Quantitative Methods

Intro to Machine Learning

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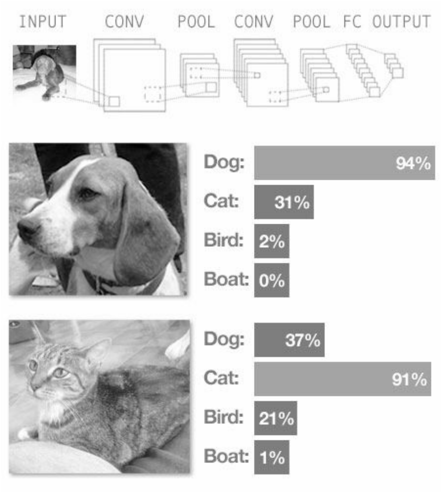
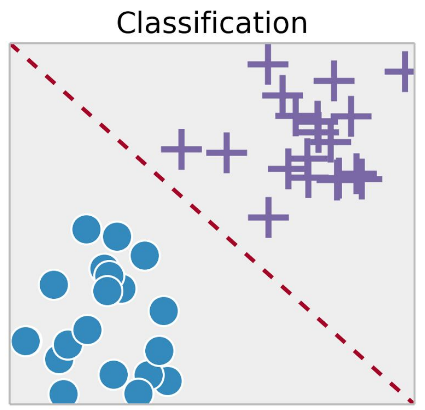
Intro to Machine Learning: Classifiers

We will here focus on predictive analytics: training a model on labeled data ("where we know the right answer, e.g. dog or cat") to then guess the answer in another similar* dataset



Examples:

- Predicting whether a picture is a picture of a cat or a dog to prevent spam on social network for cat owners
- Predicting if a mushroom is toxic or not based on a picture
- Predicting if a person is a republican or a democrat based on demographics
- or...



* Similar is a big necessary assumption here, the model learns from the data so if the data is not representative the model will not work well or even completely wrong

NATIONAL
GEOGRAPHIC
CHANNEL

Titanic dataset

The sinking of the RMS Titanic is one of the most infamous shipwrecks in history. On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers and crew.

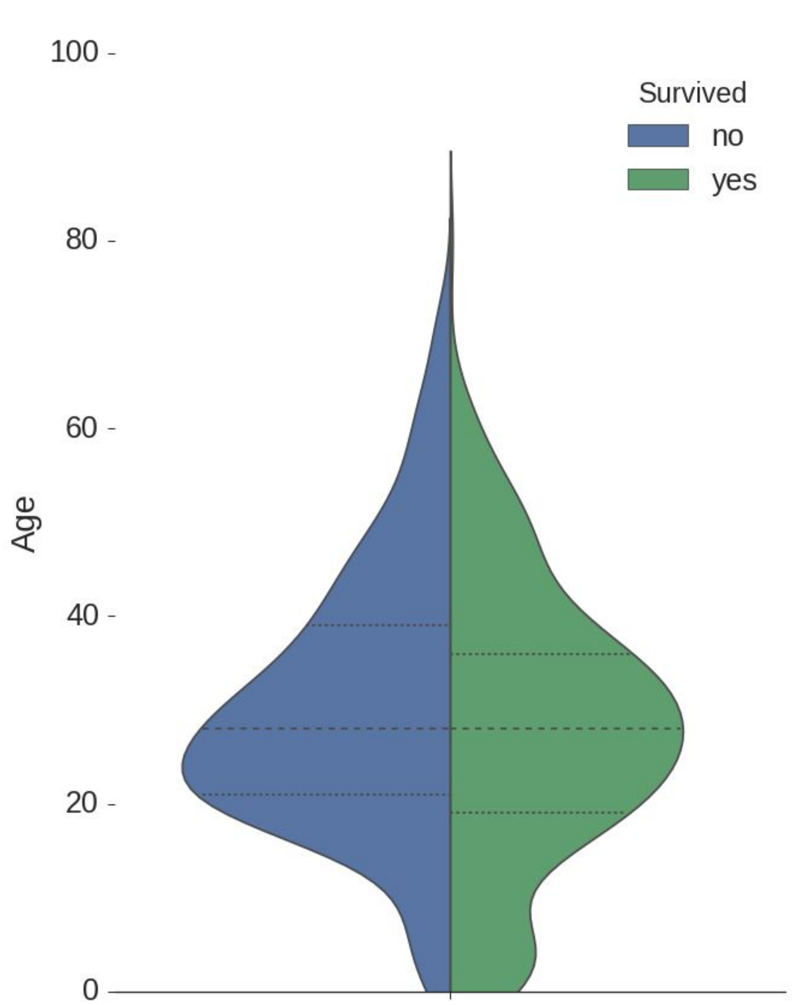
Although there is (as always) some element of luck involved in surviving the sinking of a ship, were some people more likely to survive than others?

