Know your data and how to analyze it correctly: Statistical assumptions

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Welcome to our Statistical Assumptions workshop

Purpose:

To teach the statistical assumptions of linear regression and show how you test data to see if they satisfy the assumptions. Knowing how to check these assumptions is part of "best practices" in data analysis.

Significance:

It is very important to check that your data satisfies linear regression assumptions. If your data does not meet these criteria, the use of linear regression is inappropriate. Other methods can be used, but…

Caveat (again): We aren't here to teach statistics

Need help with stats? Use these resources!

- U of T Statistical Consulting Services (click here)
- `http://www.stackoverflow.com`
- `http://stats.stackexchange.com`
- Helpful statistical tests flowchart (PDF on GitHub)
- Very helpful webpage on regression diagnostics: `http://www.ats.ucla.edu/stat/sas/webbooks/reg/chapter2/sasreg2.htm`

Notes and help during this workshop

- Go to this website:

`https://etherpad.mozilla.org/dnsWorkshops`

- Download our SAS code files from our GitHub page:

(click here)

- Download the Statistical Tests Flowchart from our GitHub page:

(click here)

Linear Regression

- Used to test associations between independent and dependent variables
- Based on a linear relationship: $y = X\beta + \varepsilon$
  - y = dependent variable(s)
  - β = slope
  - X = independent variable
  - ε = error, or residual, terms

Some Linear Regression Assumptions

- Model is good (i.e. linear relationship between predictors and outcome variable)
- Residuals[1] have a normal distribution
- Residuals are homoscadastic (have equal/constant variance)

[1] Residual (aka the error term) = observed - expected

Other Checks to Ensure Appropriate Model

- Check for collinearity (predictors that are highly linearly related – may result in inaccurate estimates of regression coefficients)
- Check for influence (i.e. outliers)

Brief aside: assumptions/diagnostics we are not covering in this workshop

- Independence (residuals of one observation are not associated with residuals of another)
- Errors in variables (predictor variables are measured without error)
- Very helpful webpage on regression diagnostics that covers these: `http://www.ats.ucla.edu/stat/sas/webbooks/reg/chapter2/sasreg2.htm`

How to check assumptions

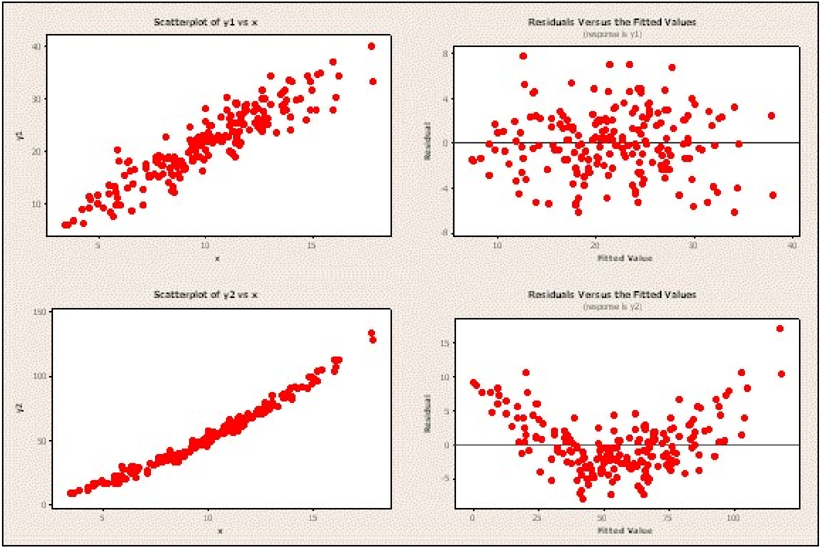
- Model fit: Make a scatterplot (check pattern)
- Distribution of residuals: Q-Q Plot
- Variance of residuals: Plot residuals vs. predicted fit (check spread of points)

Model fit

- Run a scatter plot:

```
proc sgplot data=sashelp.class;
    scatter x=height y=weight;
run;
```

Model fit



Scatterplot of y1 vs x
Residuals Versus the Fitted Values
(response is y1)
Residual
Fitted Value
Scatterplot of y2 vs x
Residuals Versus the Fitted Values
(response is y2)
Residual
Fitted Value

Residual distribution

- Run a linear regression model and output the residual and predicted terms to a new dataset:

```
proc reg data=sashelp.class;
    model height=weight;
    output out=resid residual=r predicted=fit;
run;
quit;
```

- Create a plot of the new output dataset:

```
goptions reset=all;
 proc univariate data=resid normal;
     var r;
     qqplot r / normal(mu=est sigma=est);
 run;
```

