

# CSE 150 Homework 5

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## 1 Maximum Likelihood Estimation

(a) Complete data

$$P(B = b|A = a) = \frac{\sum_{t=1}^T I(a, a_t) \cdot I(b, b_t)}{\sum_{t=1}^T I(a, a_t)}$$

$$P(C = c|A = a, B = b) = \frac{\sum_{t=1}^T I(a, a_t) \cdot I(b, b_t) \cdot I(c, c_t)}{\sum_{t=1}^T I(a, a_t) \cdot I(b, b_t)}$$

$$P(D = d|A = a, C = c) = \frac{\sum_{t=1}^T I(a, a_t) \cdot I(c, c_t) \cdot I(d, d_t)}{\sum_{t=1}^T I(a, a_t) \cdot I(c, c_t)}$$

(b) Posterior probability

$$\begin{aligned} P(a, c|b, d) &= \frac{P(a, b, c, d)}{P(b, d)} \\ &= \frac{P(a) \cdot P(b|a) \cdot P(c|a, b) \cdot P(d|a, c)}{\sum_{a'} \sum_{c'} P(a = a') \cdot P(b|a = a') \cdot P(c = c'|a = a', b) \cdot P(d|a = a', c = c')} \end{aligned}$$

(c) Posterior probability

$$P(a|b, d) = \sum_{c'} P(a, c = c'|b, d)$$

$$P(c|b, d) = \sum_{a'} P(a = a', c|b, d)$$

(d) Log-likelihood

$$\begin{aligned} L &= \sum_t \log P(B = b_t, D = d_t) \\ &= \sum_t \log \sum_a \sum_c P(A = a, B = b_t, C = c, D = d_t) \\ &= \sum_t \log \sum_a \sum_c P(A = a) \cdot P(B = b_t|A = a) \cdot P(C = c|A = a, B = b_t) \cdot P(D = d_t|A = a, C = c) \end{aligned}$$

(e) EM algorithm

$$\begin{aligned} P(A = a) &\leftarrow \frac{\widehat{\text{count}}(A = a)}{T} \\ &\leftarrow \frac{\sum_{t=1}^T P(A = a|B = b_t, D = d_t)}{T} \\ &\leftarrow \frac{\sum_{t=1}^T \sum_c P(A = a, C = c|B = b_t, D = d_t)}{T} \end{aligned}$$

$$\begin{aligned}
P(B = b|A = a) &\leftarrow \frac{\widehat{\text{count}}(A = a, B = b)}{\widehat{\text{count}}(A = a)} \\
&\leftarrow \frac{\sum_{t=1}^T P(A = a, B = b|B = b_t, D = d_t)}{\widehat{\text{count}}(A = a)} \\
&\leftarrow \frac{\sum_{t=1}^T I(b, b_t) \cdot P(A = a|B = b_t, D = d_t)}{\widehat{\text{count}}(A = a)} \\
&\leftarrow \frac{\sum_{t=1}^T \sum_c I(b, b_t) \cdot P(A = a, C = c|B = b_t, D = d_t)}{\widehat{\text{count}}(A = a)} \\
&\leftarrow \frac{\sum_{t=1}^T \sum_c I(b, b_t) \cdot P(A = a, C = c|B = b_t, D = d_t)}{\sum_{t=1}^T \sum_c P(A = a, C = c|B = b_t, D = d_t)}
\end{aligned}$$

$$\begin{aligned}
P(C = c|A = a, B = b) &\leftarrow \frac{\widehat{\text{count}}(A = a, B = b, C = c)}{\widehat{\text{count}}(A = a, B = b)} \\
&\leftarrow \frac{\sum_{t=1}^T P(A = a, B = b, C = c|B = b_t, D = d_t)}{\widehat{\text{count}}(A = a, B = b)} \\
&\leftarrow \frac{\sum_{t=1}^T I(b, b_t) \cdot P(A = a, C = c|B = b_t, D = d_t)}{\widehat{\text{count}}(A = a, B = b)} \\
&\leftarrow \frac{\sum_{t=1}^T I(b, b_t) \cdot P(A = a, C = c|B = b_t, D = d_t)}{\sum_{t=1}^T \sum_{c'} I(b, b_t) \cdot P(A = a, C = c'|B = b_t, D = d_t)}
\end{aligned}$$

$$\begin{aligned}
P(D = d|A = a, C = c) &\leftarrow \frac{\widehat{\text{count}}(A = a, C = c, D = d)}{\widehat{\text{count}}(A = a, C = c)} \\
&\leftarrow \frac{\sum_{t=1}^T P(A = a, C = c, D = d|B = b_t, D = d_t)}{\widehat{\text{count}}(A = a, C = c)} \\
&\leftarrow \frac{\sum_{t=1}^T I(d, d_t) \cdot P(A = a, C = c|B = b_t, D = d_t)}{\widehat{\text{count}}(A = a, C = c)} \\
&\leftarrow \frac{\sum_{t=1}^T I(d, d_t) \cdot P(A = a, C = c|B = b_t, D = d_t)}{\sum_{t=1}^T P(A = a, C = c|B = b_t, D = d_t)}
\end{aligned}$$

