

The background of the slide features a large, faint, light blue seal of Georgetown University. The seal is circular and contains an eagle with a shield on its chest, holding an olive branch and arrows. Above the eagle is a lyre. The text "MACI IN M" is visible at the top, "UTRAQUE UNUM" on a banner across the eagle, and "GEORGIOPOLITANA" at the bottom.

ANLY-601

Advanced Pattern Recognition

Assignment Project Exam Help
Spring 2018

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L11 – Map Estimates, Bayesian
Inference, Hyperparameter Choice

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Continuing with Bayesian Methods

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MAP Estimates, Bayesian Inference,
and Hyperparameter Choice
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Why use a MAP Estimate, they're Biased?

Consider the expected squared error of any estimator:

$$MSE = E[(\bar{\mu} - \mu)^2] = E[(\bar{\mu} - E[\bar{\mu}] + (E[\bar{\mu}] - \mu))^2]$$

$$= E[(\bar{\mu} - E[\bar{\mu}])^2] + (E[\bar{\mu}] - \mu)^2$$

$$= \text{var}(\bar{\mu}) + \text{bias}^2$$

Bias isn't the only consideration - variance is also important. There's usually a trade-off; increase the bias, and the variance drops, and vice-versa.

Bias-Variance Trade-Off and MAP Estimates

Let's go back to our MAP estimate of the mean for Gaussian data:

$$\bar{\mu} = \frac{m\lambda^2}{m\lambda^2 + \sigma^2} \frac{1}{m} \sum_{i=1}^m x_i + \frac{\sigma^2}{m\lambda^2 + \sigma^2} \mu_0$$

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The bias and variance are (show these!)

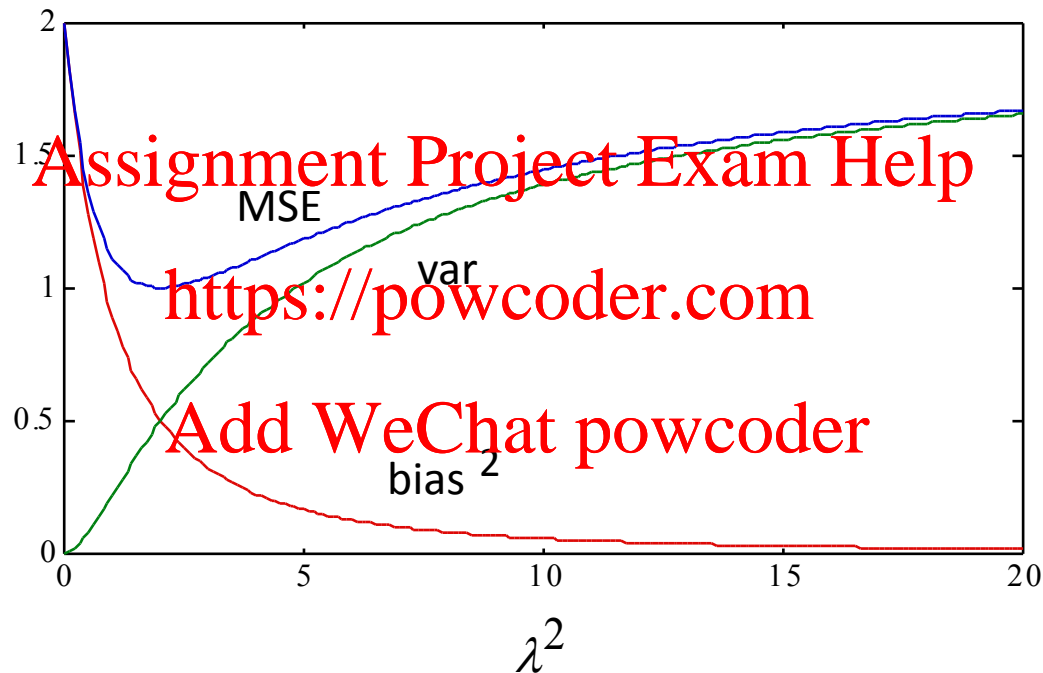
$$bias^2 = (E[\bar{\mu}] - \mu)^2 = \left(\frac{\sigma^2}{m\lambda^2 + \sigma^2} (\mu_0 - \mu) \right)^2$$

$$var(\bar{\mu}) = E[(\bar{\mu} - E[\bar{\mu}])^2] = \left(\frac{m\lambda^2}{m\lambda^2 + \sigma^2} \right)^2 \frac{\sigma^2}{m}$$