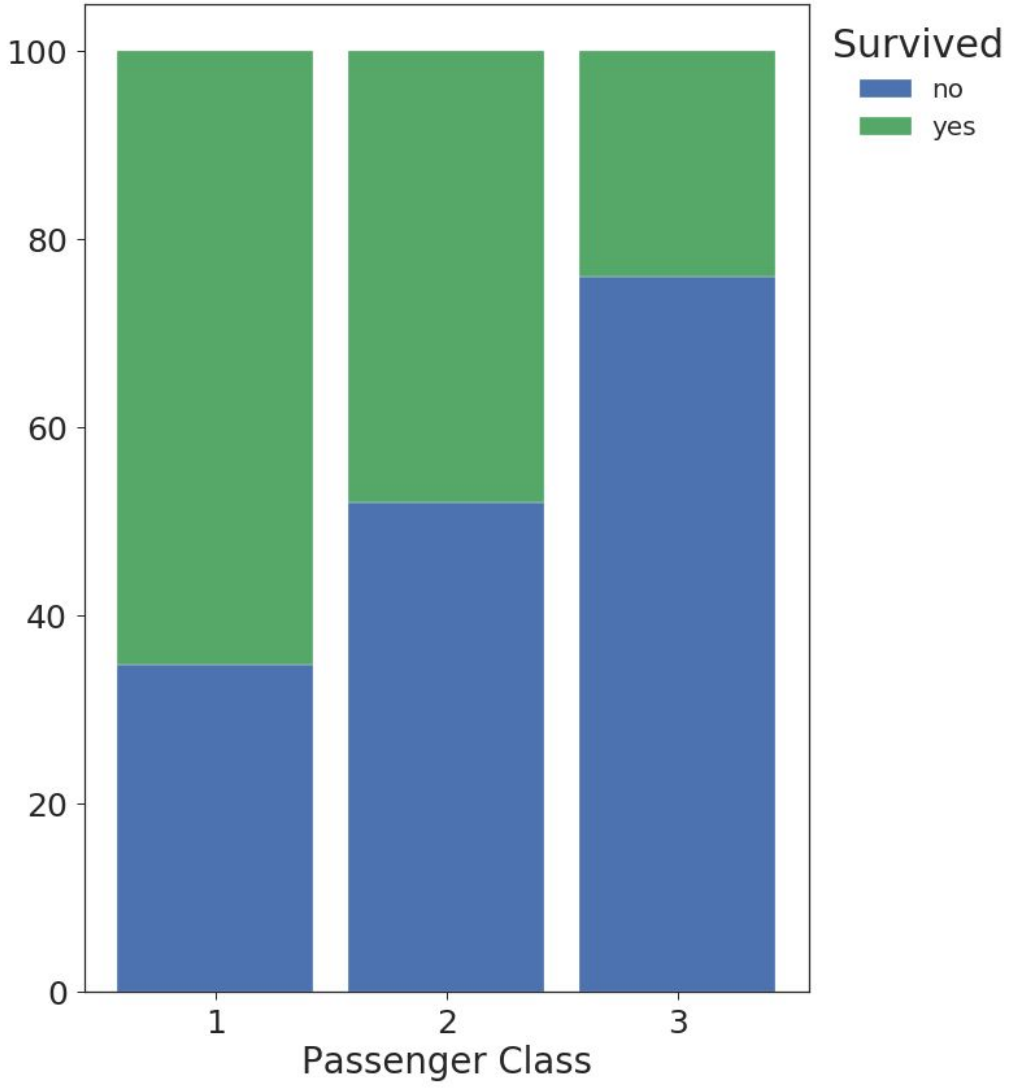
And, if yes, I could have used this to make a prediction and used this prediction to price travel insurance in 1913?

