

CSE 150 Homework 6

Pedro Sousa Meireles
A15677282

Fall 2018

1 Viterbi Algorithm

```
In [108]: import math
          import matplotlib.pyplot as plt

In [8]: pi = []
        for l in open('initialStateDistribution.txt'):

            pi.append(float(l.split()[0]))

In [10]: aij = []
        for l in open('transitionMatrix.txt'):
            numbers = l.split()
            for i in range(0, len(numbers)):
                numbers[i] = float(numbers[i])
            aij.append(numbers)

In [13]: bik = []
        for l in open('emissionMatrix.txt'):
            numbers = l.split()
            for i in range(0, len(numbers)):
                numbers[i] = float(numbers[i])
            bik.append(numbers)

In [44]: for l in open('observations.txt'):
            obs = l.split()
            for i in range(0, len(numbers)):
                obs[i] = int(obs[i])

In [25]: li1 = []
        for i in range(0, len(pi)):
            li1.append(math.log(pi[i]*bik[i][1]))

In [76]: lit = []
        lit.append(li1)

In [77]: phiit = []
        phiit.append([0]*len(lit[0]))

In [46]: def computelit(j, t):
            maximize = []
            for x in lit[t-1]:
                maximize.append(x + math.log(aij[lit[t-1].index(x)][j]))
            maximize = max(maximize)
            return maximize + math.log(bik[j][obs[t]])
```

```

In [78]: for time in range(1, len(obs)):
        actualLit = []
        actualPhiit = []
        for n in range(0, len(li1)):
            actualLit.append(computelit(n, time))
            maxlit = []
            for x in lit[time-1]:
                maxlit.append(x + math.log(aij[lit[time-1].index(x)][n]))
            actualPhiit.append(maxlit.index(max(maxlit)))
        lit.append(actualLit)
        phiit.append(actualPhiit)

In [95]: letters = ['a', 'b', 'c', 'd',
                    'e', 'f', 'g', 'h',
                    'i', 'j', 'k', 'l',
                    'm', 'n', 'o', 'p',
                    'q', 'r', 's', 't',
                    'u', 'v', 'w', 'x',
                    'y', 'z', ' ']

In [96]: S = ['']*len(phiit)
        S[-1] = lit[-1].index(max(lit[-1]))
        for time in range(len(phiit)-1, 0, -1):
            S[time-1] = phiit[time][S[time]]

In [97]: for i in range(0, len(S)):
        S[i] = letters[S[i]]

In [101]: sentence = ""
        sentence += S[0]

        for i in range(0, len(S)):
            if S[i] != sentence[-1]:
                sentence += S[i]

In [102]: print(sentence)

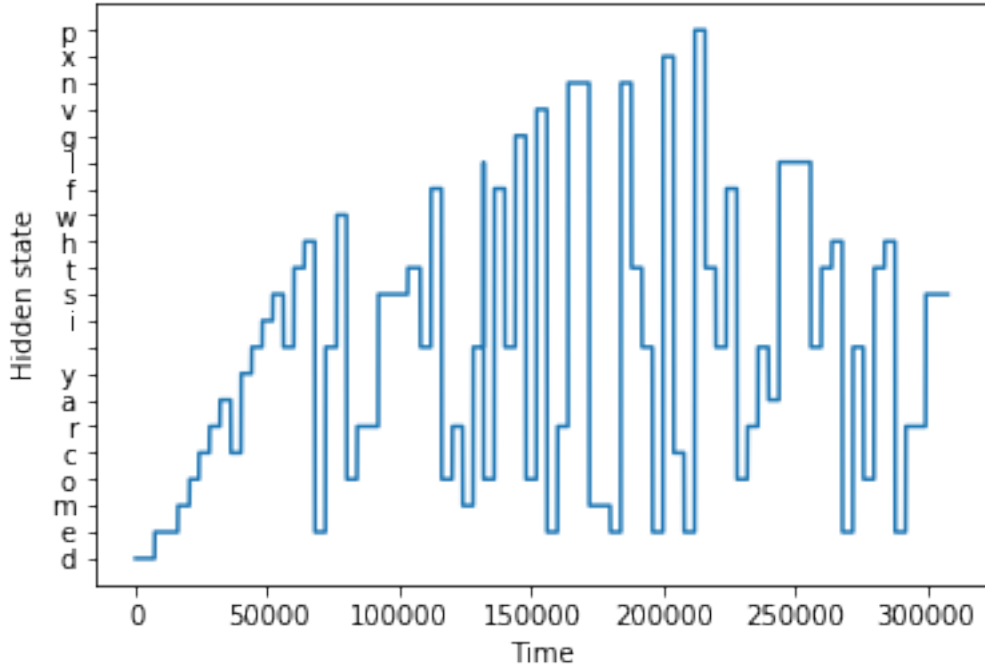
democracy is the worst form lof government except for al the others

In [104]: times = []
        for i in range(0, len(S)):
            times.append(i)

In [110]: plt.plot(times, S)
        plt.xlabel('Time')
        plt.ylabel('Hidden state')

Out[110]: Text(0,0.5,'Hidden state')

