

Q1

- 1a) The SparseVector is like a dictionary expect that it doesn't show any non-value key.
- 1b) SparseVector inherit all the method in dict but dict doesn't share the methods which are built in SparseVector

The example is shown below:

```
>>> import SparseVector as sv
>>> a= {'a' : 1}
>>> b= {'a' : 2}
>>> c=sv.SparseVector(a)
>>> d=sv.SparseVector(b)
>>> cmp(a,b)
-1
>>> cmp(c,d)
-1
>>> a.__eq__(b)
False
>>> c.__eq__(d)
False
>>> c.dot(d)
2
>>> a.dot(b)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
AttributeError: 'dict' object has no attribute 'dot'
>>>
```

1c)

```
>>> a= {'a' : 1}
>>> b= {'a' : 2}
>>> c=sv.SparseVector(a)
>>> d=sv.SparseVector(b)
>>> c + d
Into __add__ function.
{'a': 3}
>>> c.dot(d)
2
>>> c.__mul__(2)
{'a': 2}
>>> c.__rmul__(2)
{'a': 2}
>>>
```

Q2

$$2a) \quad l(\beta: x_i, y_i) = \log(1 + e^{-y\beta^T x})$$

$$\nabla l = \frac{-yx * e^{-y\beta^T x}}{1 + e^{-y\beta^T x}} = \frac{-yx}{1 + e^{y\beta^T x}}$$

$$\nabla^2 l = \frac{y^2 x^2 e^{y\beta^T x}}{(1 + e^{y\beta^T x})^2}$$

$(1 + e^{y\beta^T x})^2 > 0$  and since  $y \in \{-1, 1\}$  so  $y^2 > 0$  and  $x^2 \geq 0$  and  $e^{y\beta^T x} > 0$

$$\text{Then we have } Cl = \frac{y^2 x^2 e^{y\beta^T x}}{(1 + e^{y\beta^T x})^2} \geq 0$$

So, the function  $l(\beta: x_i, y_i) = \log(1 + e^{-y\beta^T x})$  is convex

2b) as we proved on the above

$$\nabla l = \frac{-yx * e^{-y\beta^T x}}{1 + e^{-y\beta^T x}} = \frac{-yx}{1 + e^{y\beta^T x}}$$

$$2c) \quad l(\beta: x_i, y_i) = \log(1 + e^{-y\beta^T x})$$

When  $x = 0$ ,  $l(\beta: x_i, y_i) = \log(1) = 0$

So, we know that  $l(\beta: x_i, y_i)$  do not depend on  $\beta_j$  where the coordinate  $x_j = 0$

$$\text{When } x = 0 \quad \nabla l = \frac{-yx}{1 + e^{y\beta^T x}} = \frac{0}{2} = 0$$

So, we know that  $\nabla l$  do not depend on  $\beta_j$  where the coordinate  $x_j = 0$

$$2d) \quad L(\beta) = \sum_{i=1}^n l(\beta: x_i, y_i) + \lambda \|\beta\|^2$$

Since  $l(\beta: x_i, y_i)$  is convex so  $\sum_{i=1}^n l(\beta: x_i, y_i)$  is convex.

Let  $f(\beta) = \lambda \|\beta\|^2$ . Then  $\nabla f = 2\lambda\beta$  and  $\nabla^2 f = 2\lambda$  which is a constant

So  $L(\beta) = \sum_{i=1}^n l(\beta: x_i, y_i) + \lambda \|\beta\|^2$  is convex

Q3

3a)

```
def gradLogisticLoss(beta,x,y):
    """
    Given a sparse vector beta, a sparse vector x, and
    a binary value y in {-1,+1}, compute the gradient of the logistic loss

    
$$\nabla l(\beta; x, y) = -y / (1.0 + \exp(y \langle \beta, x \rangle)) * x$$


    The input is:
    - beta: a sparse vector  $\beta$ 
    - x: a sparse vector x
    - y: a binary value in {-1,+1}

    """
    return x*((-float(y))/(1.0+np.exp(float(y)*beta.dot(x))))
```

```
def gradTotalLoss(data,beta, lam = 0.0):
    """ Given a sparse vector beta and a dataset compute the gradient of regularized total logistic loss :

    
$$\nabla L(\beta) = \sum_{(x,y) \text{ in data}} \nabla l(\beta; x, y) + 2\lambda \beta$$


    Inputs are:
    - data: a python list containing pairs of the form (x,y), where x is a sparse vector and y is a binary value
    - beta: a sparse vector  $\beta$ 
    - lam: the regularization parameter  $\lambda$ 

    """
    gradTotalLoss= SparseVector({})
    for (x,y) in data:
        gradTotalLoss = gradLogisticLoss(beta,x,y) + gradTotalLoss
    return gradTotalLoss + 2.0 * lam * beta
```

```
def logisticLoss(beta,x,y):
    """
    Given sparse vector beta, a sparse vector x, and a binary value y in {-1,+1}, compute the logistic loss

    
$$l(\beta; x, y) = \log(1.0 + \exp(-y * \langle \beta, x \rangle))$$


    The input is:
    - beta: a sparse vector  $\beta$ 
    - x: a sparse vector x
    - y: a binary value in {-1,+1}

    """
    return np.log(1.0 + np.exp (-float(y)*beta.dot(x)))
```

3b)

```
def test(data,beta):
    """ Output the quantities necessary to compute the accuracy, precision, and recall of the prediction of labels in a dataset and

    The accuracy (ACC), precision (PRE), and recall (REC) are defined in terms of the following sets:

        P = datapoints (x,y) in data for which  $\langle \beta, x \rangle > 0$ 
        N = datapoints (x,y) in data for which  $\langle \beta, x \rangle \leq 0$ 

        TP = datapoints in (x,y) in P for which y=+1
        FP = datapoints in (x,y) in P for which y=-1
        TN = datapoints in (x,y) in N for which y=-1
        FN = datapoints in (x,y) in N for which y=+1

    For #XXX the number of elements in set XXX, the accuracy, precision, and recall of parameter vector  $\beta$  over data are defined

        ACC( $\beta$ ,data) = ( #TP+#TN ) / ( #P + #N)
        PRE( $\beta$ ,data) = #TP / ( #TP + #FP)
        REC( $\beta$ ,data) = #TP / ( #TP + #FN)

    Inputs are:
        - data: an RDD containing pairs of the form (x,y)
        - beta: vector  $\beta$ 

    The return values are
        - ACC, PRE, REC

    """
```

```
totalscore = [(beta.dot(x), y) for (x,y) in data]
```

```
P=N=TP=FP=TN=FN=0
```

```
for (x,y) in totalscore:
```

```
    P += x > 0
```

```
    N += x < 0
```

```
    TP += x > 0 and float(y) == 1.0
```

```
    FP += x > 0 and float(y) == -1.0
```

```
    TN += x < 0 and float(y) == -1.0
```

```
    FN += x < 0 and float(y) == 1.0
```

```
ACC = (1.0 * (TP +TN)) / (1.0 * (P + N))
```

```
PRE = (1.0 * TP) / (1.0*(TP + FP))
```

```
REC = (1.0 * TP) / (1.0 * (TP + FN))
```

```
return ACC, PRE, REC
```

3c)