Variables:

- *Survival*: (0 = No, 1 = Yes)
- *Pclass:* Ticket class (1st, 2nd, 3rd)
- *Sex*: Sex (male/female)
- *age:* Age [years]
- *fare:* Passenger fare in Pre-1970 British Pounds
- *embarked:* Port of Embarkation (C = Cherbourg, Q = Queenstown, S = Southampton)
- Etc

Which feature might help?





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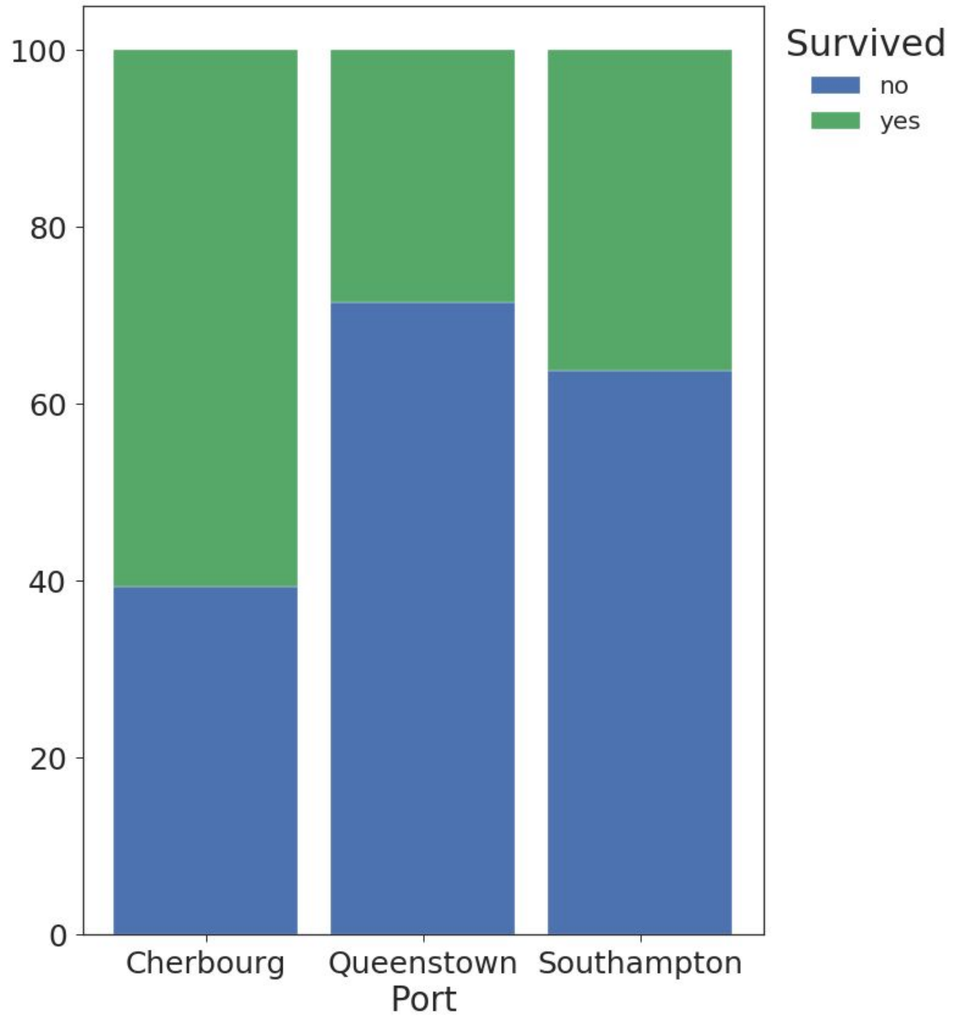

