S&DS 265 / 565

Introductory Machine Learning

Stochastic Gradient Descent and Bias-Variance Tradeoffs

September 27

Yale

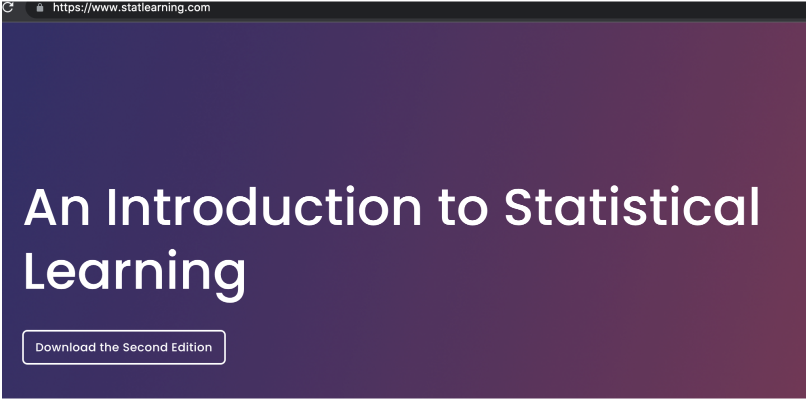
Goings on

- Assignment 1 due Thursday
- Assignment 2 posted Thursday
- Quiz 2 scores out: Average 84%, great!
- Quiz 3 posted next week
- Midterm: October 18 (in class)

Readings

					classification	
4	Sept 20, 22	Stochastic gradient descent	SGD examples	Sept 20: Classification (continued) Sept 22: Stochastic gradient descent	ISL Section 6.2.2 ISL Section 10.7.2	Thu: Quiz 2
5	Sept 27, 29	Bias and variance, cross-validation	Bias-variance tradeoff Covid trends (revisited) California housing	Sept 27: Bias and variance Sept 29: Cross-validation	ISL Section 2.2 ISL Section 5.1	Thu: Assn 1 in Assn2 out
6	Oct 4, 6	Tree-based methods	Trees and forests Visualizing trees	Oct 4: Trees Oct 6: Forests	ISL Sections 8.1, 8.2	Thu: Quiz 3

Readings



statlearning.com

Outline for today

- Stochastic gradient descent (redux)
- Regularization
- Jupyter notebook example
- Bias-variance tradeoffs

SGD idea

- For each parameter β_j, see what happens to the loss if that parameter is increased a little bit.
- If the loss goes down (up), then increase (decrease) β_j proportionately
- Do this simultaneously for all of the parameters
- Rinse and repeat

Stochastic gradient descent

Initialize all parameters to zero: $\beta_j = 0$, $j = 1, \ldots, p$.

Read through the data one record at a time, and update the model.

1. Read data item x
2. Make a prediction $\widehat{y}(x)$
3. Observe the true response/label y
4. Update the parameters β so $\widehat{y}$ is closer to y

Stochastic gradient descent

Suppose we are doing *linear regression*. We initialize all parameters to zero: $\beta_j = 0$, $j = 1, \ldots, p$.

We read through the data one record at a time, and update the model.

1. Read data item x
2. Make a prediction $\widehat{y}(x) = \sum_{j=1}^{p} \beta_j x_j$
3. Observe the true response/label y
4. Update the parameters β so $\widehat{y}$ is closer to y

SGD idea

Change β_j by a little bit:

$$\beta_j \to \beta_j + \varepsilon$$

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What happens to the squared error?

$$\begin{aligned}(y - \widehat{y})^2 &\to (y - \widehat{y} - \varepsilon x_j)^2 \\ &\approx (y - \widehat{y})^2 + \underbrace{-2(y - \widehat{y})x_j}_{\textit{derivative of loss}} \varepsilon\end{aligned}$$

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Use adjustment

$$\begin{aligned}\beta_j &\to \beta_j \overbrace{-\eta \cdot \text{derivative of loss}}^{\varepsilon} \\ &= \beta_j + \eta \cdot 2(y - \widehat{y})x_j\end{aligned}$$

SGD idea

Change β_j by a little bit:

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Use adjustment

$$\begin{aligned}\beta_j &\to \beta_j \overbrace{-\eta \cdot \text{derivative of loss}}^{\varepsilon} \\ &= \beta_j + \eta \cdot 2(y - \widehat{y})x_j\end{aligned}$$

Squared error then decreases:

$$(y - \widehat{y})^2 \approx (y - \widehat{y})^2 - \eta \cdot \text{derivative of loss } \underline{\text{squared}}$$

SGD for general loss

Suppose $L(y, \beta^T x)$ is the loss for an input (x, y), e.g., $(y - \beta^T x)^2$