As $m \rightarrow \infty$
both go to zero

Bias-Variance Trade-Off and MAP Estimates

The curves look like this



The curve of MSE has its minimum at
a non-zero value of λ . Specifically -- $\lambda_{opt}^2 = (\mu_0 - \mu)^2$

MAP Estimates and Regularizers

The log of the posterior on the parameters is

$$\log(p(\Theta | D)) = \log(p(D | \Theta)) + \log(p(\Theta)) - \log(p(D))$$

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log-likelihood – bare cost log prior -- regularizer
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We saw that maximizing the data log likelihood is equivalent to minimizing some nice cost function -- e.g. the mean-squared-error.

Maximizing the log-posterior is equivalent to minimizing a regularized cost function. **The effect of the regularizer is to reduce the parameter variance at the cost of adding parameter bias.**

MAP Regression

One can use the MAP estimate of Θ , and construct the regression function

$$E[t | x, D] = f(t | x, \hat{\Theta})$$

where $\hat{\Theta}$ is the value that maximizes the posterior $p(\Theta|D)$.

One can also use this MAP value to estimate the target density

$$p(t | x, \hat{\Theta}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp - \frac{1}{2\sigma^2} (t - f(t | x, \hat{\theta}))^2$$

Example of Map Regression – Ridge

Ridge regression uses a parameterized regressor $f(x, \theta)$, the familiar SSE cost function (Gaussian likelihood for the targets), and a Gaussian prior on the parameters, typically centered at zero

$$p(\theta) = \frac{1}{\sqrt{2\pi/\Lambda}} \exp\left(-\frac{\Lambda}{2} |\theta|^2\right)$$

The regularized cost function is thus

$$E(\Lambda, \theta) = \sum_{i=1}^M (t_i - f(x_i, \theta))^2 + \Lambda |\theta|^2$$

That for linear regression, $f(x, \theta)$ is linear in θ so E is quadratic in θ and the cost function can be minimized in closed form (just like MLE estimation for linear regression).

Bayesian Estimation

Let's continue. Suppose we have obtained the posterior on the parameters $p(\Theta | D)$ and we wish to find the probability of a new data value x . A Bayesian says that you should calculate this from his version of the distribution $p(x)$

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 $p(x|D) = \int p(x|\Theta) p(\Theta|D) d\Theta$

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A Bayesian computes the mean of any function $f(x)$ as

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$$E[f | D] = \int f(x) p(x | D) dx = \iint f(x) p(x | \Theta) p(\Theta | D) d\Theta dx$$

Bayesian and MAP Estimates

Relation to **MAP** Estimates: Suppose the posterior is sharply peaked up about its maximum value (the MAP estimate). Write a series expansion of $p(x|\Theta)$ about the maximum and substitute into the integral

$$\begin{aligned}
 p(x|D) &= \int p(x|\Theta) p(\Theta|D) d\Theta = \int \left[p(x|\hat{\Theta}) + \left. \frac{dp(x|\Theta)}{d\Theta} \right|_{\hat{\Theta}} (\Theta - \hat{\Theta}) \right. \\
 &\quad \left. + \frac{1}{2} \left. \frac{d^2 p(x|\Theta)}{d\Theta^2} \right|_{\hat{\Theta}} (\Theta - \hat{\Theta})^2 + \dots \right] p(\Theta|D) d\Theta \\
 &= p(x|\hat{\Theta}) + \left. \frac{dp(x|\Theta)}{d\Theta} \right|_{\hat{\Theta}} E[(\Theta - \hat{\Theta})|D] + \frac{1}{2} \left. \frac{d^2 p(x|\Theta)}{d\Theta^2} \right|_{\hat{\Theta}} E[(\Theta - \hat{\Theta})^2|D] + \dots
 \end{aligned}$$