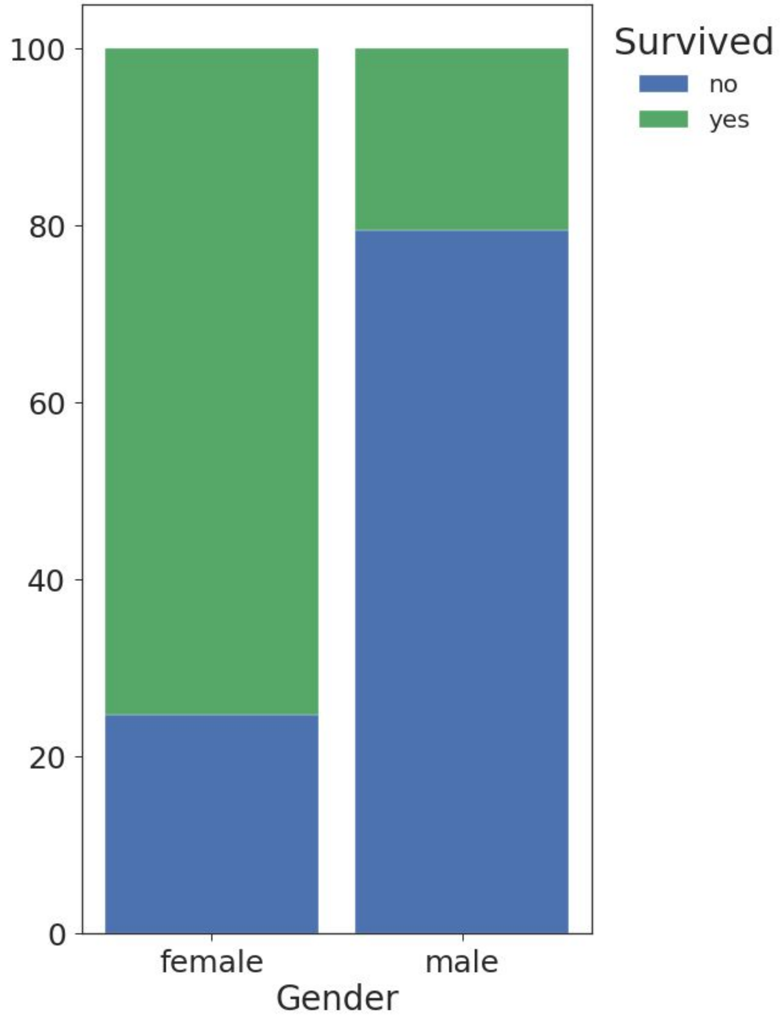

Your first classifier: Logistic regression

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titanic <- read.csv("titanic.csv")                      # load the titanic dataset
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family = binomial(logit))                                 # for logistic model
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summary(logistic.mod1)                                    # summary of regression

Call:
glm(formula = Survived ~ Fare, family = binomial(logit), data = titanic)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.5623  -0.9077  -0.8716   1.3412   1.5731

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.894502   0.107385  -8.330  < 2e-16 ***
Fare         0.015738   0.002489   6.323 2.57e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
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$$P_{surviving} = \frac{1}{(1 + \exp(-(-0.8945 + 0.0157 * fare)))}$$

We won’t spend too much time on this but 1) you can interpret significance the way you did with linear models, 2) you can interpret coefficients wrt direction and size (exact meaning is beyond scope)

Which you can then use to make predictions and compute the accuracy of your model

```
library(caret)
```

First use function predict to predict the probabilities for each person to have survived

```
fitted.results <- predict(logistic.mod1, newdata = titanic, type = "response")
# fitted.results = [0.6, 0.2, 0.2, 0.1, 0.8, ...]
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```
fitted.results <- ifelse(fitted.results > 0.5, 1, 0) # convert to binary
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fitted.results <- factor(fitted.results, levels = c(0,1), labels = c("No", "Yes"))
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```

Now we can compute the accuracy (more on the confusion matrix later)

```
confusionMatrix(fitted.results, titanic[,"Survived"])$overall[1] # to calculate model accuracy
# fitted.results =          [yes, no,  no, no, yes, ....]
# titanic[,"Survived"]) = [yes, yes, no, no, no,   ....]