## 2 EM algorithm for noisy-OR

### (a) Equivalence of models

- (i) Marginalization over  $\vec{z}$
- (ii) Product/chain rule was applied along with conditional independence between every  $z_i$  since all paths between different  $z_i$  are d-separated due to rule #3.
- (iii)  $P_B(Y = 0|\vec{Z} = \vec{z}) = 0$  for any  $z_i = 1$ , so the only remaining term is for  $\vec{Z} = 0$ .
- (iv)  $P_B(Z_i = 0|X_i = 1) = 1 - p_i$  and  $P_B(Z_i = 0|X_i = 0) = 1$ . Then  $P_B(Z_i = 0|X_i = x_i) = (1 - p_i)^{x_i}$

### (b) EM Implementation: Per-iteration statistics

iteration	number of mistakes $M$	log conditional likelihood $L$
0	175	-0.9581
1	56	-0.4959
2	43	-0.4082
4	42	-0.3646
8	44	-0.3475
16	40	-0.3346
32	37	-0.3226
64	37	-0.3148
128	36	-0.3112
256	36	-0.3102
512	36	-0.3100

(c) EM Implementation: Estimated values for  $p_i$

$i$	$p_i$
1	7.952606636558421e-05
2	0.00481741209369718
3	2.5702471621528087e-11
4	0.26533320243361963
5	1.4919335171144578e-05
6	0.009464229795569459
7	0.24030074435506368
8	0.11345165109907844
9	0.0001434658634790401
10	0.5234804065754611
11	0.4072853322527083
12	9.074568784373926e-08
13	0.6157947609276805
14	5.954608022848239e-06
15	0.04490171238688918
16	0.5899773388133327
17	0.9999999999999938
18	0.9999999821990931
19	4.154500914170821e-09
20	0.4629914874582514
21	0.3531984001127537
22	0.5248644134908856
23	0.19475859952835034

(d) EM Implementation: Source code

```
In [99]: import math

In [100]: x = []
          for l in open("hw5_noisy0r_x.txt"):
              numbers = l.split()
              numbers = [int(s) for s in numbers]
              X.append(numbers)

In [101]: y = []
          for l in open("hw5_noisy0r_y.txt"):
              #numbers = l.split()
              #numbers = [int(s) for s in numbers]
              y.append(int(l))
```

```

In [102]: p = []
          for i in range(0, 23):
              p.append(0.05)

In [103]: def updatePi():
            newP = []
            for i in range(0, 23):
                pi = 0
                Ti = 0
                for t in range(0, len(X)):
                    prod = 1
                    for j in range(0, len(X[0])):
                        prod *= (1-p[j])**X[t][j]
                    pi += y[t]*X[t][i]*p[i]/(1-prod)
                    Ti += X[t][i]
                pi = pi/Ti
                newP.append(pi)
            return newP

In [104]: def computePYX():
            PYX = []
            for i in range(0, len(X)):
                pyx = 1
                for j in range(0, len(X[0])):
                    pyx *= (1-p[j])**X[i][j]
                PYX.append(1-pyx)
            return PYX

In [105]: def loglikelihood(probabilities):
            ll = 0
            for i in range(len(y)):
                if y[i] == 0:
                    ll += math.log(1-probabilities[i])
                else:
                    ll += math.log(probabilities[i])
            ll /= len(y)
            return ll

In [106]: iterations = []

            probabilities = computePYX()
            ll = loglikelihood(probabilities)

            errors = 0
            for i in range(0, len(y)):
                if (probabilities[i] >= 0.5 and y[i] == 0)
                or (probabilities[i] < 0.5 and y[i] == 1):
                    errors +=1

            iterations.append((errors, ll))

            for i in range(0, 512):
                p = updatePi();
                probabilities = computePYX()
                ll = loglikelihood(probabilities)

