

Statistical Computing with R: Masters in Data Sciences 503, S28 First Batch, SMS, TU, 2021

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Review Preview:

- Monte Carlo simulations
 - Randomness
 - Random deviates
 - Resampling
- Use of Monte Carlo methods in Machine Learning
- Class imbalance problem
 - Statistical approach
 - Data science approach
- Missing data
 - Supervised learning
 - Unsupervised learning

Monte Carlo Simulations:

<https://bstaton1.github.io/au-r-workshop/ch4.html>

- Simulation modeling is one of the primary reasons to move away from spreadsheet-type programs (like Microsoft Excel) and into a program like R.
- R allows us to replicate the same (possibly complex and detailed) calculations over and over with different random values.
- We can then summarize and plot the results of these replicated calculations all within the same program.
- Analyses of this type are called **Monte Carlo methods**: they randomly sample from a set of quantities for the **purpose of generating and summarizing a distribution of some statistic related to the sampled quantities**.

Randomness:

- A critical part of simulation modeling is the use of random processes.
- They are tightly linked to the concept of **uncertainty**: you are unsure about the outcome the next time the process is executed.
- A **random process** is one that generates a different outcome according to some rules each time it is executed.
- There are two basic ways to introduce randomness in R:
 - **Random deviates**
 - **Resampling**

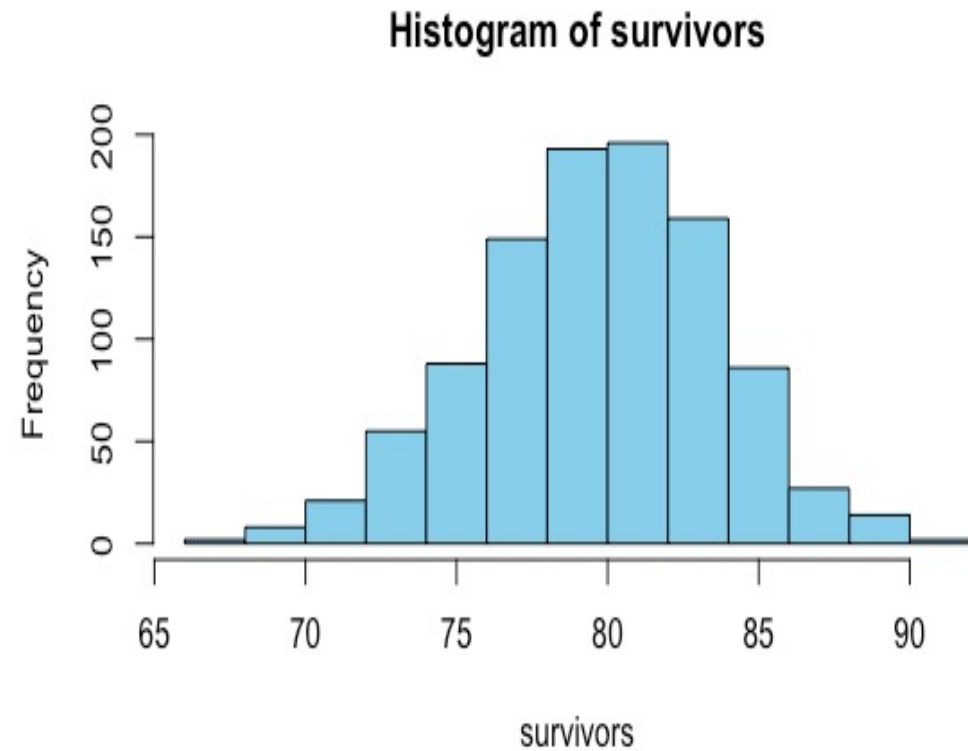
Random deviates:

- At the end of each year, each individual alive at the start can either live or die.
- There are **two outcomes here**, and suppose each individual has an 80% chance of surviving.
- The number of individuals that survive is the result of a **binomial random process** in which there were n individuals alive at the start of this year and p is the probability that any one individual survives to the next year.
- We can execute a binomial random process with $p=0.8$ and $n=100$ like this in R:
 - **`rbinom(n = 1, size = 100, prob = 0.8)`**
 - I got:
 - `[1] 83`
 - But you almost certainly get different number than this one!

