

Feel free to work with other students, but make sure you write up the homework and code on your own (no copying homework *or* code; no pair programming). Feel free to ask students or instructors for help debugging code or whatever else, though.

The starter files for problem 2 can be found under the Resource tab on course website. The plot for problem 2 generated by the sample solution has been included in the starter files for reference. Please print out all the graphs generated by your own code and submit them together with the written part, and make sure you upload the code to your Github repository.

1 (Murphy 11.3 - EM for Mixtures of Bernoullis) Show that the M step for ML estimation of a mixture of Bernoullis is given by

$$\mu_{kj} = \frac{\sum_i r_{ik} x_{ij}}{\sum_i r_{ik}}.$$

Show that the M step for MAP estimation of a mixture of Bernoullis with a $\beta(a, b)$ prior is given by

$$\mu_{kj} = \frac{(\sum_i r_{ik} x_{ij}) + a - 1}{(\sum_i r_{ik}) + a + b - 2}.$$

we start by taking the derivatives of the log likelihood:

$$\begin{aligned}
\ell(\mu) &= \sum_i \sum_k r_{ik} \log(\mathbb{P}(x_i|\theta_k)) \\
\ell(\mu) &= \sum_i \sum_k r_{ik} \left(\sum_j x_{ij} \log(\mu_{kj}) - (1 - x_{ij}) \log(1 - \mu_{kj}) \right) \\
\frac{\delta \ell}{\delta \mu_{kj}} &= \frac{\delta \ell}{\delta \mu_{kj}} \sum_i \sum_k r_{ij} \sum_j x_{ij} \log(\mu_{kj}) - (1 - x_{ij}) \log(1 - \mu_{kj}) \\
&= \sum_i r_{ik} \left(\frac{x_{ij}}{\mu_{kj}} - \frac{1 - x_{ij}}{1 - \mu_{kj}} \right) \\
&= \sum_i r_{ik} \left(\frac{x_{ij}(1 - \mu_{kj}) - \mu_{kj}(1 - x_{ij})}{\mu_{kj}(1 - \mu_{kj})} \right) \\
&= \sum_i r_{ik} \left(\frac{x_{ij} - \mu_{kj}}{\mu_{kj}(1 - \mu_{kj})} \right) \\
&= \frac{1}{\mu_{kj}(1 - \mu_{kj})} \sum_i r_{ik} (x_{ij} - \mu_{kj})
\end{aligned}$$

then we can set the equation to 0 and find the M step definition to be:

$$\begin{aligned}
0 &= \frac{1}{\mu_{kj}(1 - \mu_{kj})} \sum_i r_{ik} (x_{ij} - \mu_{kj}) \\
0 &= \sum_i r_{ik} x_{ij} - \sum_i r_{ik} \mu_{kj} \\
\sum_i r_{ik} \mu_{kj} &= \sum_i r_{ik} x_{ij} \\
\mu_{kj} \sum_i r_{ik} &= \sum_i r_{ik} x_{ij} \\
\mu_{kj} &= \frac{\sum_i r_{ik} x_{ij}}{\sum_i r_{ik}}
\end{aligned}$$

as desired.

We repeat these steps for the MAP estimation. we start by taking the derivatives of the

log likelihood:

$$\begin{aligned}
\ell(\mu) &= \sum_i \sum_k r_{ik} \log(\mathbb{P}(x_i|\mu_k)) + \log(\mathbb{P}(\mu_k)) \\
\ell(\mu) &= \sum_i \sum_k r_{ik} \sum_j x_{ij} \log(\mu_{kj}) - r_{ik}(1 - x_{ij}) \log(1 - \mu_{kj}) \\
&\quad + (a - 1) \log(\mu_{jk}) + (b - 1) \log(1 - \mu_{jk}) \\
\ell(\mu) &= \sum_i \sum_k r_{ik} \sum_j x_{ij} \log(\mu_{kj}) + (a - 1) \log(\mu_{jk}) \\
&\quad + r_{ik}(1 - x_{ij}) \log(1 - \mu_{kj}) + (b - 1) \log(1 - \mu_{jk}) \\
\ell(\mu) &= \sum_i \sum_k (r_{ik} \sum_j x_{ij} + (a - 1)) \log(\mu_{jk}) \\
&\quad - (r_{ik}(1 - x_{ij}) - (b - 1)) \log(1 - \mu_{jk}) \\
\frac{\delta \ell}{\delta \mu_{kj}} &= \sum_i \left(\frac{(r_{ik} x_{ij} + (a - 1))}{\mu_{jk}} \right) - \left(\frac{r_{ik}(1 - x_{ij}) + (b - 1)}{1 - \mu_{jk}} \right) \\
&= \sum_i \left(\frac{(r_{ik} x_{ij} + (a - 1))(1 - \mu_{jk}) - \mu_{jk}(r_{ik}(1 - x_{ij}) + (b - 1))}{\mu_{jk}(1 - \mu_{jk})} \right) \\
&= \frac{1}{\mu_{jk}(1 - \mu_{jk})} \sum_i (r_{ik} x_{ij} + (a - 1))(1 - \mu_{jk}) - \mu_{jk}(r_{ik}(1 - x_{ij}) + (b - 1)) \\
&= \frac{1}{\mu_{jk}(1 - \mu_{jk})} \sum_i (r_{ik} x_{ij} - \mu_{jk} r_{ik} x_{ij} + a - 1 - a \mu_{jk} + \mu_{jk} - \mu_{jk} r_{ik} + \mu_{jk} r_{ik} x_{ij} - \mu_{jk} b + \mu_{jk}) \\
&= \frac{1}{\mu_{jk}(1 - \mu_{jk})} \sum_i (r_{ik} x_{ij} + a - 1 - a \mu_{jk} - \mu_{jk} r_{ik} - \mu_{jk} b + 2 \mu_{jk}) = 0
\end{aligned}$$

