STA302/STA1001, Weeks 11-12

Mark Ebden, 28-30 November

With grateful acknowledgment to Alison Gibbs

Overview

- ▶ Practical example: Analysing house-price data
- ▶ Chapter 7: Variable selection, and going with the flow
- Key MLR aspects



Exploring a house-price dataset

For 26 houses sold in Chicago a long time ago, we know the selling price Y as well as eight characteristics of each house: square footage, parking information, etc.



Reference: Ashish Sen and Muni Srivastava, Regression Analysis: Theory, Methods and Applications, 2013.

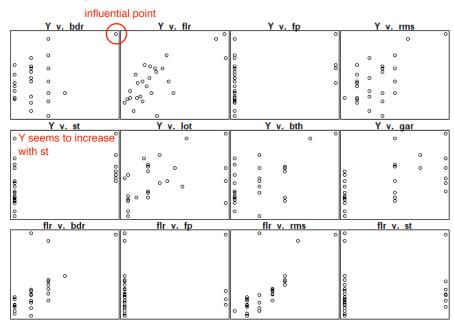
##		Y	bdr	flr	fp	rms	st	lot	bth	gar
##	1	53	2	967	0	5	0	39	1.5	0.0
##	2	55	2	815	1	5	0	33	1.0	2.0
##	3	56	3	900	0	5	1	35	1.5	1.0
##	4	58	3	1007	0	6	1	24	1.5	2.0
##	5	64	3	1100	1	7	0	50	1.5	1.5
##	6	44	4	897	0	7	0	25	2.0	1.0
##	7	49	5	1400	0	8	0	30	1.0	1.0
##	8	70	3	2261	0	6	0	29	1.0	2.0
##	9	72	4	1290	0	8	1	33	1.5	1.5
##	10	82	4	2104	0	9	0	40	2.5	1.0
##	11	85	8	2240	1	12	1	50	3.0	2.0
##	12	45	2	641	0	5	0	25	1.0	0.0
##	13	47	3	862	0	6	0	25	1.0	0.0
##	14	49	4	1043	0	7	0	30	1.5	0.0
##	15	56	4	1325	0	8	0	50	1.5	0.0
##	16	60	2	782	0	5	1	25	1.0	0.0
##	17	62	3	1126	0	7	1	30	2.0	0.0
##	18	64	4	1226	0	8	0	37	2.0	2.0
##	19	66	2	929	1	5	0	30	1.0	1.0
##	20	35	4	1137	0	7	0	25	1.5	0.0
##	21	38	3	743	0	6	0	25	1.0	0.0
##	22	43	3	596	0	5	0	50	1.0	0.0
##	23	46	2	803	0	5	0	27	1.0	0.0

The response variable and eight predictors

Variable	Meaning
Y	Selling price in thousands of dollars
bdr	Number of bedrooms
flr	Floor space in square feet
fp	Number of fireplaces
rms	Number of rooms
st	Storm windows present (indicator variable)
lot	Frontage in feet
bth	Number of bathrooms
gar	Number of garage parking spaces

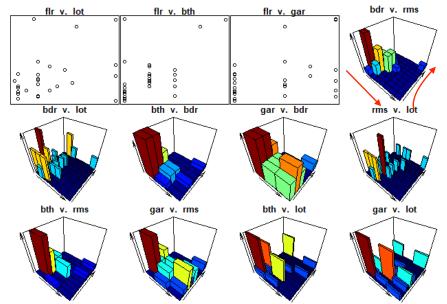
We'll use the techniques on last week's slides to analyse the dataset. The data are available on Portal.

Pairwise scatter plots 9C2 possible pairwise combination

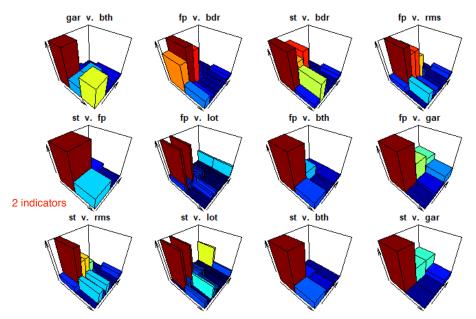


Pairwise 3D histograms

seems to have linear relation, through the diagonals



Pairwise 3D histograms



Initial findings from the scatter plots



- ▶ All X's seem to have some relationship with Y
- No obvious nonlinear relationship between Y and any of the predictors; no obvious need for transformations
- ► For later when we do the 7 C's: perhaps there exists an influential point; namely, the very first plot shows a house with eight bedrooms
- ► There are also relationships among some of the X's: for example, between bdr and rms (middle slide of the three: top right)
- But first, let's continue to explore the dataset systematically