```

```

        errors = 0
        for i in range(0, len(y)):
            if (probabilities[i] >= 0.5 and y[i] == 0)
            or (probabilities[i] < 0.5 and y[i] == 1):
                errors +=1

        iterations.append((errors, ll))

In [120]: table = []
          table.append((0, iterations[0][0], iterations[0][1]))

          i = 1
          while i <= 512:
              table.append((i, iterations[i][0], iterations[i][1]))
              i *= 2

In [121]: table

Out[121]: [(0, 175, -0.9580854082157914),
           (1, 56, -0.49591639407753635),
           (2, 43, -0.40822081705839114),
           (4, 42, -0.3646149825001877),
           (8, 44, -0.34750061620878253),
           (16, 40, -0.33461704895854844),
           (32, 37, -0.3225814031674978),
           (64, 37, -0.3148266983628557),
           (128, 36, -0.3111558472151897),
           (256, 36, -0.3101613534740759),
           (512, 36, -0.30999030298497576)]

In [122]: p

Out[122]: [7.952606636558421e-05,
           0.004817412093697185,
           2.5702471621528087e-11,
           0.26533320243361963,
           1.4919335171144578e-05,
           0.009464229795569459,
           0.24030074435506368,
           0.11345165109907844,
           0.0001434658634790401,
           0.5234804065754611,
           0.4072853322527083,
           9.074568784373926e-08,
           0.6157947609276805,
           5.954608022848239e-06,
           0.04490171238688918,
           0.5899773388133327,
           0.9999999999999938,
           0.9999999821990931,
           4.154500914170821e-09,
           0.4629914874582514,
           0.3531984001127537,
           0.5248644134908856,
           0.19475859952835034]

```

### 3 EM algorithm for binary matrix completion

#### (a) Sanity check

['The\_Last\_Airbender', 'Batman\_v\_Superman:\_Dawn\_of\_Justice', 'Justice\_League', 'Suicide\_Squad', 'It', 'Terminator\_Genisys', 'World\_War\_Z', 'The\_Shape\_of\_Water', 'Venom', 'Man\_of\_Steel', 'Tron', 'Blade\_Runner\_2049', 'The\_Lego\_Movie', 'Star\_Wars:\_The\_Phantom\_Menace', 'Jurassic\_World', 'The\_Greatest\_Showman', 'The\_Hunger\_Games', 'Terminator\_2', 'Oceans\_8', 'Star\_Wars:\_The\_Last\_Jedi', 'La\_La\_Land', 'Mad\_Max:\_Fury\_Road', 'Get\_Out', 'Furious\_7', 'Jumanji:\_Welcome\_to\_the\_Jungle', '2001:\_A\_Space\_Odyssey', 'Wonder\_Woman', 'Frozen', 'Star\_Trek\_Beyond', 'Captain\_America:\_Civil\_War', 'Guardians\_of\_the\_Galaxy\_Vol.\_2', 'Ex\_Machina', 'Harry\_Potter\_and\_the\_Deathly\_Hallows:\_Part\_2', 'Ant-Man\_and\_the\_Wasp', 'Fantastic\_Beasts\_and\_Where\_To\_Find\_Them', 'Rogue\_One', 'Logan', 'Zootopia', 'The\_Lord\_of\_the\_Rings:\_The\_Fellowship\_of\_the\_Ring', 'Thor:\_Ragnarok', 'Deadpool\_2', 'The\_Imitation\_Game', 'Guardians\_of\_the\_Galaxy', 'Iron\_Man\_3', 'Black\_Panther', 'The\_Martian', 'The\_Wolf\_of\_Wall\_Street', 'The\_Dark\_Knight', 'Jurassic\_Park\_(1993)', 'Avengers:\_Infinity\_War', 'Mission:\_Impossible\_-\_Fallout', 'Coco', 'Moana', 'Interstellar', 'The\_Matrix', 'The\_Avengers', 'WALL-E', 'Inception', 'Solo', 'Doctor\_Strange']

#### (b) Likelihood

$$\begin{aligned}
 P(\{R_j = r_j^{(t)}\}_{j \in \Omega_t}) &= \sum_{i=1}^k P(\{R_j = r_j^{(t)}\}_{j \in \Omega_t}, Y = i) && \text{(Marginalization)} \\
 &= \sum_{i=1}^k P(Y = i) \prod_{j \in \Omega_t} P(R_j = r_j^{(t)} | Y = i, R_1 = r_1^{(t)}, \dots, R_{j-1} = r_{j-1}^{(t)}) && \text{(Product rule)} \\
 &= \sum_{i=1}^k P(Y = i) \prod_{j \in \Omega_t} P(R_j = r_j^{(t)} | Y = i) && \text{(Cond. Ind. in Bayes' Net)}
 \end{aligned}$$