We can also plot it with a bit of tweaking:

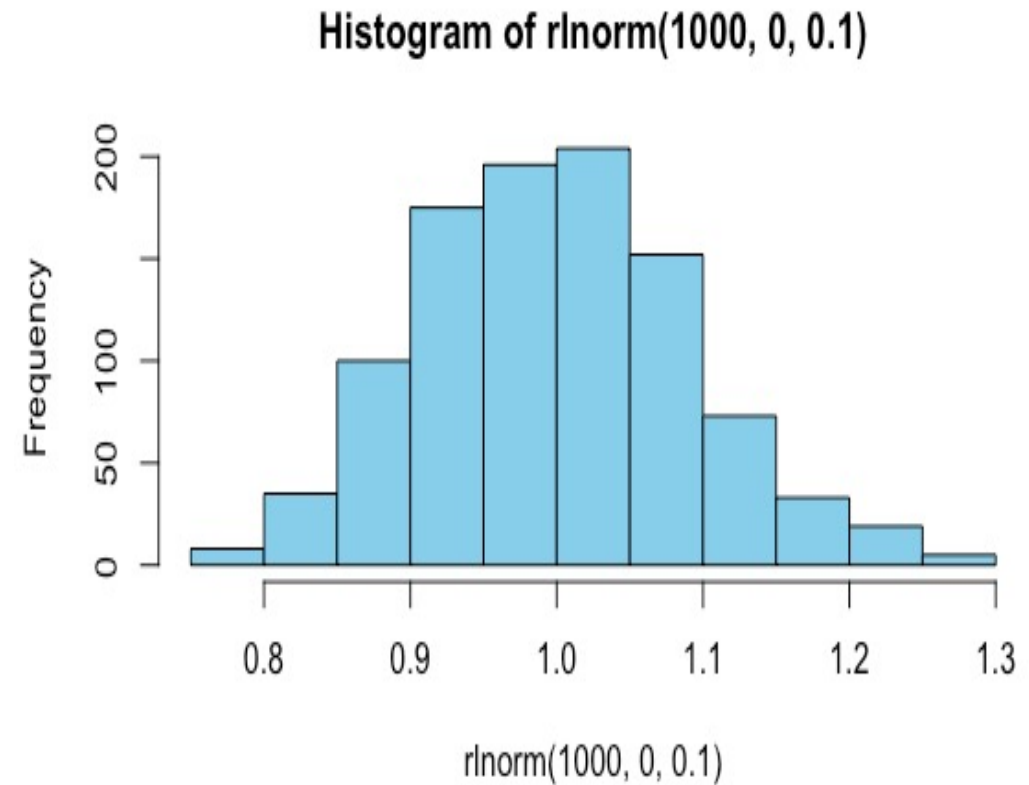
Histogram

```
survivors = rbinom(1000, 100, 0.8)  
hist(survivors, col = "skyblue")
```



We could also use other processes like log normal:

- Another random process is the **lognormal process**.
- It generates random numbers such that the log of the values are normally-distributed with mean equal to **logmean** and standard deviation equal to **logsd**
- `hist(rlnorm(1000, 0, 0.1), col = "skyblue")`



Need for sampling:

<https://machinelearningmastery.com/monte-carlo-sampling-for-probability/>

- There are many problems in probability, and **more broadly in machine learning**, where we cannot calculate an analytical solution directly.
- The desired calculation is typically a **sum of a discrete distribution or integral of a continuous distribution** and is intractable to calculate.
- **Class imbalance problem is such situation in Machine Learning!**
- The calculation may be intractable for many reasons, such as the **large number of random variables**, the stochastic nature of the domain, noise in the observations, the lack of observations, and more.
- In fact, there may be an argument that exact inference may be intractable for most practical probabilistic models.

Resampling:

- Using random deviates works great for creating new random numbers, but what if we already have a set of numbers that we wish to introduce randomness to?
- For this, we can use **resampling techniques**.
- In R, the `sample()` function is used to sample size elements from the vector `x`.

#Resampling of 1 to 10:

- `sample(x = 1:10, size = 5)`

#Sample with replacement

- `sample(x = c("a", "b", "c"), size = 10, replace = T)`

#Sample with set probabilities

- `sample(x = c("live", "die"), size = 10, replace = T, prob = c(0.8, 0.2))`

We have used it:

- `roll()` function defining roll of a fair die twice
- Training and Testing sets definition, cross-validation

Reproducing randomness:

- For reproducibility purposes, we may wish to get the same exact random numbers each time we run our script.
- To do this, we need to set the **random seed**, which is the starting point of the random number generator our computer uses.