SGD update:

$$\beta_j \longleftarrow \beta_j - \eta \frac{\partial L(y, \boldsymbol{\beta}^T x)}{\partial \beta_j}$$

$$\boldsymbol{\beta} \longleftarrow \boldsymbol{\beta} - \eta \nabla_{\beta} L(y, \boldsymbol{\beta}^T x) \quad \text{(vector notation)}$$

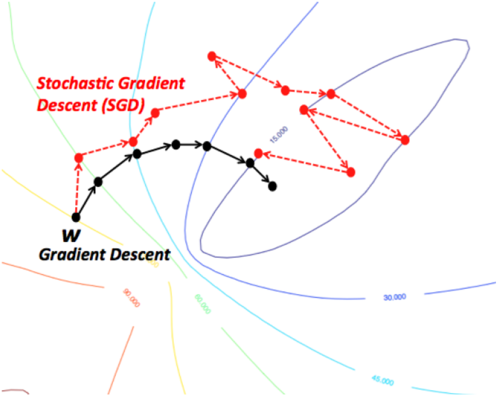
"Batch" gradient descent uses the entire training set in each step of gradient descent.

Stochastic gradient descent computes a quick approximation to this gradient, using only a single or a small "mini-batch" of data points

Batch vs. stochastic gradient descent

- The average derivative over a mini-batch can be thought of as a noisy version of the average derivative over the entire data set
- (Which can in turn be thought of as a sample estimate of a population)
- The stochastic gradient is computed more cheaply, and updating the parameters makes progress more quickly

Batch vs. stochastic gradient descent



https://wikidocs.net/3413

SGD for logistic regression

SGD Update:

$$\beta_j \longleftarrow \beta_j + \eta(y - p(x))x_j$$

$$\beta_j x_j \longleftarrow \beta_j x_j + \eta(y - p(x))x_j^2$$

$$p(x) = \frac{1}{1 + \exp(-\beta^T x)}$$

Case checking:

- Suppose $y = 1$ and probability $p(x)$ is high?

SGD for logistic regression

SGD Update:

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$$p(x) = \frac{1}{1 + \exp(-\beta^T x)}$$

Case checking:

- Suppose $y = 1$ and probability $p(x)$ is high? *small change*
- Suppose $y = 1$ and probability $p(x)$ is small?

SGD for logistic regression

SGD Update:

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Case checking:

- Suppose $y = 1$ and probability $p(x)$ is high? *small change*
- Suppose $y = 1$ and probability $p(x)$ is small? *big change* $\uparrow$
- Suppose $y = 0$ and probability $p(x)$ is small?

SGD for logistic regression

SGD Update:

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Case checking:

- Suppose $y = 1$ and probability $p(x)$ is high? *small change*
- Suppose $y = 1$ and probability $p(x)$ is small? *big change* $\uparrow$
- Suppose $y = 0$ and probability $p(x)$ is small? *small change*
- Suppose $y = 0$ and probability $p(x)$ is big?

SGD for logistic regression

SGD Update:

$$\beta_j \longleftarrow \beta_j + \eta(y - p(x))x_j$$

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Case checking:

- Suppose $y = 1$ and probability $p(x)$ is high? *small change*
- Suppose $y = 1$ and probability $p(x)$ is small? *big change* $\uparrow$
- Suppose $y = 0$ and probability $p(x)$ is small? *small change*
- Suppose $y = 0$ and probability $p(x)$ is big? *big change* $\downarrow$

SGD: choice of learning rate

A conservative choice of learning rate is

$$\eta_t = \frac{1}{t}$$

A more agressive choice is

$$\eta_t = \frac{1}{\sqrt{t}}$$

In practice: Try learning rates $C/\sqrt{t}$ for different choices of C, and monitor the error

$$\frac{1}{T}\sum_{t=1}^{T}(Y_t - \widehat{Y}_t)^2$$

SGD: Regularization

A "ridge" penalty $\frac{1}{2}\lambda \sum_{j=1}^{d} \beta_j^2$ is easily handled.

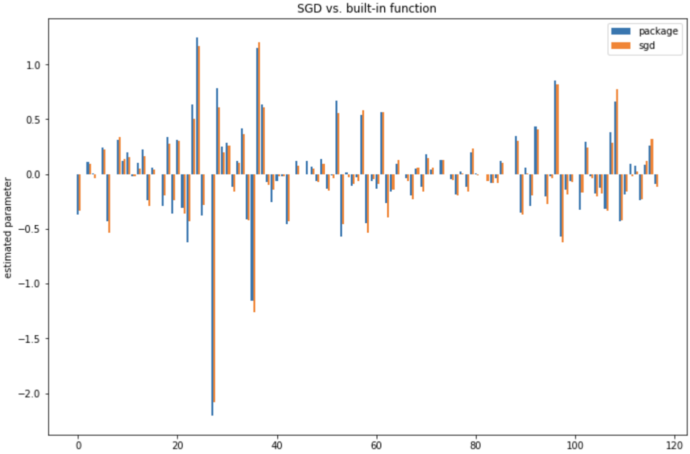
Gradient changes by an additive term $2\lambda\beta_j$. Update becomes

$$\begin{aligned} \beta_j &\longleftarrow \beta_j + \eta\{(y - p(x))x_j - \lambda\beta_j\} \\ &= (1 - \eta\lambda)\beta_j + \eta(y - p(x))x_j \end{aligned}$$

Check that this "does the right thing" whether β_j wants to be large positive or negative.

