Welcome to GBUS 738



David Svancer

Adjunct Professor of Business Analytics George Mason University

School of Information Systems and Operations Management



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GBUS 738 Skills You Will Develop In This Course

Fundamentals of Programming with R	The basics of R programming
Data Analysis with the <i>Tidyverse</i>	Data analysis and visualization techniques using the popular <i>tidyverse</i> R package
Machine Learning with <i>tidymodels</i>	Training machine learning models with the <i>tidymodels</i> R framework
Managing Analytics Projects and Communicating Business Value	Data analysis and machine learning projects from start to finish using R

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Course Goals

Computer Programming Fundamentals

Data types and structures in R

• Vectors, Matrices, Lists and Data frames

View the data

my_data

	gender	test_1_grade	hw_1_grade	session	
1	М	82	92	7 AM	
2	F	93	89	7 PM	
3	F	87	98	7 AM	

Writing Custom Functions for Data Analysis Tasks

my_result <- mean_dev_3(data)</pre>



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Course Goals Data Analysis with the *Tidyverse*



tidyverse.org

R packages for data science

The tidyverse is an opinionated collection of R packages designed for data science. All packages share an underlying design philosophy, grammar, and data structures.

Data Visualization

ggplot(data = average_delays, mapping = aes(x = month_text, y = day_text, fill = avg delay)) + geom_tile() +

scale fill gradient2() +

labs(title = "Average Flight Delay By Month and Day",

x = "Month", y = "Day")

Average Flight Delay By Month and Day



Data Manipulation

heart %>% group_by(ChestPain, HeartDisease) %>% summarise(patients n = n(), avg_chol = mean(Cholesterol), sd chol = sd(Cholesterol))

A tibble: 8 x 5

#	Groups: Che	estPain [4]			
	ChestPain	HeartDisease	patients_n	avg_chol	sd_chol
	<chr></chr>	<chr></chr>	<int></int>	<dbl></dbl>	<dbl></dbl>
1	asymptomatic	No	39	245.	48.9
2	asymptomatic	Yes	103	253.	52.9
3	nonanginal	No	65	247.	64.7
4	nonanginal	Yes	18	239	43.8
5	nontypical	No	40	241.	45.3

Data Wrangling and Reshaping

China

Country	1999	2000		Country	Year	Count
Afghanistan	745	2,666		Afghanistan	1999	745
Brazil	37,737	80,488	→	Brazil	1999	37,737
China	212,258	213,766		China	1999	212,258
			-	Afghanistan	2000	2,666
				Brazil	2000	80.488



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2000

213,766





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Machine Learning?

A subset of Artificial Intelligence that gives computers the capability to learn without being **explicitly programmed**





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Machine Learning A New Programming Paradigm

Before ML

Computers were explicitly programmed to achieve desired results

Explicit Program

If input number is even → return "Yes"

If input number is odd → return "No"

Program Execution



 $6 \longrightarrow$ Program Logic Executed \longrightarrow

Output → "Yes"

Benefit Correct output on every execution Challenge All rules to accomplish task must be known in advance



Machine Learning Explicit Programming Workflow



Machine Learning Learning From Data

Today

ML algorithms use vast amounts of data to discover patterns and relationships without relying on a predetermined equations or set of rules as a model

ML Program

Label	Data Value
Yes	2
Yes	12
No	3
Yes	4
No	5
No	39

Learned prediction function

ML Prediction Function Execution

Input		Output
6	prediction function \longrightarrow	"Yes"
4	prediction function \longrightarrow	"No"
3 →	prediction function \longrightarrow	"No"

Benefit

All steps/rules to accomplish **do not** have to be known or programmed explicitly

Challenge

Prediction error



Machine Learning Workflow





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Machine Learning Example - Image Recognition

Task

Identify handwritten digits

For a Human

Easy

For a Computer

Extremely difficult

MNIST Database of Handwritten Digits





Machine Learning Without ML – Explicit Program

Explicit Program to Identify Digits

Imagine having to develop explicit instructions for a program to correctly identify handwritten digits

- You must identify **every possible variation** of how digits appear and instruct a computer to label them correctly
- Practically impossible your program would be millions of lines long!

