Gradient Boosting Practice: Poisson Response

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Suppose we're trying to predict a distribution of count from some input covariates. The simplest distribution in this situation is the Poisson distribution:

$$p(k;\lambda) \quad = \quad \frac{e^{-\lambda}\lambda^k}{k!}$$

on $k = 0, 1, 2, 3, \ldots$ $\lambda \in (0, \infty)$.

1 Linear Conditional Probability Model

- Input: $x \in \mathbf{R}^d$.
- Output: $y \in \{0, 1, 2, \ldots\}$
- Data:

$$\mathcal{D} = ((x_1, y_1), \ldots, (x_n, y_n)) \in \left(\mathbf{R}^d \times \{0, 1, 2, \ldots\}\right)^n$$

assume is sampled i.i.d. from some distribution $P_{\mathcal{X}\times\mathcal{Y}}$.

- Action: $\lambda \in (0, \infty)$, where λ is the parameter of a Poisson distribution.

We've got to map input x to action λ in our action space, which is $(0, \infty)$.

$$x \mapsto \underbrace{w^T x}_{\text{score } s \in \mathbf{R}} \mapsto \underbrace{\lambda}_{\in (0,\infty)}$$

To map the score s into our action space, we could use the transfer function $\psi(s) = \exp(s)$. Then

$$\lambda = \exp\left(w^T x\right).$$

So if we predict λ, what's the probability of an observed count k for input vector x?

$$\begin{aligned} p(y=k \mid x; w) &= \frac{e^{-\lambda(x)}\lambda(x)^k}{k!} \\ &= \frac{e^{-\exp\left(w^T x\right)}\left[\exp\left(w^T x\right)\right]^k}{k!}. \end{aligned}$$

The conditional likelihood for particular example (x_i, y_i), (where y_i is a count) is

$$p(y=y_i \mid x_i; w) = \frac{e^{-\exp\left(w^T x_i\right)}\left[\exp\left(w^T x_i\right)\right]^{y_i}}{y_i!}.$$

Easier to work with the log:

$$\log p(y=y_i \mid x_i; w) = -\exp\left(w^T x_i\right) + y_i w^T x_i - \log(y_i!)$$

What do we need to find to fit this model? w. our strategy is to use maximum log-likelihood:

$$\begin{aligned} \log L_{\mathcal{D}}(w) &= \log p(\mathcal{D}; w) \\ &= \sum_{i=1}^{n} \log p(y=y_i \mid x_i; w) \\ &= \sum_{i=1}^{n} \left[-\exp\left(w^T x_i\right) + y_i w^T x_i - \log(y_i!)\right] \end{aligned}$$

So find w maximizing this log-likelihood and we're done. Can use standard gradient based methods.

2 Nonlinear approach

In a nonlinear approach, we'll replace the linear score function $s = w^T x$ with a nonlinear function $s = f(x)$:

$$x \mapsto \underbrace{f(x)}_{\text{score } s \in \mathbf{R}} \mapsto \underbrace{\lambda}_{\in(0,\infty)}.$$

Again, we can use the transfer function $\psi(s) = \exp(s)$. So

$$\lambda = \exp(f(x)).$$

For score function f, the probability of $y_i \mid x_i$ is:

$$p(y = y_i \mid x_i; f) = \frac{e^{-\exp(f(x_i))}\left[\exp(f(x_i))\right]^{y_i}}{y_i!}.$$

Easier to work with the log:

$$\log p(y = y_i \mid x_i; f) = -\exp(f(x_i)) + y_i f(x_i) - \log(y_i!)$$

Somehow we want to find a function f that gives high log-likelihood to our observed data:

$$\log L_{\mathcal{D}}(w) = \sum_{i=1}^{n}\left[-\exp(f(x_i)) + y_i f(x_i) - \log(y_i!)\right]$$

3 Gradient Boosting Approach

Let's differentiate $\log p(y = y_i \mid x_i; f)$ w.r.t. $f(x_i)$:

$$\frac{\partial}{\partial f(x_i)} \log p(y = y_i \mid x_i; f) = -\exp(f(x_i)) + y_i$$

Now differentating the full log-likelihooed is

$$\begin{aligned}\frac{\partial}{\partial f(x_i)}\left[\log L_{\mathcal{D}}(f)\right] &= \frac{\partial}{\partial f(x_i)}\left[-\exp(f(x_i)) + y_i f(x_i) - \log(y_i!)\right] \\ &= -\exp(f(x_i)) + y_i\end{aligned}$$

So optimal unconstrained step direction for changing the vector of evaluations $\mathbf{f} = (f(x_1), \ldots, f(x_n))$ is

$$-\mathbf{g} = \left(-y_1 + \exp(f(x_1)), \ldots, -y_n + \exp(f(x_n))\right)$$

Fix some base hypothesis space $\mathcal{H}$ of functions $h : \mathbf{R}^d \to \mathbf{R}$. Then, our actual step direction will be the $h \in \mathcal{H}$ that best fits $-\mathbf{g}$ in the least squares sense:

$$\begin{aligned}&\arg\min_{h \in \mathcal{H}} \sum_{i=1}^{n} \left(-\mathbf{g}_i - h(x_i)\right)^2 \\ = \; &\arg\min_{h \in \mathcal{H}} \sum_{i=1}^{n} \left(\left[-y_i + \exp(f(x_i))\right] - h(x_i)\right)^2\end{aligned}$$

So to recap:

1. Up to this point, our score function is f.
2. We want to improve f.
3. The optimal step direction for $f(x_i)$ is $-y_i + \exp(f(x_i))$. We can evaluate this. It's a real number.
4. So we have a bunch of $(x_i, -\mathbf{g}_i)$ pairs that we will use regression over $\mathcal{H}$ to fit.

Then we add something like $0.1h$ to f and repeat.