#Example:

- **set.seed(1234)**
- **rnorm(1)**
- [1] -1.207066

#Try without random seed

- rnorm(1)
- [1] 0.2774292

Replication:

- To use Monte Carlo methods, we need to be able to replicate some random process many times.
- There are two main ways this is commonly done: either with **replicate()** or with **for()** loops.
- The replicate() function executes some expression many times and returns the output from each execution.
- Say we have a vector x, which represents 30 observations of an animal length (mm):
 - **x = rnorm(30, 500, 30)**

Replication in R:

- We wish to build the sampling distribution of the mean length “by hand”.
- We can sample randomly from it, calculate the mean, then repeat this process many times.
- This can be done in R with:

#Code after x is defined:

```
means = replicate(n = 1000, expr = {  
  x_i = sample(x, length(x),  
  replace = T)  
  mean(x_i)  
})
```

Mean and SE same in x and 1000 replicated means of x? **Unbiased estimate of x!**

- If we take `mean(means)` and `sd(means)`, that should be very similar to `mean(x)` and `se(x)`.

- Create the `se()` function and prove this using R!

- `se = function(x) sd(x)/sqrt(length(x))`

#Check means first

- `mean(means); mean(x)`
- `-[1] 492.5897`
- `[1] 492.6636`

#Standard error of mean

`sd(means); se(x)`

`[1] 5.130683`

`[1] 5.023584`

Monte Carlo Simulations is based on **Law of Large Numbers**. It can also be used to prove **Regression to Mean** and **Central Limit Theorem**.

More on Law of Large Numbers here:
<https://machinelearningmastery.com/a-gentle-introduction-to-the-law-of-large-numbers-in-machine-learning/>

Replication with “for” loop:

- In programming, a *loop* is a command that does something over and over until it reaches some point that you specify.
- A `for()` loop repeats some action for however many times you tell it **for** each value in some vector.
- R has a few types of loops: `repeat()`, `while()`, and `for()`, to name a few.
- `for()` loops are among the most common in simulation modeling.

#For loop syntax:

```
for (var in seq) {  
    expression(var)  
}
```

Examples:

#1

```
for (i in 1:5) {  
    print(i^2)  
}
```

#2

```
results=numeric(5)  
for (i in 1:5) {  
    results[i] = i^2 }  
results
```

#Output 1

- [1] 1
- [1] 4
- [1] 9
- [1] 16
- [1] 25

#Output 2

```
[1] 1 4 9 16 25
```

More:

- `nt = 100` *# number of years*
- `N = NULL` *# container for (fish) abundance*
- `N[1] = 1000` *# first **end-of-year** abundance*