1.  $\lambda = 0$ 

```

k = 0 → t = 3.0693769455 → L( $\beta_k$ ) = 5140.37949103 → || $\nabla L(\beta_k)$ ||2 = 4273.54823303 →
→ gamma = 0.000470184984576 → ACC = 0.909 → PRE = 0.855325914149 → REC = 1.0
k = 1 → t = 6.7778429985 → L( $\beta_k$ ) = 2516.99399449 → || $\nabla L(\beta_k)$ ||2 = 3275.9864649 →
→ gamma = 0.000169266594447 → ACC = 0.92 → PRE = 0.892123287671 → REC = 0.968401486989
k = 2 → t = 9.47433996201 → L( $\beta_k$ ) = 1536.62960892 → || $\nabla L(\beta_k)$ ||2 = 802.337284031 →
→ gamma = 0.00362797056 → ACC = 0.979 → PRE = 0.965765765766 → REC = 0.996282527881
k = 3 → t = 12.833411932 → L( $\beta_k$ ) = 772.339148079 → || $\nabla L(\beta_k)$ ||2 = 980.549279124 →
→ gamma = 0.000470184984576 → ACC = 0.974 → PRE = 0.981203007519 → REC = 0.970260223048
k = 4 → t = 16.1770298481 → L( $\beta_k$ ) = 648.968995294 → || $\nabla L(\beta_k)$ ||2 = 636.730178332 →
→ gamma = 0.000470184984576 → ACC = 0.976 → PRE = 0.972426470588 → REC = 0.983271375465
k = 5 → t = 19.3420748711 → L( $\beta_k$ ) = 583.12930033 → || $\nabla L(\beta_k)$ ||2 = 390.121504419 →
→ gamma = 0.00078364164096 → ACC = 0.975 → PRE = 0.981238273921 → REC = 0.972118959108
k = 6 → t = 22.663271904 → L( $\beta_k$ ) = 554.863687101 → || $\nabla L(\beta_k)$ ||2 = 474.38957367 →
→ gamma = 0.000470184984576 → ACC = 0.981 → PRE = 0.977900552486 → REC = 0.986988847584
k = 7 → t = 25.8196530342 → L( $\beta_k$ ) = 511.658985564 → || $\nabla L(\beta_k)$ ||2 = 258.887387255 →
→ gamma = 0.00078364164096 → ACC = 0.98 → PRE = 0.981412639405 → REC = 0.981412639405
k = 8 → t = 28.9538359642 → L( $\beta_k$ ) = 486.942281985 → || $\nabla L(\beta_k)$ ||2 = 276.73548299 →
→ gamma = 0.00078364164096 → ACC = 0.984 → PRE = 0.976277372263 → REC = 0.994423791822
k = 9 → t = 32.0857009888 → L( $\beta_k$ ) = 467.333365045 → || $\nabla L(\beta_k)$ ||2 = 297.335681259 →
→ gamma = 0.00078364164096 → ACC = 0.979 → PRE = 0.981378026071 → REC = 0.979553903346
k = 10 → t = 35.3914339542 → L( $\beta_k$ ) = 449.768322793 → || $\nabla L(\beta_k)$ ||2 = 319.530735224 →
→ gamma = 0.000470184984576 → ACC = 0.984 → PRE = 0.979779411765 → REC = 0.990706319703
k = 11 → t = 38.1994228363 → L( $\beta_k$ ) = 425.924544297 → || $\nabla L(\beta_k)$ ||2 = 166.721201409 →
→ gamma = 0.002176782336 → ACC = 0.983 → PRE = 0.988742964353 → REC = 0.979553903346
k = 12 → t = 41.4900939465 → L( $\beta_k$ ) = 405.994303585 → || $\nabla L(\beta_k)$ ||2 = 388.199259096 →
→ gamma = 0.000470184984576 → ACC = 0.986 → PRE = 0.979853479853 → REC = 0.994423791822
k = 13 → t = 44.2999830246 → L( $\beta_k$ ) = 374.250964742 → || $\nabla L(\beta_k)$ ||2 = 147.167375122 →
→ gamma = 0.002176782336 → ACC = 0.987 → PRE = 0.994350282486 → REC = 0.981412639405
k = 14 → t = 47.5975329876 → L( $\beta_k$ ) = 364.103711306 → || $\nabla L(\beta_k)$ ||2 = 357.709734875 →
→ gamma = 0.000470184984576 → ACC = 0.989 → PRE = 0.985267034991 → REC = 0.994423791822
k = 15 → t = 50.2412428856 → L( $\beta_k$ ) = 335.533358123 → || $\nabla L(\beta_k)$ ||2 = 119.375620574 →
→ gamma = 0.00362797056 → ACC = 0.989 → PRE = 0.994371482176 → REC = 0.985130111524
k = 16 → t = 53.5357489586 → L( $\beta_k$ ) = 321.40210325 → || $\nabla L(\beta_k)$ ||2 = 359.393232945 →
→ gamma = 0.000470184984576 → ACC = 0.994 → PRE = 0.992592592593 → REC = 0.996282527881
k = 17 → t = 55.707572937 → L( $\beta_k$ ) = 290.83776835 → || $\nabla L(\beta_k)$ ||2 = 93.2783034072 →
→ gamma = 0.01679616 → ACC = 0.99 → PRE = 0.994382022472 → REC = 0.986988847584
k = 18 → t = 58.8442599773 → L( $\beta_k$ ) = 238.234800471 → || $\nabla L(\beta_k)$ ||2 = 427.837337396 →
→ gamma = 0.00078364164096 → ACC = 0.997 → PRE = 0.994454713494 → REC = 1.0
k = 19 → t = 61.8107469082 → L( $\beta_k$ ) = 183.512335128 → || $\nabla L(\beta_k)$ ||2 = 104.689949815 →
→ gamma = 0.0013060694016 → ACC = 0.997 → PRE = 0.994454713494 → REC = 1.0

