa,setosa,setosa
6.1,3.0,4.6,1.4,x141,versicolor,versicolor,versicolor,versicolor,versicolor
5.8,4.0,1.2,0.2,x142,setosa,setosa,setosa,setosa
7.2,3.6,6.1,2.5,x143,virginica,virginica,virginica,virginica
6.1,2.6,5.6,1.4,x144,versicolor,versicolor,versicolor,versicolor
5.5,2.5,4.0,1.3,x145,versicolor,versicolor,versicolor,versicolor
7.3,2.9,6.3,1.8,x146,virginica,virginica,virginica,virginica,
4.8,3.0,1.4,0.1,x147,setosa,setosa,setosa,setosa,setosa
7.6,3.0,6.6,2.1,x148,virginica,virginica,virginica,virginica,
6.5,3.0,5.8,2.2,x149,virginica,virginica,virginica,virginica,
5.1,3.3,1.7,0.5,x150,setosa,setosa,setosa,setosa
```

```
Problem 3
========
poly-kernel
exponent = 1
result:
=== Confusion Matrix ===
a b <-- classified as
356 73 | a = car
56 361 | b = noncar
correct 717
incorect 129
========
poly-kernel
exponent = 2
result:
=== Confusion Matrix ===
a b <-- classified as
408 21 | a = car
15 402 | b = noncar
correct 810
incorrect 36
=======
poly-kernel
exponent = 4
result:
=== Confusion Matrix ===
a b <-- classified as
401 28 | a = car
27 390 | b = noncar
correct 791
incorrect 55
========
rbf kernel
gamma = 0.01
result:
=== Confusion Matrix ===
a b <-- classified as
267 162 | a = car
```

```
70 347 | b = noncar correct 614 incorrect 232 ======== rbf kernel gamma = 1 result: === Confusion Matrix === a b <-- classified as 373 56 | a = car 26 391 | b = noncar correct 764 incorrect 82
```

From the result, poly kernel, when exponent equals 2, the number of correct instances is greater than the number of correct instances when exponent equals to 1 and 4. For rbf kernel when gamma equals to 1 the number of correct instances is greater than the number of correct instances when gamma equals to 0.01

The kernel function map the original data set to a high dimension data set. If the higher dimension data set could be separated, the SVM would achieve a better result. So for the poly kernel, when exponent equals to 2 the mapped data is more separable than the mapped data when exponent equals to 1 and 4. For the same reason, when gamma eqs to 1 the mapped data is more separable than the mapped data when gamma eqs to 0.01

Problem 4

Let support $\Phi(x) = \Phi(x_1, x_2) = x_1 + e^{x^2}$, then $K(x, z) = K(x_1, x_2, z_1, z_2) = \Phi(x) * \Phi(z)$. From the definition of kernel we can see that $K(x, x) = \Phi(x)^2$. So that $K(x, z) = x_1 * z_1 + x_1 * e^{z^2} + z_1 * e^{x^2} + e^{x^2} + z_2$ is kernel.

Problem 5

Because a0 = -0.8, a1 = 1, a2 = 6.4, a3 = -1.9, so [1,1,1] and [1,1,0] are support vectors.

$$\mathbf{w} = \sum_{\mathbf{x}_i \in SV} \alpha_i \mathbf{y}_i \mathbf{x}_i$$

Because

$$\mathbf{w} = \sum_{\mathbf{x}_i \in SV} \alpha_i \mathbf{y}_i \mathbf{x}_i$$
Because , so that $\mathbf{w} = [5,4,-1,-1]^T$, and according to
$$\mathbf{y}_i (\mathbf{w}^\mathsf{T} \mathbf{x}_i + \mathbf{b}) = \mathbf{1}$$
, so $\mathbf{b} = -4.4$.

To classify [1, 0.8, 1], we apply the formula $w^T * x + b$, which equals to -0.8. So we can conclude that even the tuple [1, 0.8, 1] lies between the support vectors, it still closer to the negative class. [1, 0.8, 1] is labeled with class -1.