Bayesian and MAP Estimates

$$\begin{aligned}
 p(x|D) &= \int p(x|\Theta) p(\Theta|D) d\Theta = \int \left[p(x|\hat{\Theta}) + \frac{dp(x|\Theta)}{d\Theta} \Big|_{\hat{\Theta}} (\Theta - \hat{\Theta}) \right. \\
 &\quad \left. + \frac{1}{2} \frac{d^2 p(x|\Theta)}{d\Theta^2} \Big|_{\hat{\Theta}} (\Theta - \hat{\Theta})^2 + \dots \right] p(\Theta|D) d\Theta \\
 &= p(x|\hat{\Theta}) + \frac{dp(x|\Theta)}{d\Theta} \Big|_{\hat{\Theta}} E[(\Theta - \hat{\Theta})|D] + \frac{1}{2} \frac{d^2 p(x|\Theta)}{d\Theta^2} \Big|_{\hat{\Theta}} E[(\Theta - \hat{\Theta})^2|D] + \dots
 \end{aligned}$$

Handwaving arg: As data increases, the posterior becomes more sharply peaked about the MAP value $\hat{\Theta}$, trailing terms will become small & integral is approximately

$$p(x|D) \approx p(x|\hat{\Theta})$$

Recursive Bayesian Estimation

Back to Bayesian estimation of $p(x|D)$

$$p(x|D) = \int p(x|\Theta) p(\Theta|D) d\Theta = \int p(x|\Theta) \frac{p(D|\Theta) p(\Theta)}{\int p(D|\Theta') p(\Theta') d\Theta'} d\Theta$$

Denote the dataset with n points by $D^n = \{x_1, x_2, \dots, x_n\}$, and its likelihood by

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$$p(D^n | \Theta) = \prod_{k=1}^n p(x_k | \Theta) = p(x_n | \Theta) p(D^{n-1} | \Theta)$$

Using the last expression, the posterior can be written

$$p(\Theta | D^n) = \frac{p(x_n | \Theta) p(\Theta | D^{n-1})}{\int p(x_n | \Theta') p(\Theta' | D^{n-1}) d\Theta'}$$

Recursive Bayesian Estimation

We have written the posterior density for the n-sample data set as

$$p(\Theta | D^n) = \frac{p(x_n | \Theta) p(\Theta | D^{n-1})}{\int p(x_n | \Theta') p(\Theta' | D^{n-1}) d\Theta'}$$

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Starting with zero data, we take $p(\Theta | D^0) = p(\Theta)$ and generate the sequence

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and thus incrementally refine our estimate of the posterior density as more and more data becomes available.

How Does a Bayesian do Regression?

Get a dataset $D \equiv \{ (x_i, t_i) \mid i = 1, \dots, m \}$

Choose a parameterized regression function $f(x; \Theta)$ to fit to the data.

Choose a model distribution function for the targets, e.g. a Gaussian

$$p(t \mid x, \sigma^2, \Theta) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[-\frac{1}{2\sigma^2} (t - f(x; \Theta))^2 \right]$$

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Choose a prior distribution on the parameters $p(\Theta, \sigma^2)$.

Calculate the data likelihood and the posterior distribution of the parameters

$$p(\Theta, \sigma^2 \mid D) = \frac{1}{p(D)} p(D \mid \Theta, \sigma^2) p(\Theta, \sigma^2)$$

How Does a Bayesian Do Regression?

Calculate the target density as a function of x by integrating over the posterior distribution of the parameters

$$p(t | x, D) = \int p(t | x, \sigma^2, \Theta) p(\sigma^2, \Theta | D) d\sigma^2 d\Theta$$

From the distribution on t , we can calculate several quantities.

- The conditional mean $E[t | x, D]$ (called the regressor, and equal to

$$\begin{aligned} E[t | x, D] &= \int t p(t | x, D) dt \\ &= \int \int t p(t | x, \sigma^2, \Theta) dt d\sigma^2 d\Theta = \int f(x; \Theta) p(\Theta | D) d\Theta \end{aligned}$$

for our Gaussian model.)