`#Loop for replication`

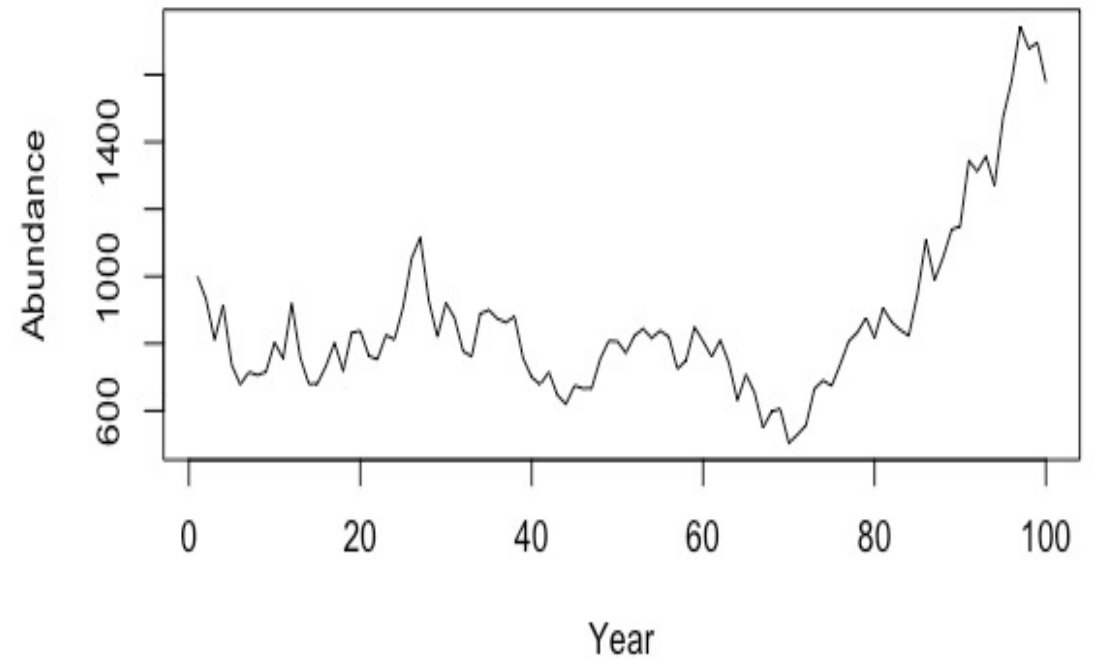
for (t in 2:nt) {

*#N this year is N last year * growth *
randomness * fraction that survive
harvest*

`N[t] = (N[t-1] * 1.1 * rlnorm(1, 0,
0.1)) * (1 - 0.08)`
`}`

Let's plot it:

- **plot**(N, type = "l", pch = 15, xlab = "Year", ylab = "Abundance")



Function writing for Monte Carlo simulation:

#In Monte Carlo analyses, it is often useful to wrap code into functions.

- This allows for easy replication and setting adjustment (e.g., if you wanted to compare the growth trajectories of two populations with differing growth rates).

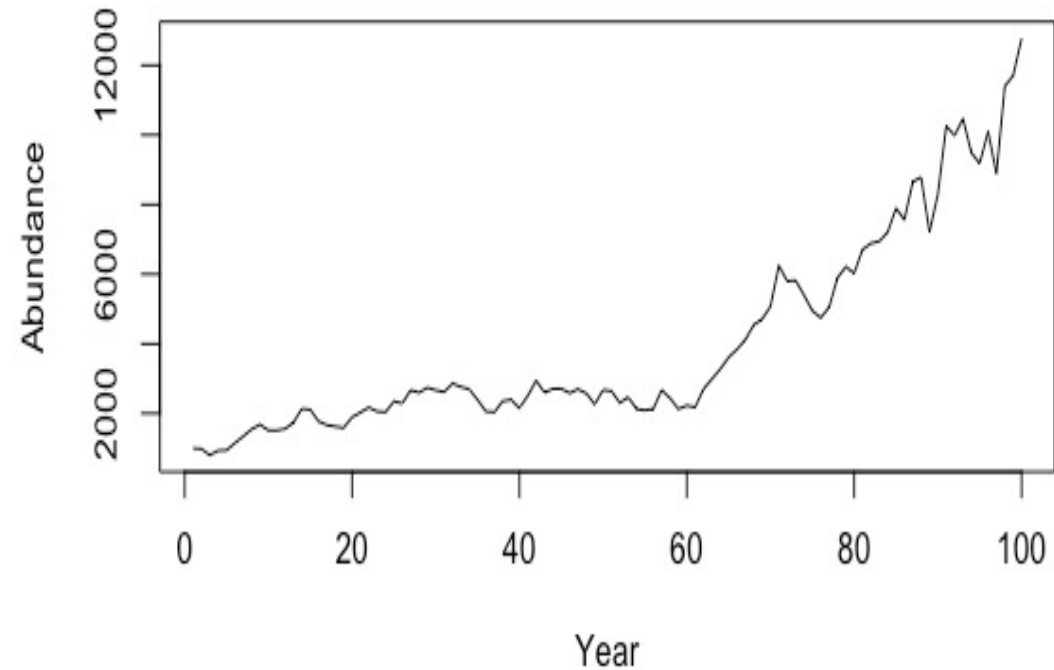
#Let's use five parameters to do so now:

- nt: the number of years,
- grow: the population growth rate,
- sd_grow: the amount of annual variability in the growth rate
- U: the annual exploitation rate
- plot: whether you wish to have a plot created.

```
pop_sim = function(nt, grow, sd_grow, U, plot = F) {  
  N = NULL  
  N[1] = 1000  
  for (t in 2:nt) {  
    N[t] = (N[t-1] * grow * rlnorm(1, 0, sd_grow)) * (1 - U)  
  }  
  if (plot) { plot(N, type = "l", pch = 15, xlab = "Year",  
    ylab = "Abundance")  
  }  
  N  
}
```