```

2.  $\lambda = 5$ 

```

k = 0 → t = 3.13104200363 → L( $\beta_k$ ) = 5140.37949103 → || $\nabla L(\beta_k)$ ||2 = 4273.54823303 →
→ gamma = 0.000470184984576 → ACC = 0.909 → PRE = 0.855325914149 → REC = 1.0
k = 1 → t = 6.85882997513 → L( $\beta_k$ ) = 2537.18159657 → || $\nabla L(\beta_k)$ ||2 = 3277.82790658 →
→ gamma = 0.000169266594447 → ACC = 0.92 → PRE = 0.892123287671 → REC = 0.968401486989
k = 2 → t = 9.57383394241 → L( $\beta_k$ ) = 1558.60586113 → || $\nabla L(\beta_k)$ ||2 = 794.293677188 →
→ gamma = 0.00362797056 → ACC = 0.979 → PRE = 0.965765765766 → REC = 0.996282527881
k = 3 → t = 12.9773328304 → L( $\beta_k$ ) = 915.720160974 → || $\nabla L(\beta_k)$ ||2 = 1143.26672935 →
→ gamma = 0.000470184984576 → ACC = 0.97 → PRE = 0.981060606061 → REC = 0.96282527881
k = 4 → t = 16.3566009998 → L( $\beta_k$ ) = 781.406954891 → || $\nabla L(\beta_k)$ ||2 = 801.415491657 →
→ gamma = 0.000470184984576 → ACC = 0.977 → PRE = 0.970749542962 → REC = 0.986988847584
k = 5 → t = 19.7643377781 → L( $\beta_k$ ) = 702.27507752 → || $\nabla L(\beta_k)$ ||2 = 498.211120758 →
→ gamma = 0.000470184984576 → ACC = 0.98 → PRE = 0.981412639405 → REC = 0.981412639405
k = 6 → t = 22.9591138363 → L( $\beta_k$ ) = 654.479647213 → || $\nabla L(\beta_k)$ ||2 = 291.418683865 →
→ gamma = 0.00078364164096 → ACC = 0.98 → PRE = 0.976102941176 → REC = 0.986988847584
k = 7 → t = 26.321792841 → L( $\beta_k$ ) = 631.507345274 → || $\nabla L(\beta_k)$ ||2 = 336.79128005 →
→ gamma = 0.000470184984576 → ACC = 0.98 → PRE = 0.981412639405 → REC = 0.981412639405
k = 8 → t = 29.3564989567 → L( $\beta_k$ ) = 605.740256935 → || $\nabla L(\beta_k)$ ||2 = 198.81186565 →
→ gamma = 0.0013060694016 → ACC = 0.984 → PRE = 0.976277372263 → REC = 0.994423791822
k = 9 → t = 32.7414338589 → L( $\beta_k$ ) = 589.009131316 → || $\nabla L(\beta_k)$ ||2 = 342.77320503 →
→ gamma = 0.000470184984576 → ACC = 0.98 → PRE = 0.97962962963 → REC = 0.983271375465
k = 10 → t = 35.7747569084 → L( $\beta_k$ ) = 564.819571171 → || $\nabla L(\beta_k)$ ||2 = 169.651898158 →
→ gamma = 0.0013060694016 → ACC = 0.984 → PRE = 0.976277372263 → REC = 0.994423791822
k = 11 → t = 39.1480169296 → L( $\beta_k$ ) = 555.998065612 → || $\nabla L(\beta_k)$ ||2 = 306.79989283 →
→ gamma = 0.000470184984576 → ACC = 0.982 → PRE = 0.979704797048 → REC = 0.986988847584
k = 12 → t = 42.2003118992 → L( $\beta_k$ ) = 536.412663316 → || $\nabla L(\beta_k)$ ||2 = 141.992440299 →
→ gamma = 0.0013060694016 → ACC = 0.984 → PRE = 0.976277372263 → REC = 0.994423791822
k = 13 → t = 45.5722129345 → L( $\beta_k$ ) = 528.459592179 → || $\nabla L(\beta_k)$ ||2 = 244.661438016 →
→ gamma = 0.000470184984576 → ACC = 0.985 → PRE = 0.981583793738 → REC = 0.990706319703
k = 14 → t = 48.6270008087 → L( $\beta_k$ ) = 515.159794983 → || $\nabla L(\beta_k)$ ||2 = 115.957447378 →
→ gamma = 0.0013060694016 → ACC = 0.986 → PRE = 0.979853479853 → REC = 0.994423791822
k = 15 → t = 51.8252668381 → L( $\beta_k$ ) = 506.701683219 → || $\nabla L(\beta_k)$ ||2 = 177.001664477 →
→ gamma = 0.00078364164096 → ACC = 0.989 → PRE = 0.988868274583 → REC = 0.990706319703
k = 16 → t = 55.1756467819 → L( $\beta_k$ ) = 501.145796447 → || $\nabla L(\beta_k)$ ||2 = 186.787072656 →
→ gamma = 0.000470184984576 → ACC = 0.988 → PRE = 0.983455882353 → REC = 0.994423791822
k = 17 → t = 58.061757803 → L( $\beta_k$ ) = 492.950591036 → || $\nabla L(\beta_k)$ ||2 = 93.6448314909 →
→ gamma = 0.002176782336 → ACC = 0.991 → PRE = 0.992551210428 → REC = 0.990706319703
k = 18 → t = 61.4283797741 → L( $\beta_k$ ) = 485.712728307 → || $\nabla L(\beta_k)$ ||2 = 209.942518822 →
→ gamma = 0.000470184984576 → ACC = 0.991 → PRE = 0.987108655617 → REC = 0.996282527881
k = 19 → t = 64.3124659061 → L( $\beta_k$ ) = 476.11914913 → || $\nabla L(\beta_k)$ ||2 = 83.0571978465 →
→ gamma = 0.002176782336 → ACC = 0.994 → PRE = 0.994423791822 → REC = 0.994423791822

```

3.lambda = 10

```

k = 0 → t = 3.06997394562 → L(β_k) = 5140.37949103 → ||∇L(β_k)||_2 = 4273.54823303 →
→ gamma = 0.000470184984576 → ACC = 0.909 → PRE = 0.855325914149 → REC = 1.0
k = 1 → t = 6.79761481285 → L(β_k) = 2557.36919865 → ||∇L(β_k)||_2 = 3279.79141961 →
→ gamma = 0.000169266594447 → ACC = 0.921 → PRE = 0.893653516295 → REC = 0.968401486989
k = 2 → t = 9.46369981766 → L(β_k) = 1580.46700693 → ||∇L(β_k)||_2 = 786.723977579 →
→ gamma = 0.00362797056 → ACC = 0.98 → PRE = 0.965827338129 → REC = 0.998141263941
k = 3 → t = 12.9577608109 → L(β_k) = 1064.08936255 → ||∇L(β_k)||_2 = 1329.31623914 →
→ gamma = 0.000282110990746 → ACC = 0.976 → PRE = 0.975925925926 → REC = 0.979553903346
k = 4 → t = 15.7814469337 → L(β_k) = 826.628992936 → ||∇L(β_k)||_2 = 322.71356109 →
→ gamma = 0.002176782336 → ACC = 0.984 → PRE = 0.976277372263 → REC = 0.994423791822
k = 5 → t = 19.1110758781 → L(β_k) = 769.911300389 → ||∇L(β_k)||_2 = 649.896610641 →
→ gamma = 0.000470184984576 → ACC = 0.977 → PRE = 0.981308411215 → REC = 0.975836431227
k = 6 → t = 22.4678769112 → L(β_k) = 704.572834024 → ||∇L(β_k)||_2 = 295.29440558 →
→ gamma = 0.000470184984576 → ACC = 0.982 → PRE = 0.977941176471 → REC = 0.988847583643
k = 7 → t = 25.6199288368 → L(β_k) = 687.554757621 → ||∇L(β_k)||_2 = 171.568212543 →
→ gamma = 0.00078364164096 → ACC = 0.981 → PRE = 0.981447124304 → REC = 0.983271375465
k = 8 → t = 28.9768409729 → L(β_k) = 677.553578933 → ||∇L(β_k)||_2 = 198.237479477 →
→ gamma = 0.000470184984576 → ACC = 0.984 → PRE = 0.979779411765 → REC = 0.990706319703
k = 9 → t = 31.9720058441 → L(β_k) = 668.019557923 → ||∇L(β_k)||_2 = 130.722159922 →
→ gamma = 0.0013060694016 → ACC = 0.983 → PRE = 0.981515711645 → REC = 0.986988847584
k = 10 → t = 35.2807548046 → L(β_k) = 659.584652805 → ||∇L(β_k)||_2 = 232.290087336 →
→ gamma = 0.000470184984576 → ACC = 0.986 → PRE = 0.979853479853 → REC = 0.994423791822
k = 11 → t = 38.4625279903 → L(β_k) = 649.522167599 → ||∇L(β_k)||_2 = 130.536027197 →
→ gamma = 0.00078364164096 → ACC = 0.986 → PRE = 0.983394833948 → REC = 0.990706319703
k = 12 → t = 41.7711257935 → L(β_k) = 644.278385475 → ||∇L(β_k)||_2 = 152.946794124 →
→ gamma = 0.000470184984576 → ACC = 0.986 → PRE = 0.979853479853 → REC = 0.994423791822
k = 13 → t = 44.7525119781 → L(β_k) = 638.714924259 → ||∇L(β_k)||_2 = 98.4101786566 →
→ gamma = 0.0013060694016 → ACC = 0.988 → PRE = 0.987037037037 → REC = 0.990706319703
k = 14 → t = 48.0632238388 → L(β_k) = 633.804194941 → ||∇L(β_k)||_2 = 173.008101859 →
→ gamma = 0.000470184984576 → ACC = 0.986 → PRE = 0.979853479853 → REC = 0.994423791822
k = 15 → t = 51.2369430065 → L(β_k) = 627.906060556 → ||∇L(β_k)||_2 = 95.9654162555 →
→ gamma = 0.00078364164096 → ACC = 0.99 → PRE = 0.987084870849 → REC = 0.994423791822
k = 16 → t = 54.3993918896 → L(β_k) = 624.494970313 → ||∇L(β_k)||_2 = 108.111406092 →
→ gamma = 0.00078364164096 → ACC = 0.988 → PRE = 0.981684981685 → REC = 0.996282527881
k = 17 → t = 57.7104058266 → L(β_k) = 621.86525317 → ||∇L(β_k)||_2 = 127.023446288 →
→ gamma = 0.000470184984576 → ACC = 0.99 → PRE = 0.987084870849 → REC = 0.994423791822
k = 18 → t = 60.6884288788 → L(β_k) = 618.17799926 → ||∇L(β_k)||_2 = 74.274509088 →
→ gamma = 0.0013060694016 → ACC = 0.989 → PRE = 0.983486238532 → REC = 0.996282527881
k = 19 → t = 64.0021719933 → L(β_k) = 615.292058287 → ||∇L(β_k)||_2 = 126.552208232 →
→ gamma = 0.000470184984576 → ACC = 0.991 → PRE = 0.988909426987 → REC = 0.994423791822