#### (c) E-step

$$\begin{aligned}
 P(Y = i | \{R_j = r_j^{(t)}\}_{j \in \Omega_t}) &= \frac{P(Y = i, \{R_j = r_j^{(t)}\}_{j \in \Omega_t})}{P(\{R_j = r_j^{(t)}\}_{j \in \Omega_t})} && \text{(Product rule)} \\
 &= \frac{P(Y = i) \prod_{j \in \Omega_t} P(R_j = r_j^{(t)} | Y = i, R_1 = r_1^{(t)}, \dots, R_{j-1} = r_{j-1}^{(t)})}{P(\{R_j = r_j^{(t)}\}_{j \in \Omega_t})} && \text{(Product rule)} \\
 &= \frac{P(Y = i) \prod_{j \in \Omega_t} P(R_j = r_j^{(t)} | Y = i)}{P(\{R_j = r_j^{(t)}\}_{j \in \Omega_t})} && \text{(Cond. Ind. in Bayes' Net)} \\
 &= \frac{P(Y = i) \prod_{j \in \Omega_t} P(R_j = r_j^{(t)} | Y = i)}{\sum_{y=1}^k P(Y = y) \prod_{j \in \Omega_t} P(R_j = r_j^{(t)} | Y = y)} && \text{(Replacing denominator)}
 \end{aligned}$$

(d) **M-step**

$$\begin{aligned}
P(Y = i) &\leftarrow \sum_{t=1}^T P(Y = i, \{R_j = r_j^{(t)}\}_{j \in \Omega_t}) && \text{(Marginalization over samples)} \\
&\leftarrow \sum_{t=1}^T P(Y = i | \{R_j = r_j^{(t)}\}_{j \in \Omega_t}) \cdot P(\{R_j = r_j^{(t)}\}_{j \in \Omega_t}) && \text{(Product rule)} \\
&\leftarrow \frac{1}{T} \sum_{t=1}^T P(Y = i | \{R_j = r_j^{(t)}\}_{j \in \Omega_t}) && (P(\{R_j = r_j^{(t)}\}_{j \in \Omega_t}) = \frac{1}{T}) \\
&\leftarrow \frac{1}{T} \sum_{t=1}^T p_{it}
\end{aligned}$$

$$\begin{aligned}
P(R_j = 1 | Y = 1) &\leftarrow \frac{P(Y = i | R_j = 1) \cdot P(R_j = 1)}{P(Y = 1)} \\
&\leftarrow \frac{\sum_t P(Y = i, \{R_j = r_j^{(t)}\} | R_j = 1) \cdot P(R_j = 1)}{P(Y = 1)} \\
&\leftarrow \frac{\sum_t P(Y = i, R_j = 1 | \{R_j = r_j^{(t)}\}) \cdot P(\{R_j = r_j^{(t)}\})}{P(Y = 1)} \\
&\leftarrow \frac{\frac{1}{T} (\sum_{t: j \in \Omega_t} P(Y = i | \{R_j = r_j^{(t)}\}) \cdot I(r_j^{(t)}, 1) + \sum_{t: j \notin \Omega_t} P(Y = i | \{R_j = r_j^{(t)}\}) \cdot P(R_j = 1 | Y = i))}{P(Y = 1)} \\
&\leftarrow \frac{\frac{1}{T} (\sum_{t: j \in \Omega_t} p_{it} \cdot I(r_j^{(t)}, 1) + \sum_{t: j \notin \Omega_t} p_{it} \cdot P(R_j = 1 | Y = i))}{P(Y = 1)} \\
&\leftarrow \frac{\frac{1}{T} (\sum_{t: j \in \Omega_t} p_{it} \cdot I(r_j^{(t)}, 1) + \sum_{t: j \notin \Omega_t} p_{it} \cdot P(R_j = 1 | Y = i))}{\frac{1}{T} \sum_{t=1}^T p_{it}} \\
&\leftarrow \frac{\sum_{t: j \in \Omega_t} p_{it} \cdot I(r_j^{(t)}, 1) + \sum_{t: j \notin \Omega_t} p_{it} \cdot P(R_j = 1 | Y = i)}{\sum_{t=1}^T p_{it}}
\end{aligned}$$

(e) **Implementation**

iteration	log-likelihood $L$
0	-27.9848
1	-15.5730
2	-13.6614
4	-12.5566
8	-12.1332
16	-12.0195
32	-12.0040
64	-12.0005
128	-12.0000

(f) **Personal categorization** Given my personal ratings, the  $i$  that maximizes  $P(Y = i | \text{my ratings})$  is  $i = 1$ , which gives a probability of 1.