> 0.666
```

Survived ~ Fare + Sex

```
Call:
glm(formula = Survived ~ Fare + Sex, family = binomial(logit),
    data = titanic)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.2652  -0.6465  -0.6014   0.8010   1.9381

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.659002   0.167464   3.935 8.31e-05 ***
Fare         0.012052   0.002623   4.595 4.33e-06 ***
Sexmale     -2.371126   0.189333 -12.524  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

fitted.results <- factor(ifelse( predict(logistic.mod2, newdata = titanic, type = "response") >
                         0.5, 1, 0), levels = c(0,1), labels = c("No", "Yes"))
confusionMatrix(fitted.results, titanic[,"Survived"])$overall[1] # to calculate model accuracy
> 0.777
```

As expected, being a men strongly decreases the likelihood of survival according to our model (and significant)

And adding gender increases accuracy

Survived ~ Fare + Age + Pclass + Sex

```
Call:
glm(formula = Survived ~ Fare + Age + Pclass + Sex, family = binomial(logit),
    data = titanic)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.7363  -0.6810  -0.3965   0.6558   2.4640

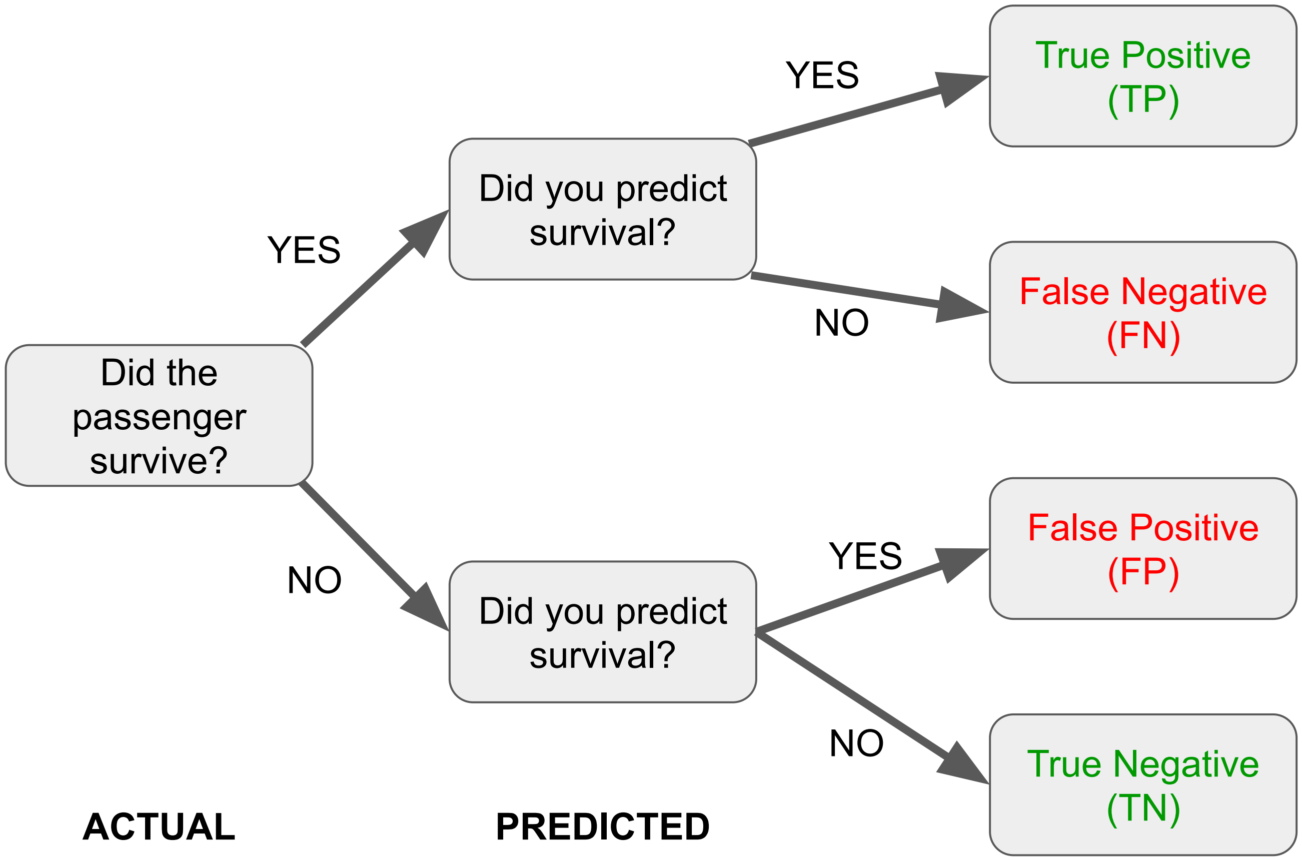
Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)      3.7149937  0.4644987   7.998 1.27e-15 ***
Fare             0.0005189  0.0022553   0.230    0.818
Age             -0.0369401  0.0077460  -4.769 1.85e-06 ***
Pclass2         -1.2682002  0.3127441  -4.055 5.01e-05 ***
Pclass3         -2.5335614  0.3278321  -7.728 1.09e-14 ***
Sexmale         -2.5096331  0.2084270 -12.041  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