```

3d) Precision is  $\frac{TP}{TP+FP}$  and Recall is  $\frac{TP}{TP+FN}$

High precision means in the normal mushroom label there's majority normal mushrooms and poor poisoned mushroom. So, in this case we should use high precision.

Q4

4a)

```
def getAllFeaturesRDD(dataRDD):
    """ Get all the features present in grouped dataset dataRDD.

    The input is:
        - dataRDD containing pairs of the form (SparseVector(x),y).

    The return value is an RDD containing the union of all unique features present in sparse vectors inside dataRDD.
    """
    featuresRDD = dataRDD.flatMap(lambda (x,y) : x.keys() )\
        .distinct()
    return featuresRDD

def totalLossRDD(dataRDD,beta,lam = 0.0):
    """ Given a sparse vector beta and a dataset compute the regularized total logistic loss :

        
$$L(\beta) = \sum_{(x,y) \text{ in data}} l(\beta;x,y) + \lambda ||\beta||_2^2$$


    Inputs are:
        - data: a python list containing pairs of the form (x,y), where x is a sparse vector and y is a binary value
        - beta: a sparse vector  $\beta$ 
        - lam: the regularization parameter  $\lambda$ 
    """
    loss = dataRDD.map(lambda (x,y) : logisticLoss(beta,x,y)).reduce(lambda x,y : x + y)
    return loss + 1.0 * lam* beta.dot(beta)

def gradTotalLossRDD(dataRDD,beta,lam = 0.0):
    """ Given a sparse vector beta and a dataset compute the gradient of regularized total logistic loss :

        
$$\nabla L(\beta) = \sum_{(x,y) \text{ in data}} \nabla l(\beta;x,y) + 2\lambda \beta$$


    Inputs are:
        - data: a python list containing pairs of the form (x,y), where x is a sparse vector and y is a binary value
        - beta: a sparse vector  $\beta$ 
        - lam: the regularization parameter  $\lambda$ 
    """
    gradTotalLoss =dataRDD.map(lambda (x,y) : gradLogisticLoss(beta,x,y))\
        .reduce(lambda x,y : x + y)
    return gradTotalLoss + 2.0 * lam * beta
```



```
def test(dataRDD,beta):
    """ Output the quantities necessary to compute the accuracy, precision, and recall of the prediction of labels in a dataset under a given  $\beta$ .

    The accuracy (ACC), precision (PRE), and recall (REC) are defined in terms of the following sets:

        P = datapoints (x,y) in data for which  $\langle \beta, x \rangle > 0$ 
        N = datapoints (x,y) in data for which  $\langle \beta, x \rangle \leq 0$ 

        TP = datapoints in (x,y) in P for which y=+1
        FP = datapoints in (x,y) in P for which y=-1
        TN = datapoints in (x,y) in N for which y=-1
        FN = datapoints in (x,y) in N for which y=+1

    For #XXX the number of elements in set XXX, the accuracy, precision, and recall of parameter vector  $\beta$  over data are defined as:

        ACC( $\beta$ ,data) = ( #TP+#TN ) / ( #P + #N )
        PRE( $\beta$ ,data) = #TP / ( #TP + #FP )
        REC( $\beta$ ,data) = #TP / ( #TP + #FN )

    Inputs are:
        - data: an RDD containing pairs of the form (x,y)
        - beta: vector  $\beta$ 

    The return values are
        - ACC, PRE, REC

    """
    totalscore = dataRDD.map(lambda (x,y): (beta.dot(x), y))
    PositiveS = totalscore.filter(lambda (x,y) : x > 0 )
    NegativeS = totalscore.filter(lambda (x,y) : x <= 0 )
    P = PositiveS.count()
    N = NegativeS.count()
    TP = PositiveS.filter(lambda (x,y) : float(y) == 1.0)\
        .count()
    FP = PositiveS.filter(lambda (x,y) : float(y) == -1.0)\
        .count()
    TN = NegativeS.filter(lambda (x,y) : float(y) == -1.0)\
        .count()
    FN = NegativeS.filter(lambda (x,y) : float(y) == 1.0)\
        .count()
    ACC = (1.0 * (TP + TN)) / (1.0 * (P + N))
    PRE = (1.0 * TP) / (1.0 * (TP + FP))
    REC = (1.0 * TP) / (1.0 * (TP + FN))
    return ACC, PRE, REC
```

```
def train(dataRDD,beta_0,lam,max_iter,eps,f,test_data=None):
    """ Train a logistic classifier from data.

    The function minimizes:

        
$$L(\beta) = \sum_{(x,y) \text{ in data}} l(\beta; x, y) + \lambda ||\beta||_2^2$$


    using gradient descent.

    Inputs are:
        - data: a python list containing pairs of the form (x,y), where x is a sparse vector and y is a binary value
        - beta_0: an initial sparse vector  $\beta_0$ 
        - lam: the regularization parameter  $\lambda$ 
        - max_iter: the maximum number of iterations
        - eps: the tolerance  $\epsilon$ 
        - test_data (optional): data over which model  $\beta$  is tested in each iteration w.r.t. accuracy, precision, and recall

    The return values are:
        - beta: the trained  $\beta$ , as a sparse vector
        - gradNorm: the norm  $||\nabla L(\beta)||_2$ 
        - k: the number of iterations

    """
```

```

k = 0
gradNorm = 2*eps
beta = beta_0
start = time()
while kmax_iter and gradNorm > eps:
    obj = totalLossRDD(dataRDD,beta,lam)

    grad = gradTotalLossRDD(dataRDD,beta,lam)
    gradNormSq = grad.dot(grad)
    gradNorm = np.sqrt(gradNormSq)

    fun = lambda x: totalLossRDD(dataRDD,x,lam)
    gamma = lineSearch(fun,beta,grad,obj,gradNormSq)

    beta = beta - gamma * grad
    if test_data == None:
        print>>>f, 'k = ',k,'\tt = ',time()-start,'\tL(\beta_k) = ',obj,'\t||\nabla L(\beta_k)||_2 = ',gradNorm,'\tgamma = ',gamma
    else:
        acc,pre,rec = test(test_data,beta)
        print>>>f, 'k = ',k,'\tt = ',time()-start,'\tL(\beta_k) = ',obj,'\t||\nabla L(\beta_k)||_2 = ',gradNorm,'\tgamma = ',gamma,'\tACC = ',acc,'\tPRE = ',pre,'\tREC = ',rec
    k = k + 1

return beta,gradNorm,k

