



Predicting with regression, multiple covariates

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Example: predicting wages

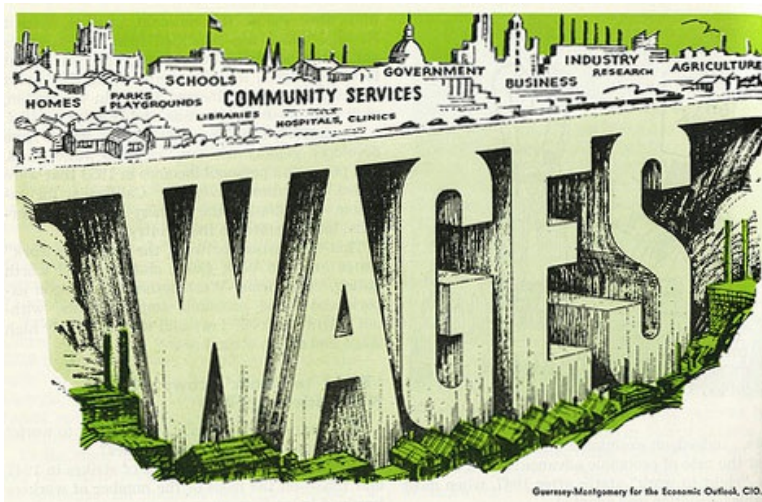


Image Credit <http://www.cahs-media.org/the-high-cost-of-low-wages>

Data from: [ISLR package](#) from the book: [Introduction to statistical learning](#)

Example: Wage data

```
library(ISLR); library(ggplot2); library(caret);  
data(Wage); Wage <- subset(Wage,select=-c(logwage))  
summary(Wage)
```

year		age		sex		maritl		race	
Min.	:2003	Min.	:18.0	1. Male	:3000	1. Never Married:	648	1. White:	2480
1st Qu.:	2004	1st Qu.:	33.8	2. Female:	0	2. Married	:2074	2. Black:	293
Median	:2006	Median	:42.0			3. Widowed	: 19	3. Asian:	190
Mean	:2006	Mean	:42.4			4. Divorced	: 204	4. Other:	37
3rd Qu.:	2008	3rd Qu.:	51.0			5. Separated	: 55		
Max.	:2009	Max.	:80.0						

education		region		jobclass		health	
1. < HS Grad	:268	2. Middle Atlantic	:3000	1. Industrial	:1544	1. <=Good	: 858
2. HS Grad	:971	1. New England	: 0	2. Information:	1456	2. >=Very Good:	2142
3. Some College	:650	3. East North Central:	0				
4. College Grad	:685	4. West North Central:	0				
5. Advanced Degree:	426	5. South Atlantic	: 0				
		6. East South Central:	0				
		(Other)	: 0				

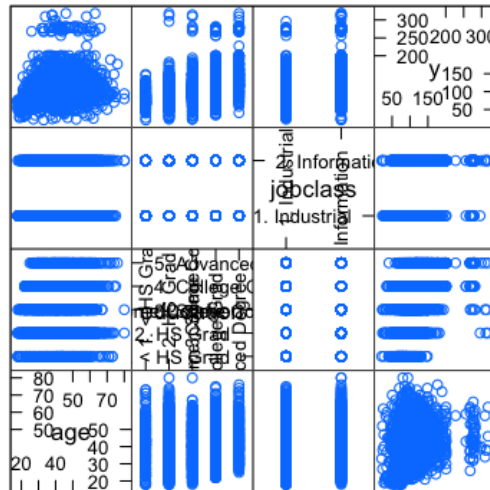
Get training/test sets

```
inTrain <- createDataPartition(y=Wage$wage,  
                                p=0.7, list=FALSE)  
training <- Wage[inTrain,]; testing <- Wage[-inTrain,]  
dim(training); dim(testing)
```

```
[1] 898 12
```