mostly positive correlation

3.28

bth

gar

2.47

2.39

0.26

	Υ	bdr	flr	fp	rms	st	lot	bth	gar
Υ		0.41	0.74	0.39	0.58	0.46	0.42	0.55	0.54
bdr	1.41		0.68	0.17	0.92	0.23	0.40	0.63	0.24
flr	4.74	3.81		0.16	0.74	0.13	0.34	0.53	0.40
fp	1.32	larger l	by comm	non sens	e0.19	-0.02	0.39	0.12	0.41
rms	2.73	<u>10.37</u>	4.81			0.23	0.43	0.69	0.30
st	1.72						-0.04	0.35	0.17
lot	1.50	1.39		1.34	1.55			0.37	0.14

Upper right: Pearson's r. Lower left: $-\log_{10}(p\text{-value})$, e.g. 2 means p=0.01

1.44

3.98

if there is correlation or not

blank = nonsignificant

- ▶ Each correlation *p*-value is equal to an SLR β_1 *t*-test's
- ▶ We mainly consider the *p*-values and signs here, and needn't pay as much attention to the magnitude of each *r*
- ▶ All X's have a statistically significant r (or R^2) with Y
- ▶ Question: Have we run an appropriate test for st?

2.23

1.40

Performing MLR

The next slide describes the MLR. (What can we conclude from the F-test?)

The fitted equation is:

$$\hat{Y}$$
 =18.6 $-$ 7.70 bdr $+$ 0.0176 flr $+$ 6.91 fp $+$ 3.90 rms $+$ 10.8187 st $+$ 0.2635 lot $+$ 2.37 bth $+$ 1.77 gar

Interpreting the coefficients:

- Recall that b_i represents the estimated change in mean selling price due to a unit change in X_i with all other variables held constant
- e.g. A 100-square-foot increase corresponds to a \$1760 increase in mean price, with everything else held constant
- ► A 1-bedroom increase corresponds to a \$7700 decrease in mean price (despite the fact that the correlation between price and bdr is positive) doesnt make sense ... Y~bdr has significant (p-value=1.41) positive relation (0.4)

Despite the significant correlation between Y and bth, the t-test on the next slide gives a p-value of 0.366 > 0.05. Why? (Hint: slide 26 from last week)

Y~bth seems to have positive linear relationship (p-value=2.47) but bth correlated with some other predictors, and MLR favors more valuable predictors and leave less important predictor out

```
## Call:
## lm(formula = Q) response variable is first column, predictor as other cols
##
## Residuals:
##
       Min
                10 Median
                                30
                                       Max
## -10.3058 -2.8417 -0.1511 3.2882 7.9518
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 18.637664 5.240957 3.556 0.002429 **
## bdr
             -7.697444 1.829426 -4.208 0.000592 ***
## flr 0.017570 0.003235 5.431 4.49e-05 ***
## fp 6.909765 3.083583 2.241 0.038680 *
## rms 3.904374 1.615617 2.417 0.027194 *
             10.818663 2.300203 4.703 0.000205 ***
## st
## lot.
            0.263522 0.135109 1.950 0.067808 .
## bth
           2.374591 2.557865 0.928 0.366221
## gar
            1.770861 1.404310 1.261 0.224334
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.717 on 17 degrees of freedom
## Multiple R-squared: 0.9044, Adjusted R-squared: 0.8595
## F-statistic: 20.11 on 8 and 17 DF, p-value: 3.147e-07
```

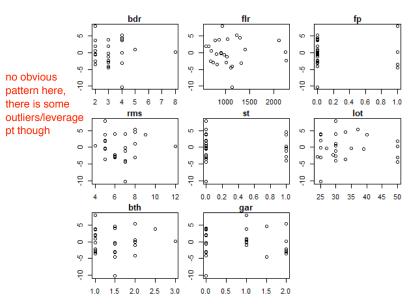
The Seven C's (7 Checks) for STA302 MLR diagnostics

In their proper order this time:

- 1. Plot standardized residuals to help determine whether the proposed regression model is a valid model
- 2. Identify any leverage points
- 3. Identify any outliers
- **4.** Assess the effect of each X on Y
- **5.** Assess multicollinearity
- **6.** Assess the assumption of error homoscedasticity
- 7. For time series: examine whether the data are correlated over time

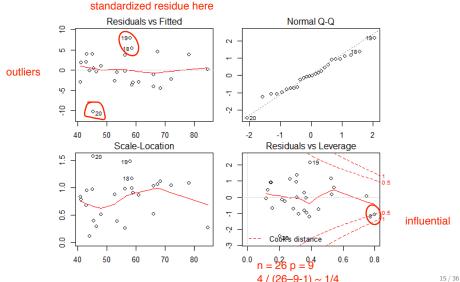
Residual plots in the house-price example residual vs predictor plots

Recall that plotting residuals versus X_j for $j \in \{1, \dots p\}$ helps us to look for curvature, influential points, and outliers.

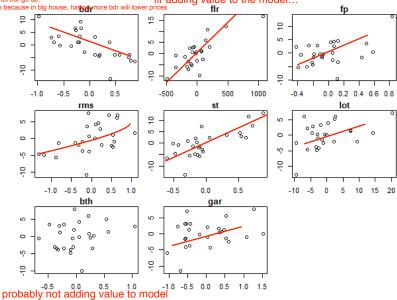


Output of plot(lm(..))

- One house with large negative residual (perhaps one large positive residual)
- At least one influential point according to the 4/(n-p-1) criterion: large Cook's distance in the bottom-right of the diagnostics panel



Check 4 in the house-price example: Added variable plots negative partial correlation Y go up as bot go up, but thats because in big house, hattigg more bdr will lower prices fir fp



Assessing assumptions in the House-price example

We view the added variable plots in context. Consider the plot of Y versus bdr:

- ▶ Not a strong linear relationship; otherwise, no concerns with non-linearity
- ▶ Potential influential point: one house has 8 bedrooms
- SLR may not be a good idea for the price bedroom relationship but may be ok in multiple regression probably not a good idea for SLR

Consider the added variable plot:

- ▶ The linear relationship is stronger (although it's now negative)
- We want to check if the influential is here. However, the large negative residual is not the house with 8 bedrooms

Summary of concerns:

- ► Large negative residual in the added variable plots
- Potential influential point in the added variable plot for flr

Summary of unusual observations

House 8:

- Influential
- Largest Cook's distance
- ▶ Very large floor space, everything else including price (*Y*) was of moderate space

House 19:

- Large positive residual
- Small house but middle-ish price; nice house?

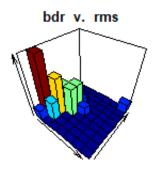
House 20:

- Large negative residual
- Smallest price, but all features middle-ish

House 11 isn't a concern:

- ▶ It has eight bedrooms but is neither an outlier nor influential
- ▶ It's expensive, but everything is big

Check 5 in the house-price example: Multicollinearity variance inflation factor



- $VIF_{rms} = 8.5$, $VIF_{bdr} = 6.5$, $VIF_{flr} = 2.5$, $VIF_{bth} = 2.1$
- Indeed we saw what might have been the effects of multicollinearity: the coefficient for bdr wasn't of the expected sign
- Details of executing the two remedial measures introduced last week (ridge regression, principal component regression) are beyond STA302's scope
- For now, awareness of possible multicollinearity informs our choice of how to simplify the model

Model simplification Assumption is Y can be modeled with 8 predictors,

- If you remove variables during MLR, the β_j values of the remaining predictors become biased, and the *p*-values from *t* and *F* statistics generally shrink below their true values
- ► Therefore, when reducing the dimensionality of your MLR problem, take into account your reduction when reporting CIs and other results

keeping more predictor tend to keep p-value high,



Model simplification method 1 conservative, more predictor leads to problem of overfitting.

Method 1: If there is multicollinearity in your data set, perform **variable** selection. e.g. choose the subset of predictors that $\frac{R^2}{R^2}$.