```

```

if __name__ == "__main__":
    parser = argparse.ArgumentParser(description = 'Logistic Regression.',formatter_class=argparse.ArgumentDefaultsHelpFormatter)
    parser.add_argument('--traindata',default=None, help='Input file containing (x,y) pairs, used to train a logistic model')
    parser.add_argument('--testdata',default=None, help='Input file containing (x,y) pairs, used to test a logistic model')
    parser.add_argument('--beta', default='beta', help='File where beta is stored (when training) and read from (when testing)')
    parser.add_argument('--lam', type=float,default=0.0, help='Regularization parameter \lambda')
    parser.add_argument('--max_iter', type=int,default=100, help='Maximum number of iterations')
    parser.add_argument('--eps', type=float, default=0.1, help='epsilon-tolerance. If the l2_norm gradient is smaller than epsilon, gradient descent terminates.')
    parser.add_argument('--out', default='out', help='The output file which saves the print result in the script')

    verbosity_group = parser.add_mutually_exclusive_group(required=False)
    verbosity_group.add_argument('--verbose', dest='verbose', action='store_true')
    verbosity_group.add_argument('--silent', dest='verbose', action='store_false')
    parser.set_defaults(verbose=True)

    args = parser.parse_args()
    sc = SparkContext(master='local[40]',appName='Parallel Logistic Regression')
    if not args.verbose :
        sc.setLogLevel("ERROR")

    f = open(args.out,'w')
    print>>>f, 'Reading training data from',args.traindata
    traindata = readDataRDD(args.traindata,sc)
    print>>>f, 'Read',traindata.count(),'data points with',getAllFeaturesRDD(traindata).count(),'features in total'

    if args.testdata is not None:
        print>>>f, 'Reading test data from',args.testdata
        testdata = readDataRDD(args.testdata,sc)
        print>>>f, 'Read',testdata.count(),'data points with',getAllFeaturesRDD(testdata).count(),'features'
    else:
        testdata = None

    beta0 = SparseVector({})
    print>>>f, 'Training on data from',args.traindata,'with \lambda = ',args.lam,', \epsilon = ',args.eps,', max iter = ',args.max_iter
    beta, gradNorm, k = train(traindata,beta_0=beta0,lam=args.lam,max_iter=args.max_iter,eps=args.eps,test_data=testdata,f=f)
    print>>>f, 'Algorithm ran for',k,'iterations. Converged:',gradNorm/k,args.eps
    print>>>f, 'Saving trained \beta in',args.beta
    writeBeta(args.beta,beta)

```

4b)

Using Parallel

```

k = 0 → t = 8.79644703865 → L(β_k) = 5140.37949103 → ||∇L(β_k)||_2 = 4273.54823303 →
→ gamma = 0.000470184984576 → ACC = 0.909 → PRE = 0.855325914149 → REC = 1.0
k = 1 → t = 18.0698699951 → L(β_k) = 2516.99399449 → ||∇L(β_k)||_2 = 3275.9864649 →
→ gamma = 0.000169266594447 → ACC = 0.92 → PRE = 0.892123287671 → REC = 0.968401486989
k = 2 → t = 24.737361908 → L(β_k) = 1536.62960892 → ||∇L(β_k)||_2 = 802.337284031 →
→ gamma = 0.00362797056 → ACC = 0.979 → PRE = 0.965765765766 → REC = 0.996282527881
k = 3 → t = 32.9485578537 → L(β_k) = 772.339148079 → ||∇L(β_k)||_2 = 980.549279124 →
→ gamma = 0.000470184984576 → ACC = 0.974 → PRE = 0.981203007519 → REC = 0.970260223048
k = 4 → t = 41.2144808769 → L(β_k) = 648.968995294 → ||∇L(β_k)||_2 = 636.730178332 →
→ gamma = 0.000470184984576 → ACC = 0.976 → PRE = 0.972426470588 → REC = 0.983271375465
k = 5 → t = 49.0069289207 → L(β_k) = 583.12930033 → ||∇L(β_k)||_2 = 390.121504419 →
→ gamma = 0.00078364164096 → ACC = 0.975 → PRE = 0.981238273921 → REC = 0.972118959108
k = 6 → t = 57.2262909412 → L(β_k) = 554.863687101 → ||∇L(β_k)||_2 = 474.38957367 →
→ gamma = 0.000470184984576 → ACC = 0.981 → PRE = 0.977900552486 → REC = 0.986988847584
k = 7 → t = 65.1177899837 → L(β_k) = 511.658985564 → ||∇L(β_k)||_2 = 258.887387255 →
→ gamma = 0.00078364164096 → ACC = 0.98 → PRE = 0.981412639405 → REC = 0.981412639405
k = 8 → t = 73.0094220638 → L(β_k) = 486.942281985 → ||∇L(β_k)||_2 = 276.73548299 →
→ gamma = 0.00078364164096 → ACC = 0.984 → PRE = 0.976277372263 → REC = 0.994423791822
k = 9 → t = 80.9365749359 → L(β_k) = 467.333365045 → ||∇L(β_k)||_2 = 297.335681259 →
→ gamma = 0.00078364164096 → ACC = 0.979 → PRE = 0.981378026071 → REC = 0.979553903346
k = 10 → t = 89.217705965 → L(β_k) = 449.768322793 → ||∇L(β_k)||_2 = 319.530735224 →
→ gamma = 0.000470184984576 → ACC = 0.984 → PRE = 0.979779411765 → REC = 0.990706319703
k = 11 → t = 96.2231118679 → L(β_k) = 425.924544297 → ||∇L(β_k)||_2 = 166.721201409 →
→ gamma = 0.002176782336 → ACC = 0.983 → PRE = 0.988742964353 → REC = 0.979553903346
k = 12 → t = 104.442292929 → L(β_k) = 405.994303585 → ||∇L(β_k)||_2 = 388.199259096 →
→ gamma = 0.000470184984576 → ACC = 0.986 → PRE = 0.979853479853 → REC = 0.994423791822
k = 13 → t = 111.281156063 → L(β_k) = 374.250964742 → ||∇L(β_k)||_2 = 147.167375122 →
→ gamma = 0.002176782336 → ACC = 0.987 → PRE = 0.994350282486 → REC = 0.981412639405
k = 14 → t = 119.487916946 → L(β_k) = 364.103711306 → ||∇L(β_k)||_2 = 357.709734875 →
→ gamma = 0.000470184984576 → ACC = 0.989 → PRE = 0.985267034991 → REC = 0.994423791822
k = 15 → t = 125.968127012 → L(β_k) = 335.533358123 → ||∇L(β_k)||_2 = 119.375620574 →
→ gamma = 0.00362797056 → ACC = 0.989 → PRE = 0.994371482176 → REC = 0.985130111524
k = 16 → t = 134.196310997 → L(β_k) = 321.40210325 → ||∇L(β_k)||_2 = 359.393232945 →
→ gamma = 0.000470184984576 → ACC = 0.994 → PRE = 0.992592592593 → REC = 0.996282527881
k = 17 → t = 139.345375061 → L(β_k) = 290.83776835 → ||∇L(β_k)||_2 = 93.2783034072 →
→ gamma = 0.01679616 → ACC = 0.99 → PRE = 0.994382022472 → REC = 0.986988847584
→ gamma = 0.01679616 → ACC = 0.99 → PRE = 0.994382022472 → REC = 0.986988847584
k = 18 → t = 147.14546895 → L(β_k) = 238.234800471 → ||∇L(β_k)||_2 = 427.837337396 →
→ gamma = 0.00078364164096 → ACC = 0.997 → PRE = 0.994454713494 → REC = 1.0
k = 19 → t = 154.476336002 → L(β_k) = 183.512335128 → ||∇L(β_k)||_2 = 104.689949815 →
→ gamma = 0.0013060694016 → ACC = 0.997 → PRE = 0.994454713494 → REC = 1.0
Algorithm ran for 20 iterations. Converged: False
Saving trained β in beta