MNIST Database of Handwritten Digits



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Machine Learning Approach

Encode Color Intensities and Apply ML Algorithms to Learn Patterns



Color intensities (0 – 255)

Number	Region_1	 Region_467	Region_468	 Region_783	Region_784
4	0	158	242	0	0
5	85	0	63	16	66
1	32	0	92	0	93
9	10	95	0	55	73
З	0	60	25	92	139



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Machine Learning Demonstration of ML Algorithm

DATA

Label by

label

label

Edit by label

Loac

UMAP

Dimension

Perplexity 🕑

Stop

Iteration: 3

Learning

rate

Supervise with

5 tensors found

TensorFlow projection tool https://projector.tensorflow.org/

- Goal find the optimal 0 way to compress digit image data to 3 dimensions so that the same digits are grouped together
- Once this model is 0 discovered, we can use it to predict new images based on where they fall in this 3-dimensional space



Embedding Projector Points: 10000 Dimension: 784 A 0 Mnist with images Color by label No ignored label w. Tag selection as Publish Download Label Sphereize data 📀 T-SNE PCA CUSTOM 3D 25 10 Supervise 🕑 Pause Perturb How to use t-SNE effectively.

Machine Learning Methods Supervised Learning

Supervised learning algorithms learn prediction functions from labeled training data.

Labeled data set from a hospital

- Each row represents a patient who eventually did or did not develop heart disease (the outcome variable – Heart Disease)
- Our goal might be to predict whether a new patient will develop heart disease using the predictor variables
 - For each set of predictor values, **we have a known outcome**
 - We also have a set of predictor values for each known outcome

Outcome (Target, Response, Dependent) variable

Heart Disease	Age	Chest Pain	Resting BP	Cholesterol
No	63	typical	145	233
Yes	67	asymptomatic	160	286
Yes	67	asymptomatic	120	229
No	37	nonanginal	130	250
No	41	nontypical	130	204

Predictor (Feature, Independent) variables



Machine Learning Methods Supervised Learning - Regression

Regression

- Supervised learning methods are used to predict *quantitative* outcome variables
- Example
 - Predict the selling price of homes using features such as square footage, age, location

Outcome	Predictor
Selling Price	Square Footage
\$105,667	1,100
\$118,659	1,490
\$134,268	1,850
\$165,000	2,300



Predicting Home Selling Price



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Machine Learning Methods Supervised Learning - Classification

Classification

Supervised learning methods used to predict **categorical** outcome variables

Example

 Predict whether a customer will purchase a product based on the seconds they have spent browsing a company's homepage and product page

Outcome	Predictors		
Purchase	Seconds Homepage	Seconds Product Page	
Did Not Purchase	4	30	
Purchased	32	43	
Did Not Purchase	2	22	
Purchased	24	36	

Segmenting the predictor values into distinct, non-overlapping regions to predict a category

Decision Boundary - Black Line





Machine Learning Methods Unsupervised Learning

In **unsupervised learning**, there are feature or input variables, but no labeled outcome variable

• no "correct" prediction

In this setting, it is typically of interest to learn the **structure** and **relationships** present in the unlabeled input data

 Methods include Clustering and Principal Components (PCA)

Marketing Example: Are there customer segments based on purchasing behavior?

‡ A tibble: 150) x 4		
Sepal.Length	Sepal.Width	Petal.Length	Petal.Width
<dbl></dbl>	<pre><dbl></dbl></pre>	<dbl></dbl>	<dbl></dbl>
1 5.1	. 3.5	1.4	0.2
2 4.9	3	1.4	0.2
3 4.7	3.2	1.3	0.2
4 4.6	3.1	1.5	0.2
5 5	3.6	1.4	0.2
6 5.4	3.9	1.7	0.4
7 4.6	3.4	1.4	0.3
8 5	3.4	1.5	0.2
9 4.4	2.9	1.4	0.2
4.9	3.1	1.5	0.1

Are there different types or species of plants present in the data below?

K-means Clustering

Finding observations that group together based on their proximity in the input data space

Sepal Length vs Petal Length