Method 2: If there isn't multicollinearity, you can conduct a **partial** *F***-test** on predictors you suspect of being unhelpful. Remove them if the result is non-significant. **method 2 more aggressive**

Applying the two methods to the house-price data:

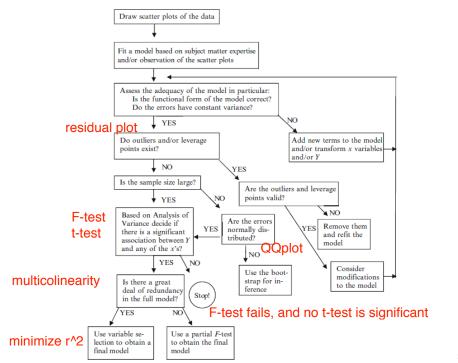
- 1. The subset turns out to be everything but bth. Therefore, bth would removed by Method 1.
- Among the choices of removing gar and/or bth, the effect on $R_{\rm adj}^2$ is small in all cases (well under 1% change). Method 1 naively maximizes $R_{\rm adj}^2$ without regard to this; the method is known for its timidity in removing predictors.
- Removing bth and gar leads to a non-significant partial F-test (p > 0.05).
 Therefore, bth and gar would be removed by Method 2. Removing any other predictor(s) instead of or in addition to these leads to a significant p-value for the partial F-test.

The MLR approach

- 1. Plot standardized residuals to help determine whether the proposed regression model is a valid model
 - 2. Identify any leverage points
 - **3.** Identify any *outliers*
- **4.** Assess the effect of each X on Y
- **5.** Assess multicollinearity
- **6.** Assess the assumption of error homoscedasticity
- For time series: examine whether the data are correlated over time cant really do check 7, since data is a slice in time

The Seven C's can also be viewed as fitting into a broader **flowchart approach** to **MLR** provided on the next slide.

- ▶ The flowchart mentions the "bootstrap", which you're not responsible for
- ▶ The bootstrap uses data resampling to numerically approximate the sampling distribution of the test statistic under H_0 (rather than using theoretical results, which we did assuming normally distributed errors)



Overview

- ▶ Practical example: Analysing house-price data
- ▶ Chapter 7: Variable selection, and going with the flow
- Key MLR aspects



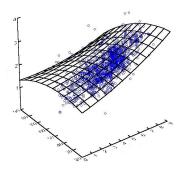
Why do regression? Two main reasons

- 1. Predict the value of a variable given the value(s) of 1+ others
 - ▶ For interpolation or extrapolation, for example in house prices
 - It doesn't matter which variables are in the model or how they were chosen (model building/variable selection OK)
 - However, we must consider the level of smoothing that's appropriate. If we overfit, predictions may not work well on new data
- 2. Understanding an underlying mechanism
 - Describe the relationships among variables
 - ▶ What are the effects of predictor(s) on the response?
 - Describe differences in relationships between different sets of data
 - For example, data sets for the Montreal Protocol (CFC data), Meadowfoam, etc
 - This is inferential modelling. The form of the model is assumed to be known but there is uncertainty about the value(s) of the coefficients

It can be risky doing inferential modelling on the same data that you used to build a model (to describe how Y might originate in general).

Why do multiple regression?

- \blacktriangleright Multiple X's give a better prediction of Y, e.g. house prices
- ▶ MLR allows polynomial fits
- MLR allows comparison of regression line for two groups, ancova e.g. meadowfoam data
- ► You can control for some X's, e.g. a baseline value in a study, such as mammals and brain size



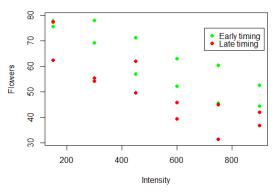
whats the regression equation like

Experiments vs Observational Studies

Experiment (e.g. for the meadowfoam dataset):

A treatment is imposed on experimental units. Advantages:

- Strength of conclusion
- ▶ If properly randomized, you can make cause-and-effect conclusions
- e.g. you can say that increasing light intensity causes a decrease in the number of flowers per plant on average

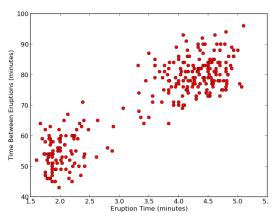


Experiments vs Observational Studies

Observational study (e.g. for the CFC data or house-price data):

Data are measured without an intervention. associations only

- ▶ You can say that there's an association, but you can't say that X causes Y
- ▶ Perhaps they are both related to a third variable
- e.g. Old Faithful data: you can't say that a longer duration causes a large interval: perhaps both are related to some other geological phenomenon



Multiple Regression

Comparison of:

- t-tests $(H_0: \beta_j = 0$, all other X's in the model)
- ▶ The ANOVA *F*-test ($H_0: \beta_1 = \cdots = \beta_p = 0$, a test for the overall model)

It's possible to have:

F-test significant (p < 0.05), and all or some *t*-tests significant:

The model has useful variables for explaining Y

F-test non-significant, and all t-tests non-significant:

There are no explanatory variables useful for explaining Y strength in numbers...