Feature plot

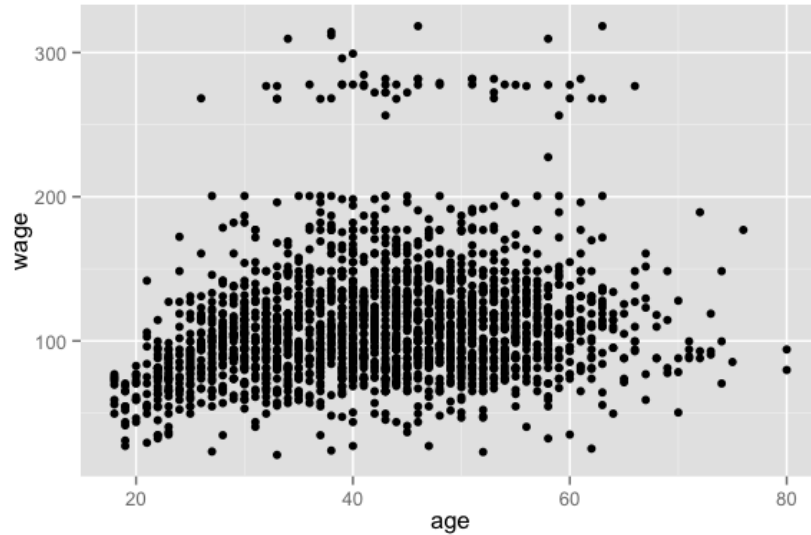
```
featurePlot(x=training[,c("age", "education", "jobclass")],  
            y = training$wage,  
            plot="pairs")
```



Scatter Plot Matrix

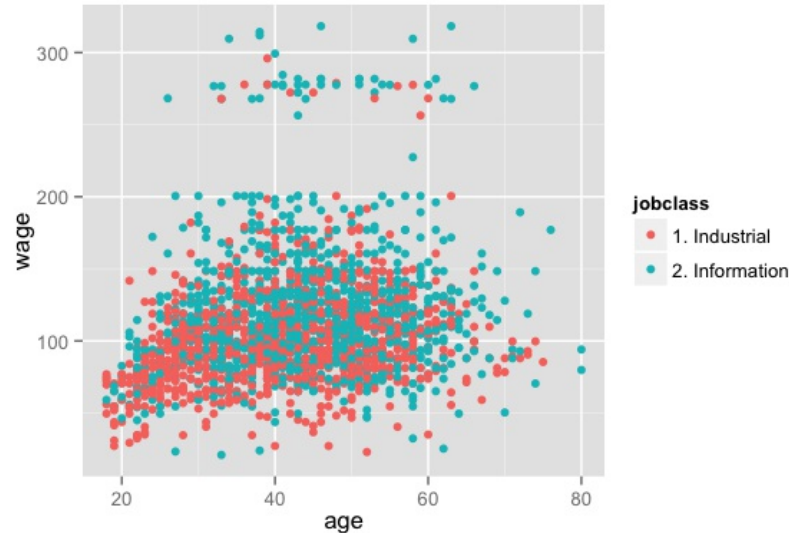
Plot age versus wage

```
qplot(age,wage,data=training)
```