(g) **Personal movie recommendations**

unseen movies	$P(R_j = 1   \text{my ratings})$
Black Panther	0.9436
The Last Airbender	0.2642
2001: A Space Odyssey	0.9494
Terminator Genisys	0.5840
Terminator 2	0.8577
Coco	0.9357
Ant-Man and the Wasp	0.8815
Venom	0.6962
Oceans 8	0.9449
The Lego Movie	0.7885
Jumanji: Welcome to the Jungle	0.8222
Solo	1.0000
Furious 7	0.8332

This list reflects my personal tastes better than the list in item (a).

#### (h) Source code

##### 3.0.1 Question 3

###### (a)

```
In [138]: X = []
          for l in open("hw5_movieRatings_fa18.txt"):
              v = []
              for x in l.split():
                  if x != '?':
                      v.append(int(x))
                  else:
                      v.append(x)
              X.append(v)

In [132]: titles = []
          for l in open("hw5_movieTitles_fa18.txt"):
              titles.append(l.split()[0])

In [154]: moviesAvg = []
          for i in range(0, len(titles)):
              moviesAvg.append([0,0,0])

          for i in range(0, len(X)):
              for j in range(0, len(titles)):
                  if X[i][j] == 1:
                      moviesAvg[j][0] += 1
                  if X[i][j] != '?':
                      moviesAvg[j][1] += 1

          for i in range(0, len(titles)):
              moviesAvg[i][2] = moviesAvg[i][0]/moviesAvg[i][1]

          moviesAvg = list(zip(titles, moviesAvg))

In [160]: moviesAvg = sorted(moviesAvg, key=lambda x:x[1][2])
```



```
In [164]: [v[0] for v in moviesAvg]
```

```
Out[164]: ['The_Last_Airbender',  
           'Batman_v_Superman:_Dawn_of_Justice',  
           'Justice_League',  
           'Suicide_Squad',  
           'It',  
           'Terminator_Genisys',  
           'World_War_Z',  
           'The_Shape_of_Water',  
           'Venom',  
           'Man_of_Steel',  
           'Tron',  
           'Blade_Runner_2049',  
           'The_Lego_Movie',  
           'Star_Wars:_The_Phantom_Menace',  
           'Jurassic_World',  
           'The_Greatest_Showman',  
           'The_Hunger_Games',  
           'Terminator_2',  
           'Oceans_8',  
           'Star_Wars:_The_Last_Jedi',  
           'La_La_Land',  
           'Mad_Max:_Fury_Road',  
           'Get_Out',  
           'Furious_7',  
           'Jumanji:_Welcome_to_the_Jungle',  
           '2001:_A_Space_Odyssey',  
           'Wonder_Woman',  
           'Frozen',  
           'Star_Trek_Beyond',  
           'Captain_America:_Civil_War',  
           'Guardians_of_the_Galaxy_Vol._2',  
           'Ex_Machina',  
           'Harry_Potter_and_the_Deathly_Hallows:_Part_2',  
           'Ant-Man_and_the_Wasp',  
           'Fantastic_Beasts_and_Where_To_Find_Them',  
           'Rogue_One',  
           'Logan',  
           'Zootopia',  
           'The_Lord_of_the_Rings:_The_Fellowship_of_the_Ring',  
           'Thor:_Ragnarok',  
           'Deadpool_2',  
           'The_Imitation_Game',  
           'Guardians_of_the_Galaxy',  
           'Iron_Man_3',  
           'Black_Panther',  
           'The_Martian',  
           'The_Wolf_of_Wall_Street',  
           'The_Dark_Knight',  
           'Jurassic_Park_(1993)',  
           'Avengers:_Infinity_War',  
           'Mission:_Impossible_-_Fallout',  
           'Coco',
```

```

'Moana',
'Interstellar',
'The_Matrix',
'The_Avengers',
'WALL-E',
'Inception',
'Solo',
'Doctor_Strange']