Residual distribution

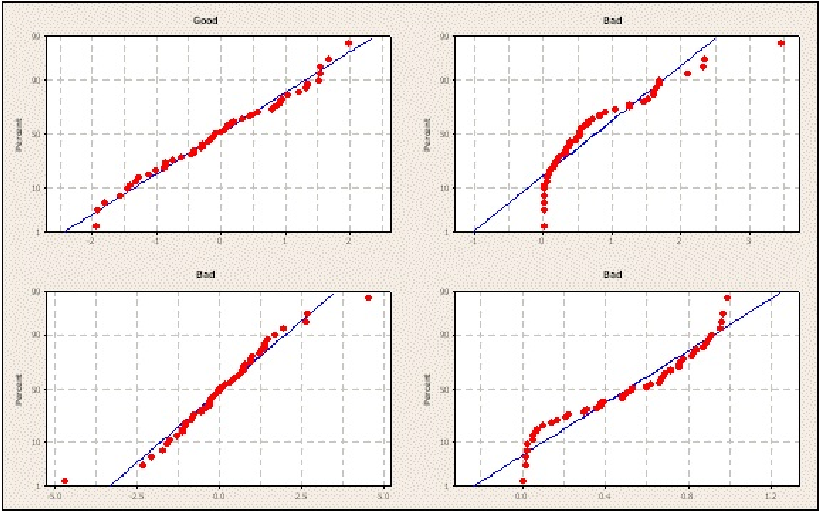


Figure 2:

Residual variance

- Run a linear regression model and plot residuals against predicted values:

```
proc reg data=sashelp.class;
    model height=weight / spec;
    plot r.*p.;
run;
quit;
```

Residual variance

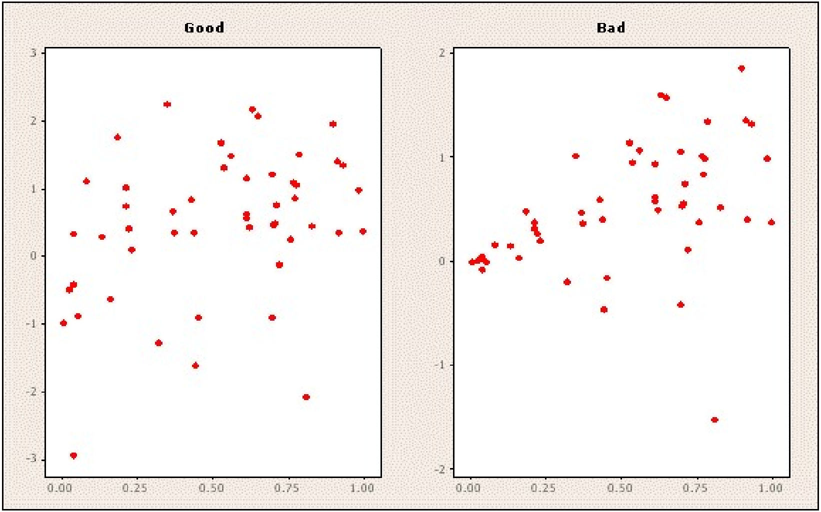


Figure 3:

What do you do if your data does not meet these assumptions?

- Try transforming the data (log, square root)

```
data new;
    set sashelp.fish;
    logWt = log(Weight);
    run;
```

What do you do if your data does not meet these assumptions?

- Try transforming the data (log, square root)

```
data new;
    set sashelp.fish;
    logWt = log(Weight);
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- Use a non-parametric statistical test if can not obtain normal distribution of residuals after attempting a transformation

Collinearity

- What is it? Two or more predictors in a model that are moderately to highly correlated with one another (e.g. BMI and body weight)

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- Check VIF (variance inflation factor)
  - OR Check tol (tolerance = 1/vif)

```
proc reg data=sashelp.class;
    model height = weight age / vif tol;
run;
quit;
```

- VIF > 10 or tol < 0.1 suggest collinearity is present

Influence

- Make a scatterplot of all observations

```
proc sgplot data=sashelp.class;
    scatter x=height y=weight;
run;
```

Or another way to make a scatterplot:

```
proc gplot data=sashelp.class;
    plot height*weight=1 / vaxis=axis1;
run; quit;
```

Influence

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- Do a visual check for extreme observations

Influence cnt'd

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Influence cnt'd

- Another method: proc univariate will output extreme observations
- Observation is "influential" if removing it substantially changes the estimate of coefficients (sometimes! exception: genetics–extreme observations may be hyper/hypo-responders)

Practice

1. Perform these checks on your own research data.
2. Conclude if linear regression is appropriate and if collinearity or influence is present in your model.