- *The penalty shrinks β_j toward zero*

Recall from demo



Bias and variance

Bias: How much are we off—on average?

Variance: How variable are we—on average?

Bias and variance

Bias: $\theta - \mathbb{E}\widehat{\theta}$

Variance: $\mathbb{E}(\widehat{\theta} - \mathbb{E}\widehat{\theta})^2$

Bias and variance

Examples of $\theta, \widehat{\theta}$:

Estimating height, population, election outcome, ad click rate...

Bias and variance

Bias: $\theta - \mathbb{E}\widehat{\theta}$

Variance: $\mathbb{E}(\widehat{\theta} - \mathbb{E}\widehat{\theta})^2$

Bias and variance

Bias: $\theta - \mathbb{E}\widehat{\theta}$

Variance: $\mathbb{E}(\widehat{\theta} - \mathbb{E}\widehat{\theta})^2$

- $\widehat{\theta}$ is an estimate from a sample
- $\mathbb{E}$ is the expectation (average) with respect to the sample
- So $\mathbb{E}\widehat{\theta}$ is the average estimate
- We can only directly compute $\widehat{\theta}$ for the sample we have
- *We don't know θ*

Bias and variance

Bias and variance are two sides of the same coin: As squared bias goes up, variance goes down

Bias-variance tradeoff

$$\text{Risk} = \text{Bias}^2 + \text{Variance}$$

Bias-variance tradeoff

$$\mathbb{E}(\theta - \widehat{\theta})^2 = \text{Bias}(\widehat{\theta})^2 + \text{Variance}(\theta)$$

Bias-variance tradeoff

$$\mathbb{E}(\theta - \widehat{\theta})^2 = (\theta - \mathbb{E}\widehat{\theta})^2 + \mathbb{E}(\widehat{\theta} - \mathbb{E}\widehat{\theta})^2$$

Bias-variance tradeoff

Proof:

$$\mathbb{E}(\theta - \widehat{\theta})^2 = \mathbb{E}(\theta - \mathbb{E}\widehat{\theta} + \mathbb{E}\widehat{\theta} - \widehat{\theta})^2$$

Bias-variance tradeoff

Proof:

$$\begin{aligned}\mathbb{E}(\theta - \widehat{\theta})^2 &= \mathbb{E}(\theta - \mathbb{E}\widehat{\theta} + \mathbb{E}\widehat{\theta} - \widehat{\theta})^2 \\ &= \mathbb{E}(\theta - \mathbb{E}\widehat{\theta})^2 - 2\mathbb{E}\left\{(\theta - \mathbb{E}\widehat{\theta})(\widehat{\theta} - \mathbb{E}\widehat{\theta})\right\} + \mathbb{E}(\widehat{\theta} - \mathbb{E}\widehat{\theta})^2\end{aligned}$$

Bias-variance tradeoff

Proof:

$$
\begin{aligned}
\mathbb{E}(\theta - \widehat{\theta})^2 &= \mathbb{E}(\theta - \mathbb{E}\widehat{\theta} + \mathbb{E}\widehat{\theta} - \widehat{\theta})^2 \\
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&= \mathbb{E}(\theta - \mathbb{E}\widehat{\theta})^2 - 2(\theta - \mathbb{E}\widehat{\theta})\mathbb{E}(\widehat{\theta} - \mathbb{E}\widehat{\theta}) + \mathbb{E}(\widehat{\theta} - \mathbb{E}\widehat{\theta})^2
\end{aligned}
$$

Bias-variance tradeoff

Proof:

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Bias-variance tradeoff

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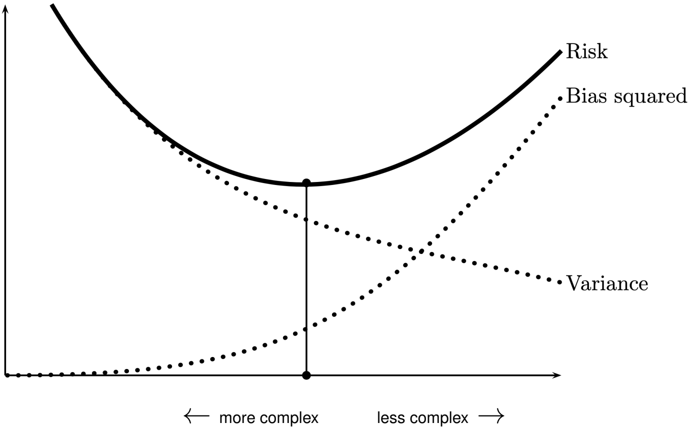
&= \mathbb{E}(\theta - \mathbb{E}\widehat{\theta})^2 + \mathbb{E}(\widehat{\theta} - \mathbb{E}\widehat{\theta})^2 \\
&= \mathrm{Bias}(\widehat{\theta})^2 + \mathrm{Variance}(\widehat{\theta})
\end{aligned}
$$

Bias-variance tradeoff



Example: Regularization

Suppose that $\mathbb{E}(Y) = \theta^*$ and we estimate

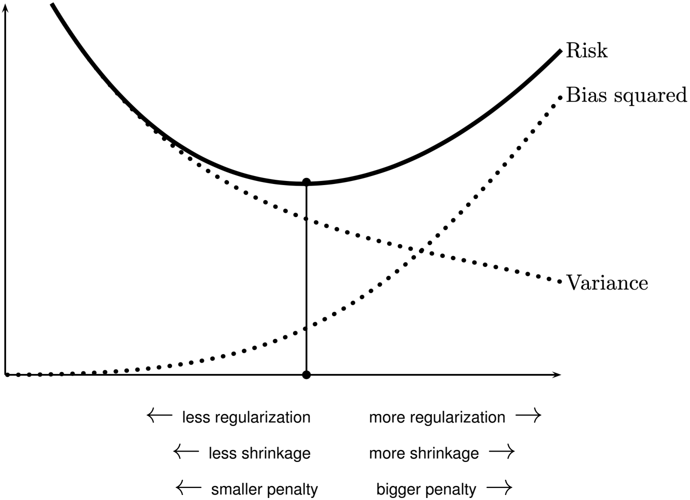
$$\widehat{\theta} = \arg\min_{\theta} (Y - \theta)^2 + \lambda\theta^2$$

Then $\widehat{\theta} = \frac{Y}{1+\lambda}$. What are the squared bias and variance?

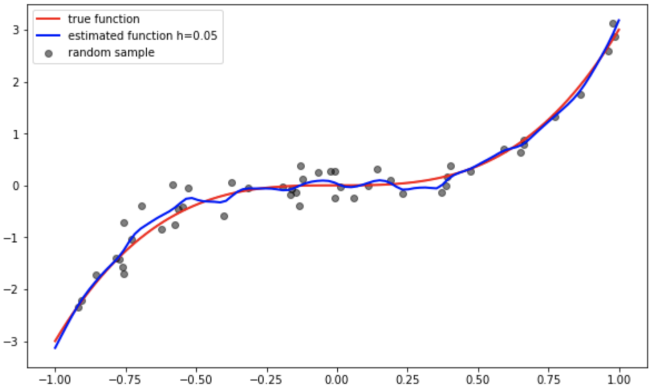
$$\text{Bias}^2 = \theta^{*2} \left(\frac{\lambda}{1+\lambda}\right)^2$$

$$\text{Variance} = \left(\frac{1}{1+\lambda}\right)^2 \text{Variance}(Y)$$

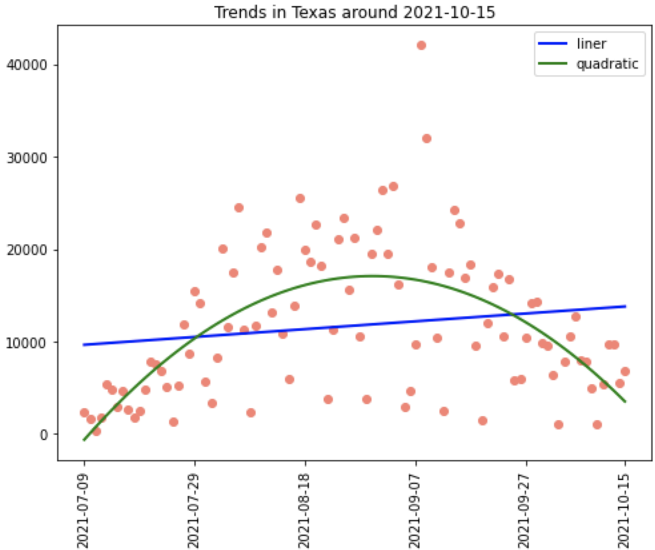
Bias-variance tradeoff



Let's go to the first notebook



Let's go to the second notebook



What did we learn today?

- In SGD, a parameter is updated according to how much the loss changes when that parameter is changed by a little bit
- Mean squared error splits into squared bias plus variance
- As model complexity increases, squared bias decreases while variance increases