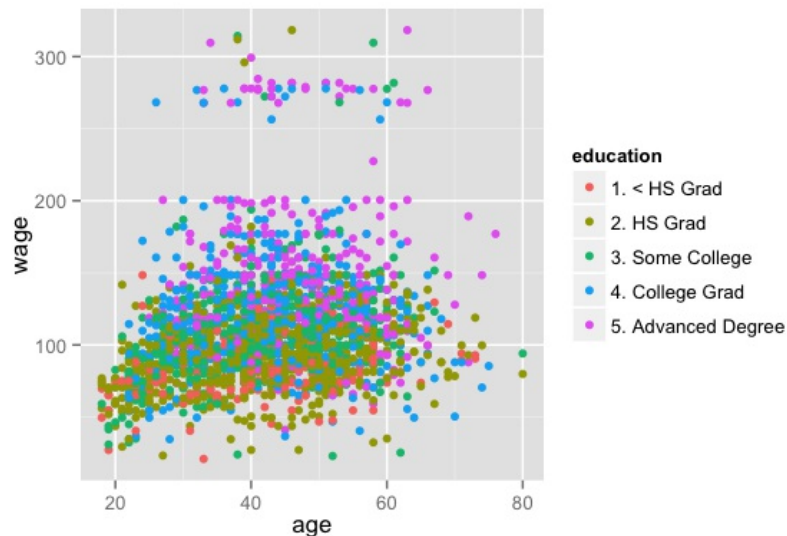
Plot age versus wage colour by jobclass

```
qplot(age,wage,colour=jobclass,data=training)
```



Plot age versus wage colour by education

```
qplot(age,wage,colour=education,data=training)
```



Fit a linear model

$$ED_i = b_0 + b_1 \text{age} + b_2 I(\text{Jobclass}_i = \text{"Information"}) + \sum_{k=1}^4 \gamma_k I(\text{education}_i = \text{level}_k)$$

since jobclass and educ. are factors, R automatically creates the corresponding dummy vars

```
modFit<- train(wage ~ age + jobclass + education,  
              method = "lm",data=training)  
finMod <- modFit$finalModel  
print(modFit)
```

Linear Regression

2102 samples

11 predictors 10 predictors because of the dummy variables

No pre-processing

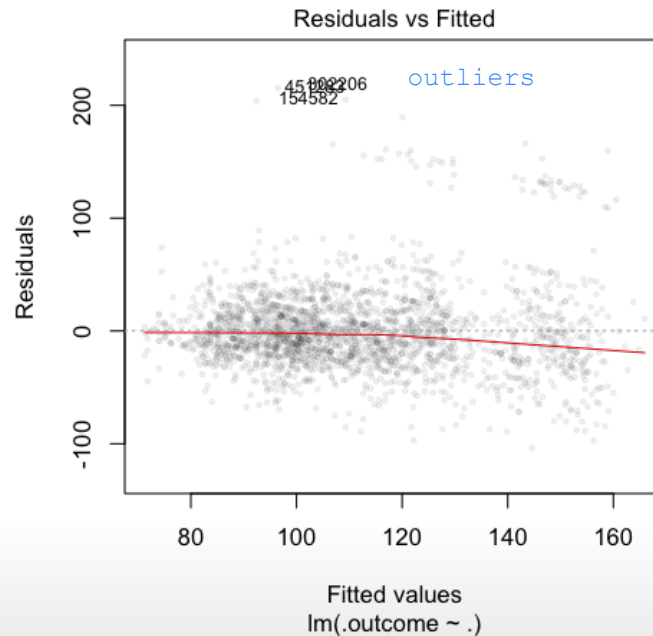
Resampling: Bootstrapped (25 reps)

Summary of sample sizes: 2102, 2102, 2102, 2102, 2102, 2102, ...

Resampling results

Diagnostics

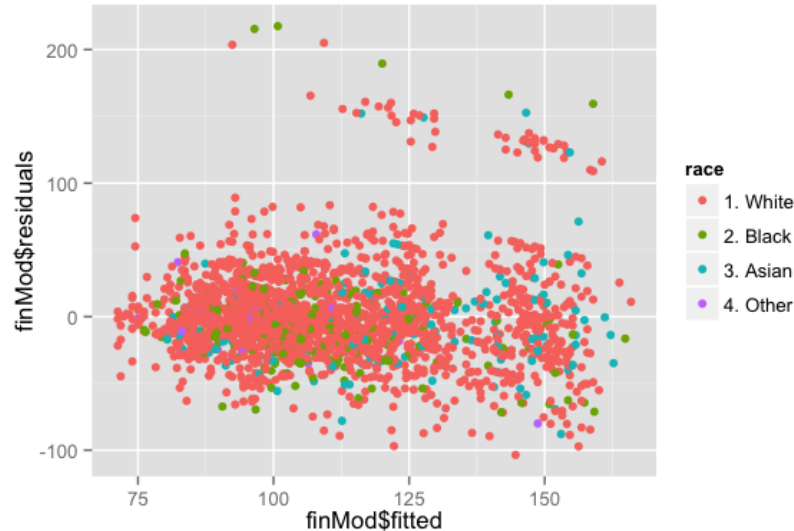
```
plot(finMod,1,pch=19,cex=0.5,col="#00000010")
```