```

logisticRegression use 63s however ParallelLogisticRegression use 154s which is slower. Thus, using parallel in small data set doesn't improve the speed

4c)

## LogisticRegression

```

k = 0 → t = 23.08573699 → L(β_k) = 825.538292047 → ||∇L(β_k)||_2 = 583.67949253 →
→ gamma = 0.0060466176 → ACC = 0.862547288777 → PRE = 0.786427145709 → REC = 0.994949494949
k = 1 → t = 50.644258976 → L(β_k) = 235.997770698 → ||∇L(β_k)||_2 = 298.527990692 →
→ gamma = 0.00362797056 → ACC = 0.923076923077 → PRE = 0.98833819242 → REC = 0.856060606061
k = 2 → t = 78.1819589138 → L(β_k) = 165.313481914 → ||∇L(β_k)||_2 = 170.445788056 →
→ gamma = 0.00362797056 → ACC = 0.958385876419 → PRE = 0.939467312349 → REC = 0.979797979798
k = 3 → t = 104.127202988 → L(β_k) = 127.084846636 → ||∇L(β_k)||_2 = 70.1305338894 →
→ gamma = 0.0060466176 → ACC = 0.959646910467 → PRE = 0.971502590674 → REC = 0.94696969697
k = 4 → t = 128.61430788 → L(β_k) = 113.21669691 → ||∇L(β_k)||_2 = 58.8631689157 →
→ gamma = 0.010077696 → ACC = 0.954602774275 → PRE = 0.928571428571 → REC = 0.984848484848
k = 5 → t = 154.757153988 → L(β_k) = 102.790003817 → ||∇L(β_k)||_2 = 73.7283234092 →
→ gamma = 0.0060466176 → ACC = 0.965952080706 → PRE = 0.971867007673 → REC = 0.959595959596
k = 6 → t = 177.578147888 → L(β_k) = 88.4034890022 → ||∇L(β_k)||_2 = 39.9420196745 →
→ gamma = 0.01679616 → ACC = 0.959646910467 → PRE = 0.93961352657 → REC = 0.982323232323
k = 7 → t = 201.926411867 → L(β_k) = 79.6646784348 → ||∇L(β_k)||_2 = 58.5179490289 →
→ gamma = 0.010077696 → ACC = 0.962168978562 → PRE = 0.98670212766 → REC = 0.936868686869
k = 8 → t = 226.398449898 → L(β_k) = 69.2890442477 → ||∇L(β_k)||_2 = 42.2328868211 →
→ gamma = 0.010077696 → ACC = 0.970996216898 → PRE = 0.965087281796 → REC = 0.977272727273
k = 9 → t = 247.73533988 → L(β_k) = 61.5010061918 → ||∇L(β_k)||_2 = 27.2594855791 →
→ gamma = 0.0279936 → ACC = 0.960907944515 → PRE = 0.99727520436 → REC = 0.924242424242
k = 10 → t = 272.140666962 → L(β_k) = 57.1027717799 → ||∇L(β_k)||_2 = 48.0178834958 →
→ gamma = 0.010077696 → ACC = 0.972257250946 → PRE = 0.9675 → REC = 0.977272727273
k = 11 → t = 291.771583796 → L(β_k) = 46.8764140886 → ||∇L(β_k)||_2 = 17.4834056128 →
→ gamma = 0.046656 → ACC = 0.965952080706 → PRE = 0.994638069705 → REC = 0.936868686869
k = 12 → t = 314.727641821 → L(β_k) = 40.3072811261 → ||∇L(β_k)||_2 = 28.17195718 →
→ gamma = 0.01679616 → ACC = 0.970996216898 → PRE = 0.967418546366 → REC = 0.974747474747
k = 13 → t = 334.465430975 → L(β_k) = 34.7375225095 → ||∇L(β_k)||_2 = 13.9589882034 →
→ gamma = 0.046656 → ACC = 0.974779319042 → PRE = 0.994736842105 → REC = 0.954545454545
k = 14 → t = 355.685072899 → L(β_k) = 31.1045706768 → ||∇L(β_k)||_2 = 19.5463166714 →
→ gamma = 0.0279936 → ACC = 0.96973518285 → PRE = 0.965 → REC = 0.974747474747
k = 15 → t = 375.305197001 → L(β_k) = 27.5298505433 → ||∇L(β_k)||_2 = 13.6770946229 →
→ gamma = 0.046656 → ACC = 0.974779319042 → PRE = 0.994736842105 → REC = 0.954545454545
k = 16 → t = 396.650461912 → L(β_k) = 25.1736211979 → ||∇L(β_k)||_2 = 16.2624151488 →
→ gamma = 0.0279936 → ACC = 0.973518284994 → PRE = 0.974683544304 → REC = 0.972222222222
k = 17 → t = 413.194274902 → L(β_k) = 21.8901100291 → ||∇L(β_k)||_2 = 8.24527473729 →
→ gamma = 0.1296 → ACC = 0.965952080706 → PRE = 0.994638069705 → REC = 0.936868686869
k = 18 → t = 434.416885853 → L(β_k) = 20.0810908656 → ||∇L(β_k)||_2 = 19.118647409 →
→ gamma = 0.0279936 → ACC = 0.973518284994 → PRE = 0.982005141388 → REC = 0.964646464646
k = 19 → t = 444.548135996 → L(β_k) = 15.4223747302 → ||∇L(β_k)||_2 = 4.96431570345 →
→ gamma = 1.0 → ACC = 0.947036569987 → PRE = 0.997191011236 → REC = 0.896464646465