Run: `pop_sim(100, 1.1, 0.1, 0.08, T)` to get

- [1] 1000.0000 982.3888 802.9221 930.8944 942.8799 1147.2425 1343.0696
- [8] 1547.2829 1679.2181 1514.6867 1513.1179 1560.9256 1736.7056 2135.8081
- [15] 2106.6725 1775.4615 1665.7489 1623.7020 1589.0171 1889.1755 2029.1288
- [22] 2170.6199 2058.1873 2038.3532 2347.5983 2290.1806 2671.5877 2598.8134
- [29] 2738.5065 2669.0003 2617.4264 2859.6799 2764.8132 2694.8130 2388.6001
- [36] 2057.0187 2041.2244 2351.3923 2395.7745 2151.1563 2509.3455 2943.5983
- [43] 2599.5925 2706.5242 2710.5283 2587.0943 2696.7068 2573.2741 2267.4747
- [50] 2676.7501 2638.4771 2306.5914 2464.6563 2126.1586 2090.3945 2131.9059
- [57] 2676.4949 2435.6190 2128.2608 2225.5276 2179.7877 2706.6805 2989.4001
- [64] 3277.0129 3609.7139 3843.7520 4117.0917 4546.7481 4706.4806 5077.8774
- [71] 6248.7845 5797.8300 5824.2902 5400.6019 4948.3756 4747.5507 5046.0663
- [78] 5894.9432 6207.3198 6030.4074 6706.5260 6884.1739 6946.1890 7204.8305
- [85] 7895.0993 7563.0521 8655.1318 8783.0285 7210.3333 8300.1920 10254.6761
- [92] 9983.9319 10467.9362 9487.7283 9186.1128 10096.7386 8892.1724 11403.9986
- [99] 11699.4072 12772.6927



Replicating the simulation:

#Replicate the simulation for 1000 times

- `out = replicate(n = 1000, expr = pop_sim(100, 1.1, 0.1, 0.08, F))`

- `out = large matrix (10000 elements, 800.2 kb)`

#View this matrix in R Studio:

- `View(out)`

Summarization of simulation:

- After replicating a calculation many times, we will need to summarize the results.

- We must show the central tendency and variability

- We can also show Frequencies and cross-tabulations

#Central Tendency: mean

- `N_mean = apply(out, 1, mean)`
- `N_mean[1:10]`

#Variability:

`N_sd = apply(out, 1, sd)`

`N_sd[1:10]`

Summarization of simulation:

#Frequencies 1

```
out10 = ifelse(out[10,] < 1000,  
"less10", "greater10")
```

```
table(out10)
```

#Frequencies 2

```
out20 = ifelse(out[20,] < 1100,  
"less20", "greater20")
```

```
table(out20)
```

#Cross-tabulations

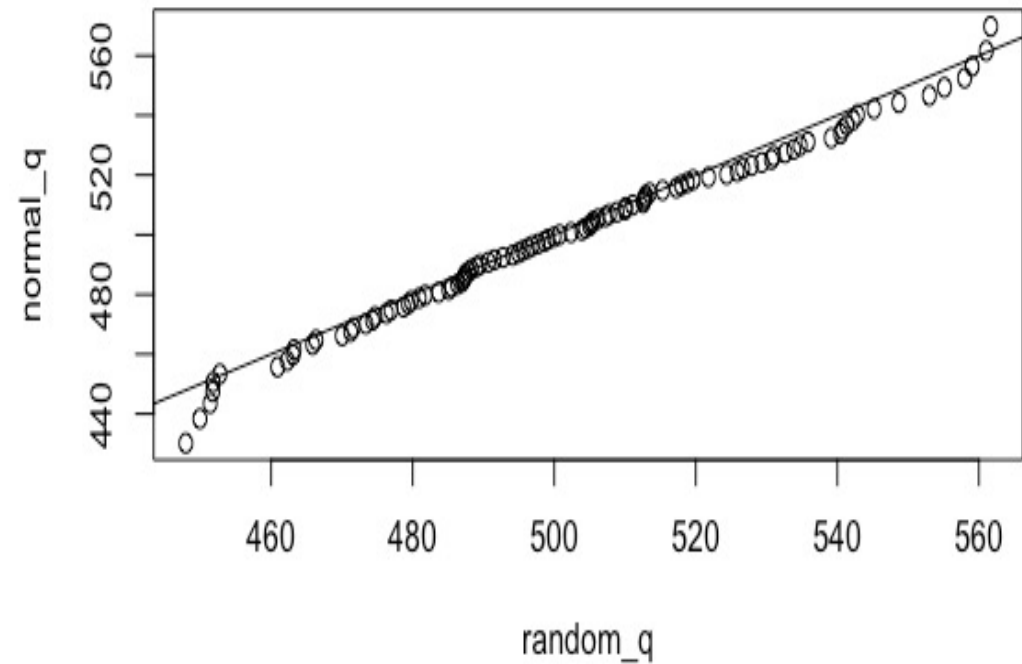
- `table(out10, out20)`

#Cross-tabulations with probabilities

- `round(table(out10, out20)/1000, 2)`

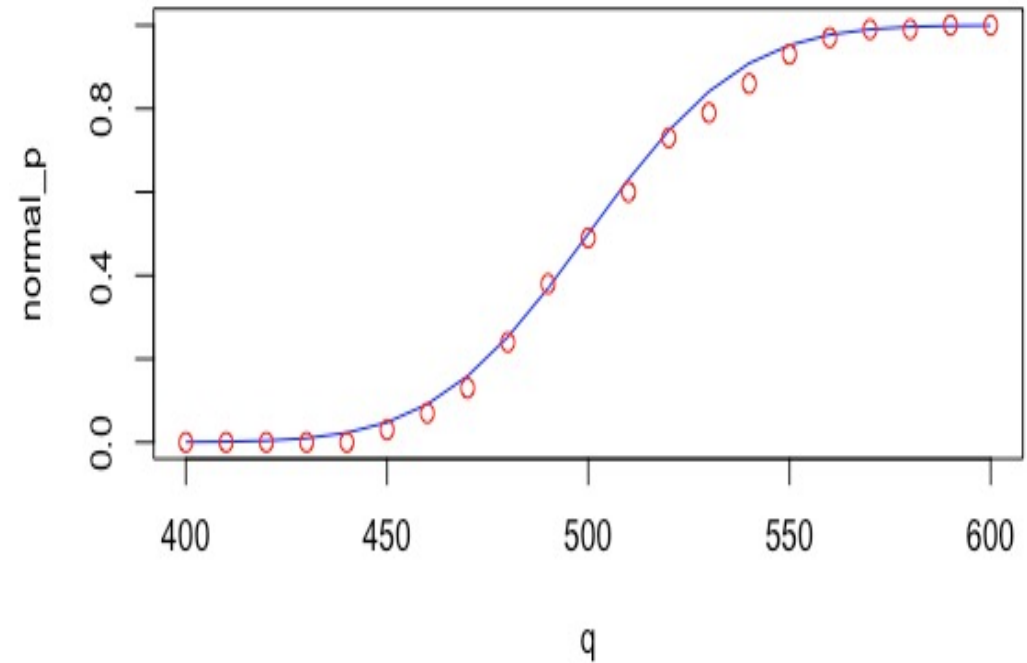
Simulation Based Learning: Example 1

- $\mu = 500$; $\sigma = 30$
- `random = rnorm(100, mu, sig)`
- `p = seq(0.01, 0.99, 0.01)`
`random_q = quantile(random, p)`
`normal_q = qnorm(p, mu, sig)`
- `plot(normal_q ~ random_q);`
`abline(c(0,1))`



Simulation Based Learning: Example 2

- `q = seq(400, 600, 10)`
- `random_cdf = ecdf(random)`
- `random_p = random_cdf(q)`
- `normal_p = pnorm(q, mu, sig)`
- `plot(normal_p ~ q, type = "l", col = "blue") points(random_p ~ q, col = "red")`



Use in Machine learning:

<https://machinelearningmastery.com/monte-carlo-sampling-for-probability/>

- In machine learning, Monte Carlo methods provide the basis for resampling techniques like the bootstrap method for estimating a quantity, such as the accuracy of a model on a limited dataset.
- We have seen its use in:
 - Resampling algorithms
 - Random hyperparameter tuning (caret package)
 - Ensemble learning algorithms
- Random sampling of model hyperparameters when **tuning a model is a Monte Carlo** method
- **Ensemble models** used to overcome challenges **such as the limited size and noise in a small data sample and the stochastic variance** in a learning algorithm **are all examples of Monte Carlo methods.**

Question/queries so far?

Class imbalance problem: Binary dep. var. (y)

- It happens in the classification problems
- When we have a categorical binary dependent variable then distribution of 1 and 0 may not be equal (or very skewed)
- When it is very skewed then it is known as “class imbalance”
- We can deal with it using statistics or data science
- Statistical approach
 - Instead of binary logistic regression
 - Use exact logistic regression
 - Use Poisson regression
 - Use zero-inflated Poisson regression
 - Use negative binomial regression
- Data science approach
 - Generate new data using simulations, make the balanced class and get accuracy measures

Class imbalance problem: Categorical “y”

- It happens in the classification problems
- When we have a categorical dependent variable then distribution of 0, 1 or 2 may not be equal (or very skewed)
- When it is very skewed then it is known as “class imbalance”
- We can deal with it using statistics or data science
- Statistical approach
 - Instead of multinomial or ordinal logistic regression
 - Use exact multinomial/ordinal logistic regression
 - Use Poisson regression
 - Use zero-inflated Poisson regression
 - Use negative binomial regression
- Data science approach
 - Generate new data using simulations, make the balanced class and get accuracy measures

In statistics, we are more concerned with “Simpson’s Paradox” than the Class Imbalance problems!
UCLA Admission “paradox”: Overall **few females were admitted** but **more females were admitted** when the same data was analyzed by departments! **Same can happen with all the supervised models!**

Example: binary.csv data

#Admission to UCLA

- Four variables in the data
- admit = Admitted or not
- gre = GRE score
- gpa = GPA score
- rank = Rank of the institute where they got their GPA

#Class imbalance problem data

```
data <- read.csv("binary.csv",  
header = T)
```

```
str(data)
```

```
summary(data)
```

#Change the admit as factor variable

```
data$admit <-  
as.factor(data$admit)
```

```
summary(data)
```

Outputs:

	admit	gre	gpa	rank
•	Min. :0.0000	Min. :220.0	Min. :2.260	Min. :1.000
•	1st Qu.:0.0000	1st Qu.:520.0	1st Qu.:3.130	1st Qu.:2.000
•	Median :0.0000	Median :580.0	Median :3.395	Median :2.000
•	Mean :0.3175	Mean :587.7	Mean :3.390	Mean :2.485
•	3rd Qu.:1.0000	3rd Qu.:660.0	3rd Qu.:3.670	3rd Qu.:3.000
•	Max. :1.0000	Max. :800.0	Max. :4.000	Max. :4.000

- prop. table(table(data\$admit))

•	0	1
•	0.6825	0.3175

	admit	gre	gpa	rank
•	0:273	Min. :220.0	Min. :2.260	Min. :1.000
•	1:127	1st Qu.:520.0	1st Qu.:3.130	1st Qu.:2.000
		Median :580.0	Median :3.395	Median :2.000
		Mean :587.7	Mean :3.390	Mean :2.485
		3rd Qu.:660.0	3rd Qu.:3.670	3rd Qu.:3.000
		Max. :800.0	Max. :4.000	Max. :4.000

Class imbalance as dependent variable “admit” has 273 (68.25%) cases in 0 (not admitted category) and 127 (31.75%) in 1 (admitted) category.

In statistics, we deal it using different methods but in data science we deal it with making these classes “balanced”

Let's predict without correcting imbalance:

#Data partition

#set.seed(1234)

- `Ind <- sample(2, nrow(data),
replace=T, prob=c(0.7,0.3))`

- `train <- data[ind==1,]`

- `test <- data[ind==2,]`

- #Check the imbalance in the train data

- `table(train$admit)`

- 0 1

- 196 83

- `prop.table(table(train$admit))`

- 0 1

- **0.702509 0.297491 (Is this really imbalance!)**

Let's predict without correcting imbalance:

#Prediction model

#Random forest model

```
library(randomForest)
rfm.train <- randomForest(admit~.,
data=train)
```

#Model evaluation with test data using caret package

```
library(caret)
confusionMatrix(predict(rfm.train,
test), test$admit, positive = '1')
```

• #Outputs

	Reference	
Prediction	0	1
0	73	32
1	4	12

Accuracy : 0.7025 (**misleading!**)

95% CI : (0.6126, 0.7821)

Sensitivity : 0.27273 (**not good for 1**)

Specificity : 0.94805 (**good for 0**)

This is due to “class imbalance” problem!