F-test significant, and all *t*-tests non-significant:

▶ Multicollinearity; individual X's don't predict Y over and above the others

F-test non-significant, and some *t*-tests significant:

▶ There are two possible ways this can happen (next slide)

Significant *t*-test results accompanying a non-significant *F*-test result t-test falsely significant due to type 1 error 1. The model has no predictive value, but in your *t*-test analysis there were

The model has no predictive value, but in your t-test analysis there were some Type I errors (falsely rejecting H_0). This is always a risk with multiple tests



too many predictors diluted effect of 1 useful predictor

2. The predictors were chosen poorly. e.g. if there was one useful predictor among many not useful predictors, the contribution from the useful one may not be enough for the *F*-test to be significant



Problems with Regression Models and their Consequences

You might have the wrong model for several reasons:

- 1. The true relationship is nonlinear:
- ▶ Biased $\hat{\beta}$'s
- ► Meaningless *t* and *F*-tests / Cls
- 2. You omitted an important predictor variable:
- ▶ Biased $\hat{\beta}$'s
- ► Meaningless *t* and *F*-tests / Cls

Actual model:
$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + e$$

Fitted model: $\hat{Y} = b_0 + b_1 x_1$ and thus $E(b_1) \neq \beta_1$

- 3. You included an unimportant predictor variable:
- \triangleright $\hat{\beta}$'s aren't biased
- ► The variance is unnecessarily large (inefficient) add more noise

Problems with Regression Models and their Consequences

The Gauss-Markov conditions might not be met:

1. Non-constant variance:

- \triangleright $\hat{\beta}$'s aren't biased
- \triangleright S^2 is a biased estimate
- ▶ Invalid *t* and *F*-tests / Cls

2. Correlated errors:

- \triangleright $\hat{\beta}$'s aren't biased
- \triangleright S^2 isn't estimating the right thing
- ▶ Invalid t- and F-tests / Cls

3. Non-normal errors:

- \triangleright $\hat{\beta}$'s aren't biased
- S^2 is an unbiased estimate for σ^2
- ▶ Invalid t- and F-tests / Cls, except for large sample sizes
- ► Invalid Pls

Other problems with Regression Models and their Consequences

1. Multicollinearity:

ightharpoonup var($\hat{\beta}$) will be high — inefficient

2. The predictor variables were measured with error:

- ▶ Biased $\hat{\beta}$ and S^2 Sxx inflated
- ▶ Invalid t- and F-tests / Cls
- Generally ok provided the variance in X's is small
- ▶ To fix: take multiple measurements, or use Structural Equation Modelling



"Ask the realtor if we can list the litter box as a third bathroom."

Exam results by Section

After the exams are marked, I'll check for any significant differences between the grades of Sections 1 and 2. If one exists then the marks may be tweaked to eliminate this.

If you're in Section 1 but have been attending Section 2's lectures and wish to be viewed within Section 2 for the purposes of exam marks adjustment (or vice versa), please let me know directly by Friday 8 December and give your reasons.



The expectation is that Sections 1 and 2 will perform similarly on the shared exam, having been taught the same. Therefore, hopefully this slide is pointless!

Course Evaluations



FAS Fall 2017 Undergrad for Meth Data Analysis STA302H1-F-LEC0101

Medium	Online
Timing	Scheduled
	Start Date 2017-11-23 00:00
	End Date 2017-12-08 23:59

Response R	ate			
	Responded	Invited	% Rate	
Students	39	341	11.44%	

Please visit https://courseevaluations.utoronto.ca

Next steps

- ► Solutions to Chapter 6 have been posted on Portal under 'Homework'
- ► Chapter 7: You may wish to attempt the $R_{\rm adj}^2$ portion of 1(a), 2(a), or 3(a), but not all three
- No more homework!