```



2 Conditional Independence

$$P(S_t|S_{t-1}) = P(S_t|S_{t-1}, O_t)$$

False

$$P(S_t|S_{t-1}) = P(S_t|S_{t-1}, O_{t-1})$$

True

$$P(S_t|S_{t-1}) = P(S_t|S_{t-1}, S_{t+1})$$

False

$$P(S_t|O_{t-1}) = P(S_t|O_1, O_2, \dots, O_{t-1})$$

False

$$P(O_t|S_{t-1}) = P(O_t|S_{t-1}, O_{t-1})$$

True

$$P(O_t|O_{t-1}) = P(O_t|O_1, O_2, \dots, O_{t-1})$$

False

$$P(O_1, O_2, \dots, O_T) = \prod_{t=1}^T P(O_t|O_1, O_2, \dots, O_{t-1})$$

True

$$P(S_2, S_3, \dots, S_T|S_1) = \prod_{t=2}^T P(S_t|S_{t-1})$$

True

$$P(S_1, S_2, \dots, S_{T-1}|S_T) = \prod_{t=1}^{T-1} P(S_t|S_{t+1})$$

True

$$P(S_1, S_2, \dots, S_T|O_1, O_2, \dots, O_T) = \prod_{t=1}^T P(S_t|O_t)$$

False

$$P(S_1, S_2, \dots, S_T, O_1, O_2, \dots, O_T) = \prod_{t=1}^T P(S_t, O_t)$$

False

$$P(O_1, O_2, \dots, O_T|S_1, S_2, \dots, S_T) = \prod_{t=1}^T P(O_t|S_t)$$

True

3 More conditional independence

(a)

$$P(S_t|S_{t+1}, S_{t+2}, \dots, S_T) = P(S_t|S_{t+1})$$

$$P(S_t|O_t, O_{t-1}, O_{t+1}) = P(S_t|O_t, O_{t-1}, O_{t+1})$$

$$P(S_t|O_t, O_{t+1}, \dots, O_T) = P(S_t|O_t, O_{t+1}, \dots, O_T)$$

$$P(O_t|O_1, O_2, \dots, O_{t-1}) = P(O_t|O_1, O_2, \dots, O_{t-1})$$

$$P(O_t|S_{t-2}, S_{t-1}, S_{t+1}, S_{t+2}) = P(O_t|S_{t-1}, S_{t+1})$$

$$P(O_t|O_{t-1}, O_{t+1}, S_1, S_T) = P(O_t|O_{t-1}, O_{t+1}, S_1, S_T)$$

(b)

$$P(S_t|O_t, O_{t-1}, O_{t+1}, S_{t-1}, S_{t+1}) = P(S_t|O_t, S_{t-1}, S_{t+1})$$

$$P(S_t|S_1, S_T, O_1, O_t, O_T) = P(S_t|S_1, S_T, O_t)$$

$$P(O_t|O_1, O_2, \dots, O_{t-1}, S_{t-1}) = P(O_t|S_{t-1})$$

$$P(O_t|O_1, O_2, \dots, O_{t-1}, S_{t-2}) = P(O_t|O_{t-1}, S_{t-2})$$

4 Belief updating

(a)

$$\begin{aligned} P(Y_1|X_1) &= \sum_{x_0} P(Y_1, X_0 = x_0|X_1) \\ &= \sum_{x_0} P(Y_1|X_0 = x_0, X_1) \cdot P(X_0 = x_0|X_1) \\ &= \sum_{x_0} P(Y_1|X_0 = x_0, X_1) \cdot P(X_0 = x_0) \end{aligned}$$