Predictor line near 0: good

Color by variables not used in the model

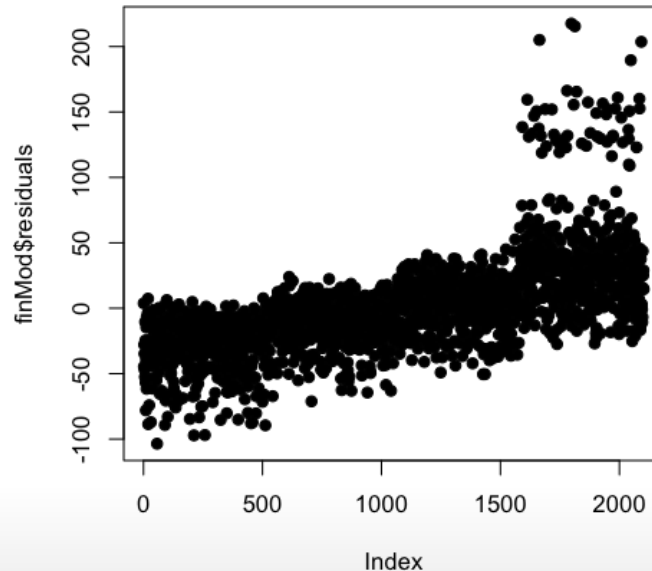
```
qqplot(finMod$fitted, finMod$residuals, colour=race, data=training)
```



Plot by index

the index is just the row number of the dataset

```
plot(finMod$residuals,pch=19)
```



hm...outliers are all at the bottom of the table. And row index correlates with residuals... strange

So probably the table was sorted by some continuous variable like eg. age!

Predicted versus truth in test set

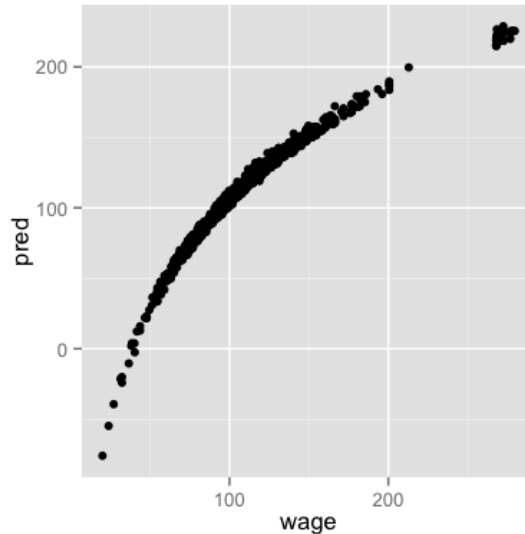
```
pred <- predict(modFit, testing)
qplot(wage, pred, colour=year, data=testing)
```



but now if we find some trend here, looking at the test set, we can't use this information to update the model anymore!

If you want to use all covariates

```
modFitAll<- train(wage ~ ., data=training, method="lm")  
pred <- predict(modFitAll, testing)  
qplot(wage, pred, data=testing)
```



Notes and further reading

- Often useful in combination with other models
- [Elements of statistical learning](#)
- [Modern applied statistics with S](#)
- [Introduction to statistical learning](#)