```

## ParallelLogisticRegression

```

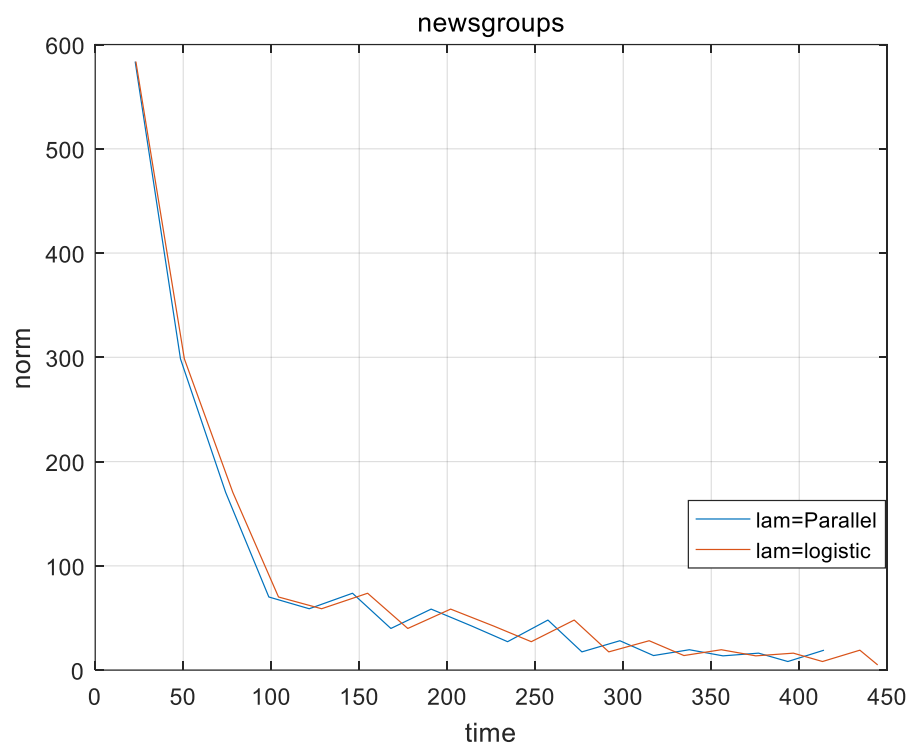
k = 0 → t = 22.574409008 → L(β_k) = 825.538292047 → ||∇L(β_k)||_2 = 583.67949253 →
→ gamma = 0.0060466176 → ACC = 0.863808322825 → PRE = 0.788 → REC = 0.994949494949
k = 1 → t = 48.6189448833 → L(β_k) = 235.997770698 → ||∇L(β_k)||_2 = 298.527990692 →
→ gamma = 0.00362797056 → ACC = 0.923076923077 → PRE = 0.98833819242 → REC = 0.856060606061
k = 2 → t = 74.6104660034 → L(β_k) = 165.313481914 → ||∇L(β_k)||_2 = 170.445788056 →
→ gamma = 0.00362797056 → ACC = 0.958385876419 → PRE = 0.939467312349 → REC = 0.979797979798
k = 3 → t = 99.3507430553 → L(β_k) = 127.084846636 → ||∇L(β_k)||_2 = 70.1305338894 →
→ gamma = 0.0060466176 → ACC = 0.959646910467 → PRE = 0.971502590674 → REC = 0.94696969697
k = 4 → t = 122.550463915 → L(β_k) = 113.21669691 → ||∇L(β_k)||_2 = 58.8631689157 →
→ gamma = 0.010077696 → ACC = 0.954602774275 → PRE = 0.928571428571 → REC = 0.984848484848
k = 5 → t = 146.998682976 → L(β_k) = 102.790003817 → ||∇L(β_k)||_2 = 73.7283234092 →
→ gamma = 0.0060466176 → ACC = 0.965952080706 → PRE = 0.971867007673 → REC = 0.959595959596
k = 6 → t = 169.122973919 → L(β_k) = 88.4034890022 → ||∇L(β_k)||_2 = 39.9420196745 →
→ gamma = 0.01679616 → ACC = 0.959646910467 → PRE = 0.93961352657 → REC = 0.982323232323
k = 7 → t = 192.062329054 → L(β_k) = 79.6646784348 → ||∇L(β_k)||_2 = 58.5179490289 →
→ gamma = 0.010077696 → ACC = 0.962168978562 → PRE = 0.98670212766 → REC = 0.936868686869
k = 8 → t = 215.216693878 → L(β_k) = 69.2890442477 → ||∇L(β_k)||_2 = 42.2328868211 →
→ gamma = 0.010077696 → ACC = 0.970996216898 → PRE = 0.965087281796 → REC = 0.977272727273
k = 9 → t = 235.935568094 → L(β_k) = 61.5010061918 → ||∇L(β_k)||_2 = 27.2594855791 →
→ gamma = 0.0279936 → ACC = 0.960907944515 → PRE = 0.99727520436 → REC = 0.924242424242
k = 10 → t = 259.068108082 → L(β_k) = 57.1027717799 → ||∇L(β_k)||_2 = 48.0178834958 →
→ gamma = 0.010077696 → ACC = 0.972257250946 → PRE = 0.9675 → REC = 0.977272727273
k = 11 → t = 278.502521992 → L(β_k) = 46.8764140886 → ||∇L(β_k)||_2 = 17.4834056128 →
→ gamma = 0.046656 → ACC = 0.965952080706 → PRE = 0.994638069705 → REC = 0.936868686869
k = 12 → t = 300.533195972 → L(β_k) = 40.3072811261 → ||∇L(β_k)||_2 = 28.17195718 →
→ gamma = 0.01679616 → ACC = 0.970996216898 → PRE = 0.967418546366 → REC = 0.974747474747
k = 13 → t = 319.591930866 → L(β_k) = 34.7375225095 → ||∇L(β_k)||_2 = 13.9589882034 →
→ gamma = 0.046656 → ACC = 0.974779319042 → PRE = 0.994736842105 → REC = 0.954545454545
k = 14 → t = 340.013494015 → L(β_k) = 31.1045706768 → ||∇L(β_k)||_2 = 19.5463166714 →
→ gamma = 0.0279936 → ACC = 0.96973518285 → PRE = 0.965 → REC = 0.974747474747
k = 15 → t = 359.024389029 → L(β_k) = 27.5298505433 → ||∇L(β_k)||_2 = 13.6770946229 →
→ gamma = 0.046656 → ACC = 0.974779319042 → PRE = 0.994736842105 → REC = 0.954545454545
k = 16 → t = 379.424942017 → L(β_k) = 25.1736211979 → ||∇L(β_k)||_2 = 16.2624151488 →
→ gamma = 0.0279936 → ACC = 0.973518284994 → PRE = 0.974683544304 → REC = 0.972222222222
k = 17 → t = 396.005378962 → L(β_k) = 21.8901100291 → ||∇L(β_k)||_2 = 8.24527473729 →
→ gamma = 0.1296 → ACC = 0.965952080706 → PRE = 0.994638069705 → REC = 0.936868686869
k = 18 → t = 416.722774029 → L(β_k) = 20.0810908656 → ||∇L(β_k)||_2 = 19.118647409 →
→ gamma = 0.0279936 → ACC = 0.973518284994 → PRE = 0.982005141388 → REC = 0.964646464646
k = 19 → t = 428.148526907 → L(β_k) = 15.4223747302 → ||∇L(β_k)||_2 = 4.96431570345 →
→ gamma = 1.0 → ACC = 0.947036569987 → PRE = 0.997191011236 → REC = 0.896464646465
Algorithm ran for 20 iterations. Converged: False

```

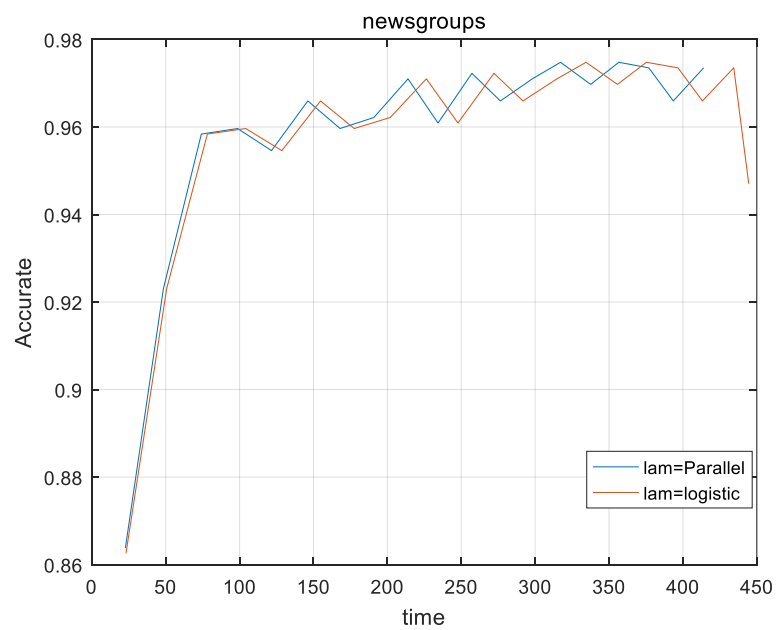
logisticRegression use 444s however ParallelLogisticRegression use 428 which is faster. Thus, using parallel in large data set can improve the speed

