

Assignment 2

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Problem 1

(a)

$$Z = \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{pmatrix}_{n \times 1} \quad A = \begin{pmatrix} a_{11} & \dots & a_{1d} \\ a_{21} & \dots & a_{2d} \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nd} \end{pmatrix}_{n \times d} \quad y = Z^T A = \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{pmatrix}$$

$$y = Z^T A = (z_1 \ z_2 \ \dots \ z_n) \begin{pmatrix} a_{11} & \dots & a_{1d} \\ a_{21} & \dots & a_{2d} \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nd} \end{pmatrix} = \left(\underbrace{z_1 a_{11} + z_2 a_{21} + \dots + z_n a_{n1}}_{y_1}, \dots, \underbrace{z_1 a_{1d} + z_2 a_{2d} + \dots + z_n a_{nd}}_{y_d} \right)$$

$$= (y_1, \dots, y_d)_{1 \times d}$$

$$P(X=i) = s_i, i \in [1, d]$$

$$S = (s_1, \dots, s_d) = \text{softmax}(y)$$

$$\text{The softmax of } v: \text{softmax}(v)_i = \frac{\exp(v_i)}{\sum_{j=1}^K \exp(v_j)}$$

so the softmax of d -dimensional vector y is defined as:

$$\text{softmax}(y)_i = \frac{\exp(y_i)}{\sum_{j=1}^K \exp(y_j)}$$

Because we have

$$P(X=i) = s_i$$

$$s_i = \text{softmax}(y)_i$$

$$\text{so } P(X=i) = \text{softmax}(y)_i = \frac{\exp(y_i)}{\sum_{j=1}^K \exp(y_j)}$$

(b)

$$P(X=i) = \frac{\exp(y_i)}{\sum_{j=1}^K \exp(y_j)}, \quad Q(X=i) = r_i \quad r = (r_1, \dots, r_d)$$

The cross-entropy is

$$H(Q;P) = -E_{X \sim Q} \log(P(X)) = -\sum_{i=1}^d Q(x_i) \log P(x_i) = -\sum_{i=1}^d r_i \log \left(\frac{\exp(y_i)}{\sum_{j=1}^K \exp(y_j)} \right)$$

We should find y_k that is ~~minimal~~ ^{minimum} in y .

If y_k is minimum, r_k should be 1. Then the cross-entropy $H(Q;P)$ is minimal.

Problem 2

(a)

We can show the log-likelihood of this:

$$l(P_1, P_2, \dots, P_K) = \log n! - \sum_{i=1}^K \log x_i! + \sum_{i=1}^K x_i \log P_i$$

We should take the constraint into account by using the Lagrange multipliers.

$$L(P_1, P_2, \dots, P_K, \lambda) = l(P_1, P_2, \dots, P_K) + \lambda \left(1 - \sum_{i=1}^K P_i \right)$$

By posing all the derivatives to be 0, we get the most natural estimate

$$\hat{P}_i = \frac{x_i}{n}$$

(b)

We first produce a sample:

```
In [2]: TRUE_LAMBDA = 6
X = np.random.poisson(TRUE_LAMBDA, 10000)
```

For our sample, we estimate a value for λ using MLE:

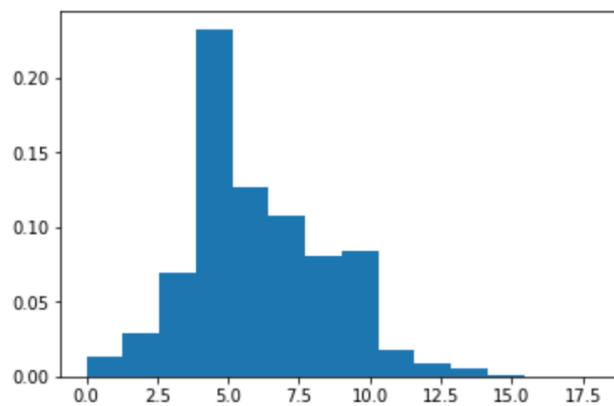
```
In [3]: def poisson_lambda_MLE(X):
# TODO
# total number of observations
n = X.size
x = np.ones(n)
lamda = x.dot(X)/n
return lamda

lambda_mle = poisson_lambda_MLE(X)
lambda_mle
```

```
Out[3]: 6.0266000000000002
```

We finally plot the sample and the resulting distribution:

```
In [4]: # TODO
count, bins, ignored = plt.hist(X, 14, normed=True)
plt.show()
```



Problem 3

The log likelihood of the Poisson distribution is:

$$\begin{aligned} l(\lambda) &= \log \prod_{i=1}^k \left(\frac{e^{-\lambda} \lambda^{x_i}}{x_i!} \right) = \sum_{i=1}^k \log \left(\frac{e^{-\lambda} \lambda^{x_i}}{x_i!} \right) \\ &= -k\lambda + \left(\sum_{i=1}^k x_i \right) \log \lambda - \sum_{i=1}^k \log(x_i!) \end{aligned}$$

We find the maximum by finding the derivative:

$$\frac{\partial}{\partial \lambda} l(\lambda) = -k + \left(\sum_{i=1}^k x_i \right) \frac{1}{\lambda} = 0 \quad \text{which implies that the estimate should be:}$$
$$\hat{\lambda} = \frac{1}{k} \sum_{i=1}^k x_i \quad \leftarrow$$

Problem 4

```
materiell — -bash — 114x30
[tangruideMacBook-Pro:materiell loisdawn$
tangruideMacBook-Pro:materiell loisdawn$ python multinomial_solution_rui_tang.py "shakespeare.txt" "stopwords.txt"
estimated probabilities:
p_1      ,      0.44781
p_2      .      0.19983
p_3      ;      0.09453
p_4      :      0.05768
p_5      !      0.05760
p_6      ?      0.05580
p_7      thou   0.02925
p_8      thy    0.02086
p_9      shall  0.01966
p_10     thee   0.01698

enter observation:
X_1=1000
X_2=990
X_3=800
X_4=700
X_5=450
X_6=440
X_7=400
X_8=300
X_9=200
X_10=100

result: {' ': 0.18587360594795538, '.': 0.18401486988847585, ';': 0.14869888475836432, ':': 0.13011152416356878, '
!': 0.08364312267657993, '?': 0.08178438661710037, 'thou': 0.07434944237918216, 'thy': 0.055762081784386616, 'shal
l': 0.03717472118959108, 'thee': 0.01858736059479554}
tangruideMacBook-Pro:materiell loisdawn$
```