(b)

$$\begin{aligned} P(Y_1) &= \sum_{x_0} \sum_{x_1} P(Y_1, X_0 = x_0, X_1 = x_1) \\ &= \sum_{x_0} \sum_{x_1} P(Y_1|X_0 = x_0, X_1 = x_1) \cdot P(X_0 = x_0, X_1 = x_1) \\ &= \sum_{x_0} \sum_{x_1} P(Y_1|X_0 = x_0, X_1 = x_1) \cdot P(X_0 = x_0) \cdot P(X_1 = x_1) \end{aligned}$$

(c)

$$\begin{aligned}
& P(X_t | Y_1, Y_2, \dots, Y_{t-1}) \\
&= \sum_x P(X_t, X_{t-1} = x | Y_1, Y_2, \dots, Y_{t-1}) \quad (\text{Marginalization}) \\
&= \sum_x P(X_t | X_{t-1} = x, Y_1, Y_2, \dots, Y_{t-1}) \cdot P(X_{t-1} = x | Y_1, Y_2, \dots, Y_{t-1}) \quad (\text{Prod. rule}) \\
&= \sum_x P(X_t | X_{t-1} = x, Y_{t-1}) \cdot P(X_{t-1} = x | Y_1, Y_2, \dots, Y_{t-1}) \quad (\text{C.I.}) \\
&= \sum_x \frac{P(Y_{t-1} | X_t, X_{t-1} = x) \cdot P(X_t | X_{t-1} = x)}{P(Y_{t-1} | X_{t-1} = x)} \cdot P(X_{t-1} = x | Y_1, Y_2, \dots, Y_{t-1}) \quad (\text{Bayes' rule}) \\
&= \sum_x \frac{P(Y_{t-1} | X_t, X_{t-1} = x) \cdot P(X_t)}{\sum_{x'} P(Y_{t-1}, X_t = x' | X_{t-1} = x)} \cdot P(X_{t-1} = x | Y_1, Y_2, \dots, Y_{t-1}) \quad (\text{C.I. and Marginalization}) \\
&= \sum_x \frac{P(Y_{t-1} | X_t, X_{t-1} = x) \cdot P(X_t)}{\sum_{x'} P(Y_{t-1} | X_t = x', X_{t-1} = x) \cdot P(X_t = x' | X_{t-1} = x)} \cdot P(X_{t-1} = x | Y_1, Y_2, \dots, Y_{t-1}) \quad (\text{Prod. Rule}) \\
&= \sum_x \frac{P(Y_{t-1} | X_t, X_{t-1} = x) \cdot P(X_t)}{\sum_{x'} P(Y_{t-1} | X_t = x', X_{t-1} = x) \cdot P(X_t = x')} \cdot P(X_{t-1} = x | Y_1, Y_2, \dots, Y_{t-1}) \quad (\text{C.I.})
\end{aligned}$$

(d)

$$\begin{aligned}
P(Y_t | X_t, Y_1, \dots, Y_{t-1}) &= \sum_x P(Y_t, X_{t-1} = x | X_t, Y_1, \dots, Y_{t-1}) \quad (\text{Marginalization}) \\
&= \sum_x P(Y_t | X_{t-1} = x, X_t, Y_1, \dots, Y_{t-1}) \cdot P(X_{t-1} = x | X_t, Y_1, \dots, Y_{t-1}) \quad (\text{Prod. Rule}) \\
&= \sum_x P(Y_t | X_{t-1} = x, X_t) \cdot P(X_{t-1} = x | Y_1, \dots, Y_{t-1}) \quad (\text{C.I.})
\end{aligned}$$

(e)

$$\begin{aligned}
P(Y_t | Y_1, \dots, Y_{t-1}) &= \sum_{x, x'} P(Y_t, X_{t-1} = x, X_t = x' | Y_1, \dots, Y_{t-1}) \quad (\text{Marginalization}) \\
&= \sum_{x, x'} P(Y_t | X_{t-1} = x, X_t = x', Y_1, \dots, Y_{t-1}) \cdot P(X_{t-1} = x, X_t = x' | Y_1, \dots, Y_{t-1}) \quad (\text{Prod. Rule}) \\
&= \sum_{x, x'} P(Y_t | X_{t-1} = x, X_t = x') \cdot P(X_{t-1} = x) \cdot P(X_t = x') \quad (\text{C.I.})
\end{aligned}$$

5 Most likely hidden states

(a) No.

(b) Yes.

(c) No.

(d) No.