Q5

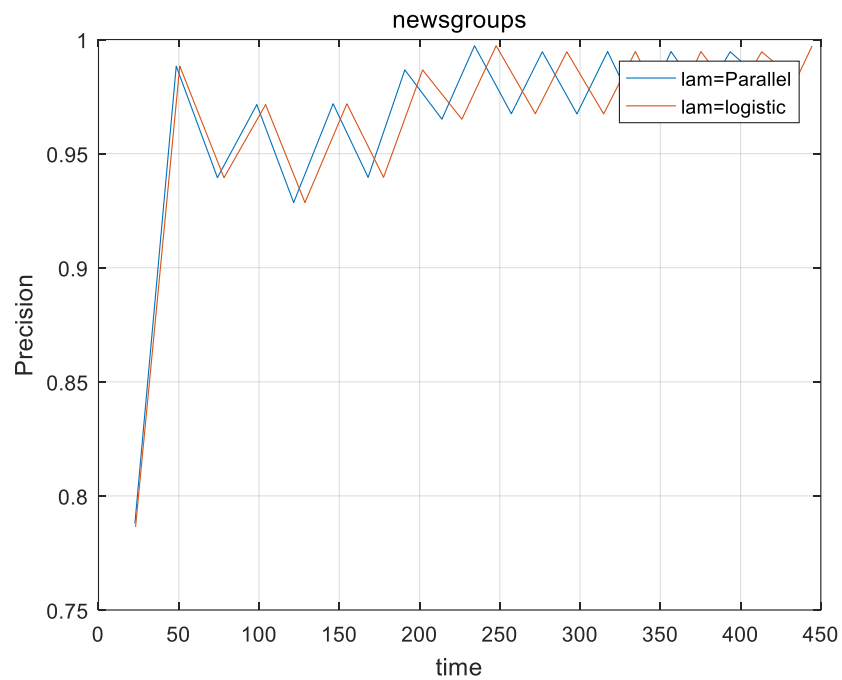
5a)



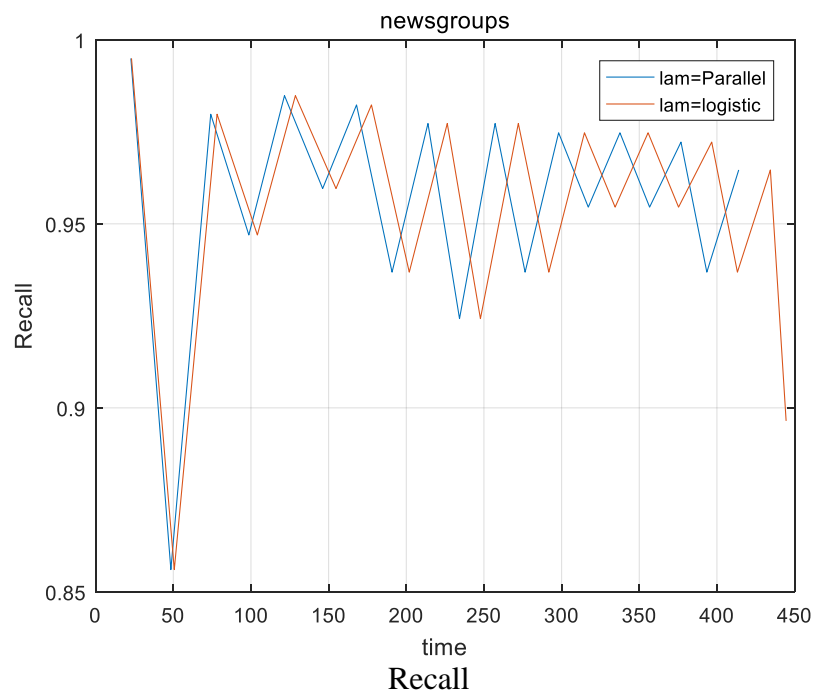
Gradient norm 2



Accurate

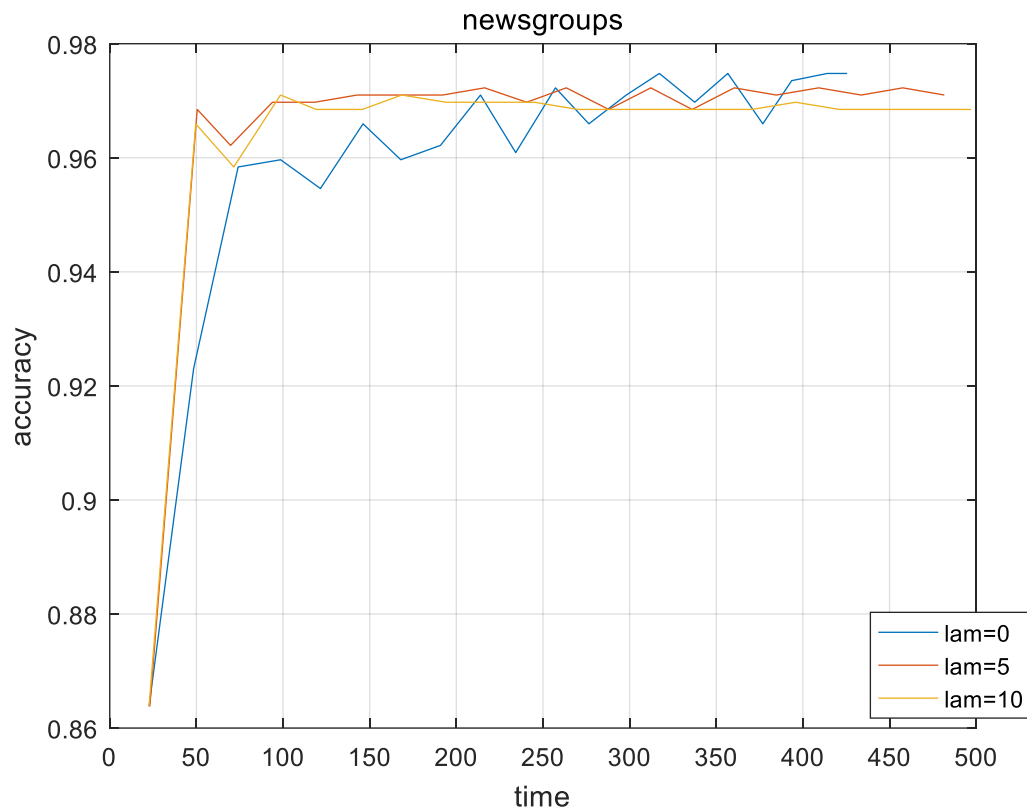


Precision



Recall

5b)

c)  $\lambda = 0$  has the greatest result

10 Most Negative

'basebal'	-2.568237000000000
'game'	-2.103109000000000
'player'	-1.949769000000000
'team'	-1.911795000000000
'yanke'	-1.609647000000000
'win'	-1.457832000000000
'philli'	-1.382178000000000
'plai'	-1.382044000000000
'stat'	-1.309810000000000
'pitch'	-1.248245000000000



## 10 Most Positive

' inform'	1.253351000000000
' doctor'	1.187401000000000
' effect'	1.148001000000000
' treatment'	1.036993000000000
' diseas'	1.036535000000000
' medic'	0.917249000000000
' treat'	0.884590000000000
' problem'	0.878204000000000
' health'	0.808931000000000
' peopl'	0.778835000000000