then we can set the equation to 0 and find the M step definition to be:

$$\begin{aligned}
0 &= \frac{1}{\mu_{jk}(1 - \mu_{jk})} \sum_i (r_{ik} x_{ij} + a - 1 - a \mu_{jk} - \mu_{jk} r_{ik} - \mu_{jk} b + 2 \mu_{jk}) \\
\sum_i (a \mu_{jk} + \mu_{jk} r_{ik} + \mu_{jk} b - 2 \mu_{jk}) &= \sum_i (r_{ik} x_{ij} + a - 1) \\
\mu_{jk} \sum_i (a + r_{ik} + b - 2) &= \sum_i (r_{ik} x_{ij} + a - 1) \\
\mu_{jk} &= \frac{\sum_i (r_{ik} x_{ij}) + a - 1}{\sum_i (r_{ik} + a + b - 2)}
\end{aligned}$$

as desired. ■

2 (Lasso Feature Selection) In this problem, we will use the online news popularity dataset we used in hw2pr3. In the starter code, we have already parsed the data for you. However, you might need internet connection to access the data and therefore successfully run the starter code.

First, ignoring undifferentiability at $x = 0$, take $\frac{\partial |x|}{\partial x} = \text{sign}(x)$. Using this, show that $\nabla \|\mathbf{x}\|_1 = \text{sign}(\mathbf{x})$ where sign is applied elementwise. Derive the gradient of the ℓ_1 regularized linear regression objective

$$\text{minimize: } \|\mathbf{Ax} - \mathbf{b}\|_2^2 + \lambda \|\mathbf{x}\|_1$$

Then, implement a gradient descent based solution of the above optimization problem for this data. Produce the convergence plot (objective vs. iterations) for a non-trivial value of λ . In the same figure (and different axes) produce a 'regularization path' plot. Detailed more in section 13.3.4 of Murphy, a regularization path is a plot of the optimal weight on the y axis at a given regularization strength λ on the x axis. Armed with this plot, provide an ordered list of the top five features in predicting the log-shares of a news article from this dataset (with justification).

We are given that $\frac{\partial |x|}{\partial x}$ thus we can take the gradient as follows:

$$\begin{aligned} \nabla \|\mathbf{Ax} - \mathbf{b}\|_2^2 + \lambda \|\mathbf{x}\|_1 &= \nabla \|\mathbf{Ax} - \mathbf{b}\|_2^2 + \lambda \|\mathbf{x}\|_1 \\ &= \nabla \mathbf{x}^\top \mathbf{A}^\top \mathbf{Ax} - 2\mathbf{b}^\top \mathbf{Ax} + \mathbf{b}^\top \mathbf{b} + \lambda \|\mathbf{x}\|_1 \\ &= 2\mathbf{A}^\top \mathbf{Ax} - 2\mathbf{b}^\top \mathbf{A} + \mathbf{b}^\top \mathbf{b} + \lambda \text{sign}(\mathbf{x}) \end{aligned}$$

for implementation purposes, we wrap the gradient descent step with a threshold function:

$$\text{prox}_\gamma(\mathbf{x})_i = \begin{cases} x_i - \gamma & \text{if } x_i < \gamma \\ 0 & \text{if } |x_i| \leq \gamma \\ x_i + \gamma & \text{if } x_i > \gamma \end{cases}$$

where $x_{i+1} = \text{prox}_\gamma(x_i - \gamma \nabla f(x_i))$.

We get the following plots:

