LINEAR REGRESSION II

11.16.2018

HOMEWORK 4

* is due monday after next!



RECAP

- * how do we solve linear regression problems?
 - * find weights that minimize the sum of squared errors!
 - * (squared error function is a PARABOLA)
 - * this requires *simultaneously* estimating all the weights

RECAP

- * gradient descent!
 - * given the current settings of the weights, what small change would decrease the error the most?
 - * take many tiny steps, this will eventually lead to the right answer
- * or.. an analytic solution!

ANALYTIC REGRESSION

- * there is an equation that can exactly solve the least-squared-error problem
 - * (if this is what you want to do! sometimes it is, sometimes it isn't)

$$\hat{\beta} = (X^{\top} X)^{-1} X^{\top} Y$$

ANALYTIC REGRESSION

- * np.linalg.lstsq solves least squares regression (example)
- * it returns 4 things:
 - * the regression weights (beta)
 - * the residuals (final squared error)
 - * the rank (we'll talk about this later)
 - * the singular values (ditto)

- * how do you know if a regression model is good?
- * one common metric is R², also called the coefficient of determination or variance explained

- * $R^2 = 1 (RSS / TSS)$
- * where RSS is the "residual sum of squares" (this is squared error, which we've seen)
- * and TSS is the "total sum of squares" (like squared error if your model always predicted zero)

* we can also define it in terms of variance

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* R^2 = 1 - (var(y-y_hat) / var(y))
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* what's the difference between squared error and variance?

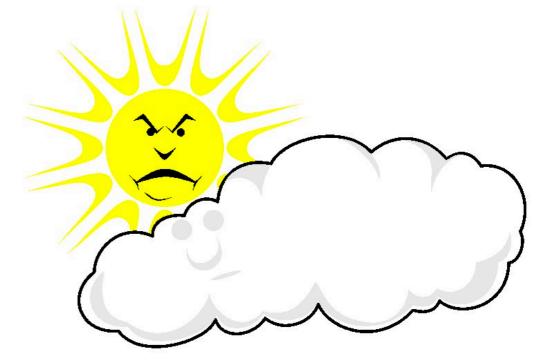
- * suppose that we are given a matrix of variables (aka regressors) X, and a vector of outputs Y
- * we fit a linear model Y_hat = X . beta
- * then we evaluate it by computing \mathbf{R}^2 using \mathbf{X} and \mathbf{Y}
- * what are the possible values of R2?

IN-SET VS. OUT-OF-SET EVALUATION

- * evaluating a regression model using the same data that we used to train/estimate/fit it is called in-set evaluation
- * in-set evaluation is biased *upward*, and the amount of bias depends on the number of regressors in the model

IN-SET VS. OUT-OF-SET EVALUATION

- * for example: suppose we have N data points and N regressors that are pure noise—they have no relationship to the output whatsoever
- * in-set variance explained is EXACTLY 1.0
- * THE MODEL IS PERFECT
- * **THIS IS BOGUS**



IN-SET VS. OUT-OF-SET EVALUATION

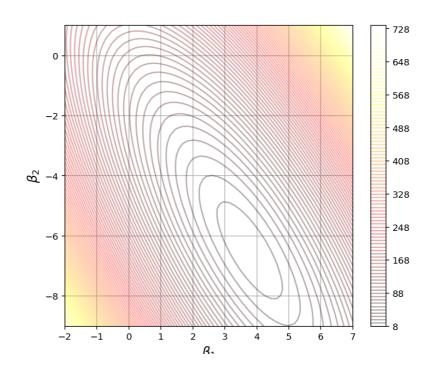
- * instead, what if you split up your X and Y into "training" and "test" sets?
- * you could fit your regression model using (X_trn, Y_trn), and then test how well it works on (X_test, Y_test)!
- * is **R**² biased in this case? What possible values can it take?

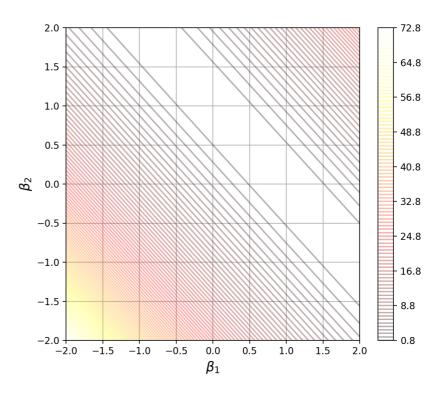
- * as hinted at on wednesday, ordinary least squares regression has a problem:
- * if two regressors are similar (i.e. correlated), then there are many possible weight combinations that would give ~the same answer!
- * which set of weights is "best" ends up being totally determined by noise (example)

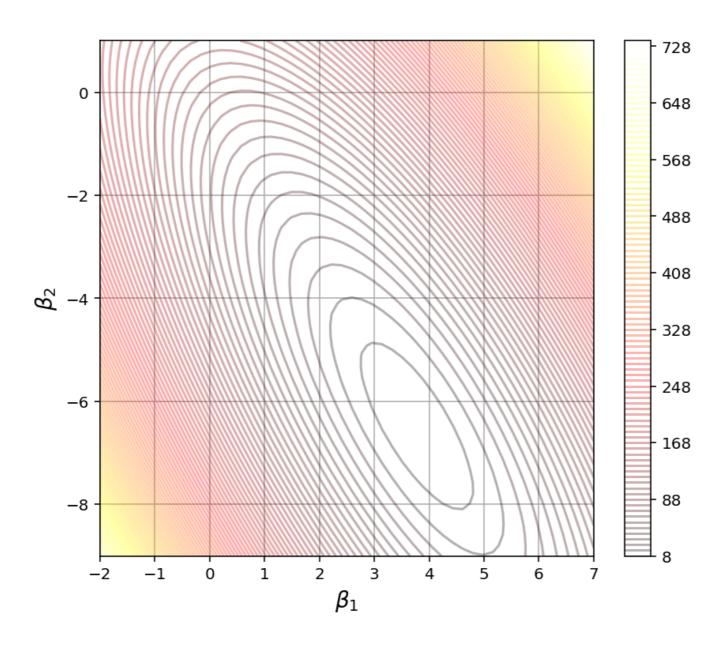
- * this is bad: if your weights are essentially random, they are ~impossible to interpret, and model performance can suffer, so:
- * (1) let's figure out when this is happening, and
- * (2) let's stop it from happening

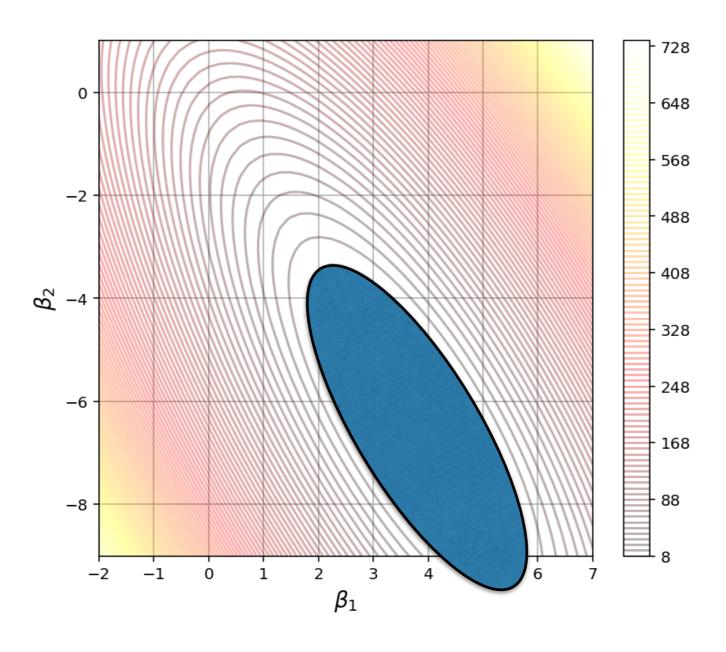
* how do we know when regression is unstable?

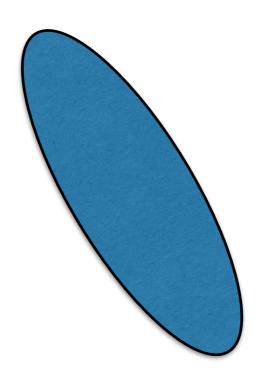
* it's related to the shape of the error function!

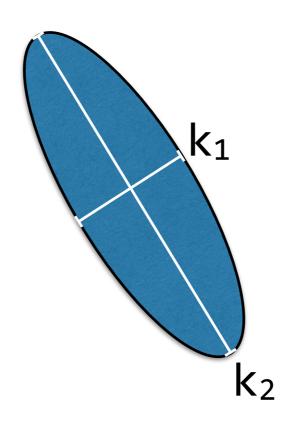


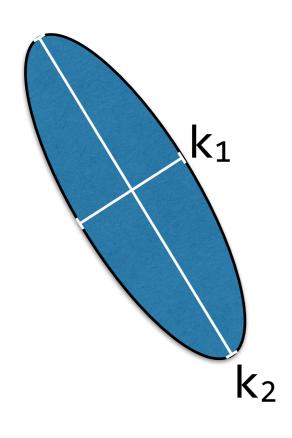


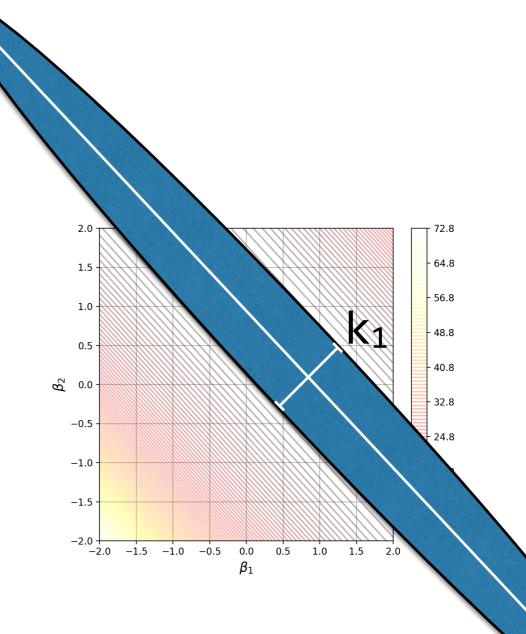












- * the dimensions of the error ellipse, k_1 and k_2 , are related to the **singular values** returned by np.linalg.lstsq!
- * if the singular values (ordered from largest to smallest) are s₁, s₂, etc.,
- * then $k_1 \propto s_1^{-1}$, $k_2 \propto s_2^{-1}$, etc.

- * so it's easy to detect when a regression is unstable: look for tiny singular values! (example)
- * (or at least, tiny relative to the largest singular value)

- * but what do you do if the regression is unstable?
- * how could you possibly solve this problem?

END