- The most likely value(s) of t $\arg \max_t p(t | x, D)$
- The target variance $\text{var}(t | x, D)$.

Hyperparameters and Model Selection

Our prior on model parameters is itself a parameterized distribution. Recall for our Gaussian density model, we put a prior on the distribution of the mean

$$p(\mu \mid \mu_0, \lambda^2) = \frac{1}{\sqrt{2\pi\lambda^2}} \exp\left[-\frac{1}{2\lambda^2} (\mu - \mu_0)^2\right]$$

But how were the hyperparameters chosen μ_0, λ^2

Hyperparameter Selection

- We could calculate the likelihood function for particular values

$$p(D | \mu_0, \lambda^2) = \int p(D | \mu) p(\mu | \mu_0, \lambda^2) d\mu$$

and choose the values of the hyperparameters that maximizes it.

- We could set up a hyperprior on the hyperparameters and choose maximum a posteriori values for the hyperparameters by maximizing

$$p(\mu_0, \lambda^2 | D) \propto p(D | \mu_0, \lambda^2) p(\mu_0, \lambda^2)$$

(but the hyperprior is going to have its own parameters ...).

- Use some sort of empirical technique.

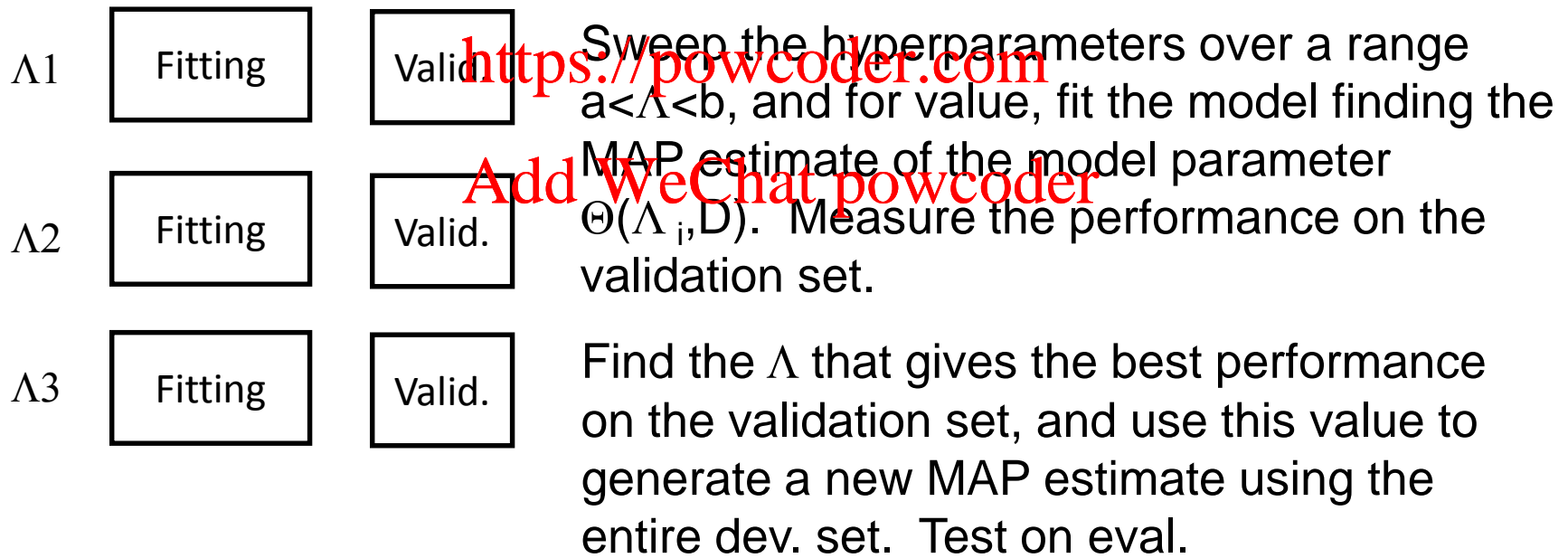
Empirical Hyperparameter Selection

Using a 'validation' set and MAP estimates.

Divide data into two pieces, development and evaluation



Further divide the development set into fitting and validation



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