Conditional Exponential Distributions: A Worked Example

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1 Conditional Exponential Distributions

Suppose we want to model the amount of time one will have to wait for a taxi pickup based on the location and the time. The exponential distribution is a natural candidate for this situation. The exponential distribution is a continuous distribution supported on $[0, \infty)$. The set of all exponential probability density functions is given by

$$\text{ExpDists} = \{p_\lambda(y) = \lambda e^{-\lambda y}1(y \in [0, \infty)) \mid \lambda \in (0, \infty)\}.$$  

Let $x \in \mathbb{R}^d$ represent the input features from which we want to predict an exponential distribution. We can represent an element of ExpDists by the parameter $\lambda$.

1.1 GLM Approach

We will start with a "generalized linear model" (GLM) approach, in which for a given input $x$, we predict $\lambda = \psi(w^T x)$ for some function $\psi$ and some parameter vector $w \in \mathbb{R}^d$.

1. In a GLM, the function $\psi$ is chosen by the data scientist as part of the model choice. Suggest a reasonable function $\psi$ to map $w^T x$ to $\lambda$. Then write an expression for $p_w(y \mid x)$, the predicted probability density function conditioned on $x$. Because of subsequent problems, you are encouraged to choose a function that is differentiable.

Solution: Since $\lambda \in (0, \infty)$, the range of $\psi$ should also be $(0, \infty)$. Functions that are monotonically increasing as a function of the score
$w^T x$ are preferred, as is differentiability. Thus we will choose $\psi(\cdot) = \exp(\cdot)$. The predicted probability density for a given $x$ is

$$p_w(y \mid x) = e^{w^T x} e^{-\exp(w^T x)y}$$

for $y \geq 0$ and 0 otherwise.

2. Once $\psi$ is chosen, $w \in \mathbb{R}^d$ is determined by maximum likelihood on a training set, say $(x_1, y_1), \ldots, (x_n, y_n)$ sampled i.i.d. $P_{X \times Y}$, where $x_i \in \mathbb{R}^d$ and $y_i \in [0, \infty)$ for $i = 1, \ldots, n$. Give the optimization problem you would solve to fit the GLM.

**Solution:** By independence, the likelihood for the dataset is

$$\prod_{i=1}^n p_w(y_i \mid x_i) = \prod_{i=1}^n e^{w^T x} e^{-\exp(w^T x)y}$$

and the log-likelihood is

$$J(w) = \log \left[ \prod_{i=1}^n p_w(y_i \mid x_i) \right] = \sum_{i=1}^n \left[ w^T x_i - y_i \exp(w^T x_i) \right].$$

Maximizing the likelihood is equivalent to maximizing the log-likelihood. The optimization problem to solve is

$$w^* = \arg \max_{w \in \mathbb{R}^d} J(w).$$

It’s a maximum because we want the maximum likelihood. We can also look for $\arg \min_{w \in \mathbb{R}^d} [-J(w)]$, to be back in our usual minimization setting.

3. Is $-J(w)$ convex?

**Solution:** Yes. $w^T x_i$ is an affine function of $w$ (in fact, it is linear). $\exp(\cdot)$ is a convex function. The composition of a convex function and an affine function is convex. [You can also just remember that $\exp(f(x))$ is convex whenever $f(x)$ is.]. $y_i \geq 0$, so $y_i \exp(w^T x_i)$ is convex, and subtracting off $w^T x_i$ (a linear function) is still convex. [Since $-w^T x_i$ is also convex, we can view $y_i \exp(w^T x_i) + (-w^T x_i)$ as the sum of two convex functions. Finally, the sum over $i$ is a nonnegative [convex] combination of convex functions, and so it’s convex.]
4. Give a numerical method for finding $w^*$. No need to specify a step size plan or a termination plan. Just give the step directions you will use.

**Solution:** We’ll use SGD. At each step we’ll choose a random data point $(x_i, y_i)$ and we’ll take the step

$$w \leftarrow w + \eta \left[ x_i - y_i \exp (w^T x_i) x_i \right],$$

for some step size $\eta$.

### 1.2 GBM Approach

Suppose we are not convinced that $w^T x$ extracts enough information from $x$ to make a good prediction of $\lambda$, and we want to use a nonlinear function of $x$. We can use a gradient boosting approach for this. Rather than predicting $x \mapsto \psi(w^T x)$, where $w$ is learned from the data, we will now predict $x \mapsto \psi(f(x))$, where $f$ is some more general function learned from the data.

1. Write our new objective function $J(f)$, where $f$ is now the function described above.

**Solution:**

$$J(f) = \sum_{i=1}^{n} \left[ f(x_i) - y_i \exp (f(x_i)) \right].$$

2. We can find $f$ using gradient boosting. Let $\mathcal{H}$ be our base hypothesis space of real-valued functions. In each step of gradient boosting, we choose a function $h \in \mathcal{H}$ that solves a particular regression problem. Give this regression problem.

**Solution:** For gradient boosting, we need to compute the gradient at the datapoints. So

$$\frac{\partial}{\partial f(x_i)} J(f) = 1 - y_i \exp [f(x_i)].$$

This is the unconstrained gradient. We want to find the best fit to the negative of this gradient direction among functions in $\mathcal{H}$. This is the following regression problem:

$$h^* = \arg \min_{h \in \mathcal{H}} \sum_{i=1}^{n} \left[ - \frac{\partial}{\partial f(x_i)} J(f) - h(x_i) \right]^2$$

$$= \arg \min_{h \in \mathcal{H}} \sum_{i=1}^{n} \left[ - (1 - y_i \exp [f(x_i)]) - h(x_i) \right]^2$$
3. Give the full GBM algorithm for finding the maximum likelihood function \( f \). No need to specify a stopping criterion. You may assume that the algorithm takes \( M \) steps, if that it makes the algorithm easier to express:

**Solution:**

(a) Initialize \( f_0(x) = 0 \).

(b) For \( m = 1 \) to \( M \):

   i. Compute:
   \[
   g_m = (1 - y_i \exp[f_{m-1}(x_i)])^{n}_{i=1}
   \]

   ii. Fit regression model to \(-g_m\):
   \[
   h_m = \arg \min_{h \in \mathcal{H}} \sum_{i=1}^{n} (-g_m)_i - h(x_i))^2.
   \]

   A. Choose fixed step size \( \nu_m = \nu \in (0, 1] \), or take
   \[
   \nu_m = \arg \max_{\nu > 0} J(f_{m-1} + \nu h_m).
   \]

   B. Take the step:
   \[
   f_m(x) = f_{m-1}(x) + \nu_m h_m(x)
   \]