Let's predict with correction: Oversampling

#Correcting class imbalance by oversampling: Using Randomly Oversampling Examples (ROSE) package

- `library(ROSE)`
- `over.samp <- ovun.sample(admit~., data = train, method = "over", N = 196*2)$data`
- `table(over.samp$admit)`

- Here 196 is used as there was an imbalance in the train data

- `table(train$admit)`

- 0 1

- **196** 83

#We will get equal values now:

- `table(over.samp$admit)`

- 0 1

- **196** **196**

#Resampling of observed values of category=1 is used to get more 1s!

Let's predict with correction: Oversampling

#Check summary for changes in the other variables too!

- `summary(over.samp)`

#Random Forrest model with over sampled data

- `rfm.os <- randomForest(admit~., data=over.samp)`
- `confusionMatrix(predict(rfm.os, test), test$admit, positive = '1')`

Prediction	Reference	
	0	1
0	59	22
1	18	22
Accuracy : 0.6694		
95% CI : (0.5781, 0.7522)		
Sensitivity : 0.5000		
Specificity : 0.7662		

Sensitivity improved (good if we wanted to improve prediction for 1) but overall accuracy decreased!

What else can be done with ROSE package?

- We can do the undersampling and check the model accuracy, sensitivity and specificity again
- We can create a synthetic data, fit the model, predict it to check the model accuracy, sensitivity, specificity etc.
- We can do both i.e. oversampling and undersampling and check the model accuracy, sensitivity and specificity again
- While creating synthetic data, we must use random seed too in the function to get replicable results!

More on Synthetic Minority Oversampling (SMOTE) here:
https://www.youtube.com/watch?v=dkXB8HH_4-k

Missing values:

<https://towardsdatascience.com/7-ways-to-handle-missing-values-in-machine-learning-1a6326adf79e>

- The real-world data often has a lot of missing values. The cause of missing values can be data corruption or failure to record data.
- **The handling of missing data is very important during the preprocessing of the dataset as many machine learning algorithms do not support missing values.**
- Visit the link to learn more about handling missing values to learn:
- The 7 ways to handle missing values in the dataset
 - Deleting Rows with missing values
 - Impute missing values for continuous variable (mean, median etc.)
 - Impute missing values for categorical variable (predict the categories)
 - Other Imputation Methods
 - Using Algorithms that support missing values
 - Prediction of missing values
 - Imputation using Deep Learning Library — Datawig

Missing values checking and handling in R:

#Check missing values in R

- *colsum(is.na(data frame))*
- *sum(is.na(data frame\$column name))*

#Strategies

- List-wise deletion
- Pair-wise deletion
- Mean/ Mode/ Median Imputation
 - Generalized Imputation
 - Similar case Imputation
- Prediction Model
- KNN Imputation

#List of R Packages

- **MICE**
- Amelia
- missForest
- Hmisc
- mi
- etc.

<https://medium.com/coinmonks/dealing-with-missing-data-using-r-3ae428da2d17>

<https://www.analyticsvidhya.com/blog/2016/03/tutorial-powerful-packages-imputing-missing-values/>

MICE package:

- MICE (Multivariate Imputation via Chained Equations) is one of the commonly used package by R users. Creating multiple imputations as compared to a single imputation (such as mean) takes care of uncertainty in missing values.
- MICE assumes that the missing data are **Missing at Random (MAR)**, which means that the probability that a **value is missing depends only on observed value and can be predicted** using them.
- It imputes data on a variable by variable basis by specifying an imputation model per variable.
- The methods used by this package are:
 - PMM (**Predictive Mean Matching**) — For numeric variables
 - logreg(**Logistic Regression**) — For Binary Variables(with 2 levels)
 - polyreg(**Bayesian polytomous regression**) — For Factor Variables (≥ 2 levels)
 - **Proportional odds model (ordered and censored variables, ≥ 2 levels)**

More here: <https://medium.com/coinmonks/dealing-with-missing-data-using-r-3ae428da2d17>

Use of MICE with an example data is here: <https://www.youtube.com/watch?v=An7nPLJ0fsg>

Question/queries?

- Next classes
- Communicating the results of data science projects
- Defining projects in R studio
- R markdown “nitty gritty”
- R notebook

Thank you!

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