```

(e)

```

In [170]: pY = []
          for l in open("hw5_probType_init_fa18.txt"):
              pY.append(float(l.split()[0]))

          pRY = []
          for l in open("hw5_probRatingGivenType_init_fa18.txt"):
              probs = [float(x) for x in l.split()]
              pRY.append(probs)

In [189]: def computePit():
          vPit = []
          for t in range(0, len(X)):
              vPt = []
              for i in range(0, len(pY)):
                  prod = pY[i]
                  for j in range(0, len(pRY)):
                      if X[t][j] == 1:
                          prod *= pRY[j][i]
                      elif X[t][j] == 0:
                          prod *= (1-pRY[j][i])
                  vPt.append(prod)
              vPt = [x/sum(vPt) for x in vPt]
              vPit.append(vPt)
          return list(map(list, zip(*vPit)))

In [208]: def updatePY(Pit):
          newPY = []
          for i in range(0, len(pY)):
              sum = 0
              for t in range(0, len(X)):
                  sum += Pit[i][t]
              sum /= len(X)
              newPY.append(sum)
          return newPY

In [203]: def updatePRY(Pit):
          newPRY = []
          for j in range(0, len(pRY)):
              newPy = []
              for i in range(0, len(pY)):
                  sumT = 0
                  sumNotT = 0
                  for t in range(0, len(X)):

```

```

        if X[t][j] == 1:
            sumT += Pit[i][t]
        elif X[t][j] == '?':
            sumNotT += Pit[i][t]*pRY[j][i]
        newPy.append((sumT + sumNotT)/sum(Pit[i]))
    newPRY.append(newPy)
    return newPRY

In [214]: def computePR(Pit, t):
    sum = 0
    for i in range(0, len(pY)):
        prod = pY[i]
        for j in range(0, len(pRY)):
            if X[t][j] == 1:
                prod *= pRY[j][i]
            elif X[t][j] == 0:
                prod *= (1-pRY[j][i])
        sum += prod
    return sum

In [215]: def loglikelihood(Pit):
    ll = 0
    for t in range(0, len(X)):
        ll += math.log(computePR(Pit, t))
    ll /= len(X)
    return ll

In [220]: loglikelihood(computePit())

Out[220]: -27.98479373624261

In [221]: iterations = []

    pit = computePit()
    ll = loglikelihood(pit)

    iterations.append([0, ll])

    for i in range(0,128):
        pY = updatePY(pit)
        pRY = updatePRY(pit)
        pit = computePit()
        ll = loglikelihood(pit)

        iterations.append([i+1, ll])

In [223]: table = []
    table.append(iterations[0])
    i=1
    while i <= 128:
        table.append(iterations[i])
        i *= 2

In [224]: table

```

```
Out[224]: [[0, -27.98479373624261],
           [1, -15.572996571571787],
           [2, -13.66141481085908],
           [4, -12.556587236861157],
           [8, -12.13316136441514],
           [16, -12.019531087089582],
           [32, -12.004032227091116],
           [64, -12.000469747436933],
           [128, -12.00004068559657]]
```

(f)

```
In [238]: myRatings = ['?', 1, '?', 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, '?', 1, '?',
 '?', 1, '?', '?', '?', '?', 1, '?', 1, 1, 1, '?', 1, 0, 1, 1, '?', 1, 0, 1, 1, '?']
```

```
In [239]: X.index(myRatings)
```

```
Out[239]: 111
```

```
In [240]: myProbs = [p[111] for p in pit]
```

```
In [241]: myProbs
```

```
Out[241]: [1.0, 5.151841717383405e-86, -3.573574433350554e-63, 0.0]
```

(g)

```
In [244]: unseenMovies = []
          for j in range(0, len(myRatings)):
              sum = 0
              if myRatings[j] == '?':
                  for i in range(0, len(pY)):
                      sum += pit[i][111]*pRY[j][i]
              unseenMovies.append([titles[j], sum])
```

```
In [245]: unseenMovies
```

```
Out[245]: [['Black_Panther', 0.9435799253823884],
           ['The_Last_Airbender', 0.2641657488701842],
           ['2001:_A_Space_Odyssey', 0.9494494359912142],
           ['Terminator_Genisys', 0.5840336593899693],
           ['Terminator_2', 0.8577013829345648],
           ['Coco', 0.935731301447267],
           ['Ant-Man_and_the_Wasp', 0.8815382276129842],
           ['Venom', 0.6962129331476755],
           ['Oceans_8', 0.944858959209109],
           ['The_Lego_Movie', 0.7885033530939412],
           ['Jumanji:_Welcome_to_the_Jungle', 0.8222240618014134],
           ['Solo', 0.9999999999999997],
           ['Furious_7', 0.8331588178649978]]
```