confusionMatrix(fitted.results, titanic[,"Survived"])$overall[1] # to calculate model accuracy
> 0.792
```

Pclass can take 3 values, 2 and 3 are the effect of being in 2nd and 3rd class as opposed to being in 1st which is the default value (same as men in the previous slide and here)

Beyond accuracy: Evaluating how often and how is my model wrong

There are four possible outcomes of a prediction I (well, my model) made:



My model predicted Positive and was right

My model predicted Negative and was wrong

My model predicted Positive and was wrong

My model predicted Negative and was right

This is called a confusion matrix

This is usually summarised in a matrix:

	Prediction: Yes - Survived	Prediction: No - Died
Actual: Yes - Survived	True Positives (TP)	False Negatives (FN)
Actual: No - Died	False Positives (FP)	True Negatives (TN)

Clearly, we would like to get as many True Negatives and True Positives as possible (my model was **right**) and as few False Positives and False Negatives as possible (my model was **wrong**).

From this I can compute accuracy which is $Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$

Confusion matrix and performance measures in *R*

We can extract all of these metrics from the confusion matrix in R

```
confusionMatrix(fitted.results, titanic[,"Survived"])$table

>          Reference
Prediction  No  Yes
      No   357   81
      Yes   67  207
```

The accuracy:

```
confusionMatrix(fitted.results, titanic[,"Survived"])$overall[1]
> 0.792
```

Let’s compete

Competition: best accuracy

For this exercise you will need to estimate a logistic regression on a crime dataset.

The variable of interest is larcenies per capita (larcPerPop). The variable is equal to one when larcenies per capita are high, and equal to zero when larcenies per capita are low.

The variables you can use are listed on the app:
-- **agePct12t29**: percentage of population that is 12-29 in age (numeric - decimal)
-- **agePct16t24**: percentage of population that is 16-24 in age (numeric - decimal)
-- **agePct65up**: percentage of population that is 65 and over in age (numeric - decimal)
-- **numbUrban**: number of people living in areas classified as urban (numeric - expected to be integer)
-- **pctUrban**: percentage of people living in areas classified as urban (numeric - decimal)
-- **medIncome**: median household income (numeric - may be integer)