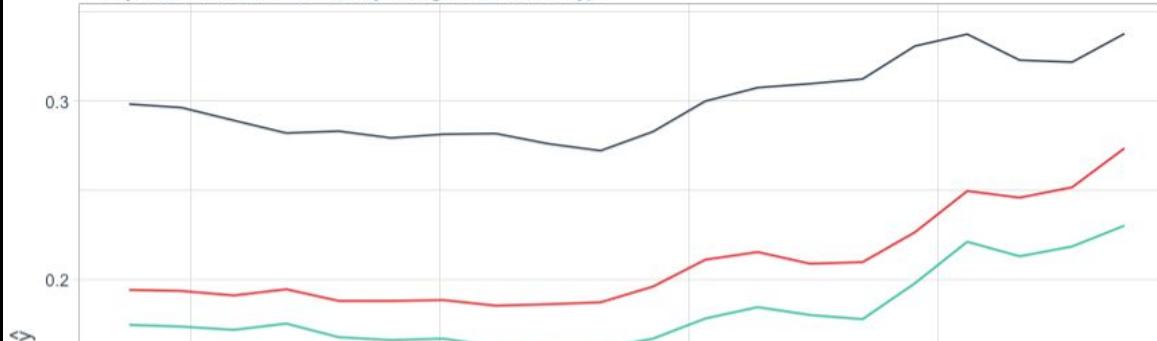


```
10 library(rsample)
11 library(recipes)
12 library(h2o)
13
14 library(iml)
15 library(DALEX)
16
17 library(correlationfunnel)
18 library(DataExplorer)
19
```

How Random Forest Models Churn  
2-Way Interaction between Monthly Charges & Contract Type



# Explaining Machine Learning

For Customer Churn

Difficulty: **Intermediate**

Contract — Month-to-month — One year — Two year

Matt Dancho & David Curry  
*Business Science Learning Lab*





# Learning Lab Structure

- **Presentation**  
(20 min)
- **Demo's**  
(30 min)
- **Pro-Tips**  
(15 mins)



**Matt Dancho**

Founder of Business Science, Matt designs and executes educational courses and workshops that deliver immediate value to organizations. His passion is up-leveling future data scientists coming from untraditional backgrounds.



**David Curry**

Founder of Sure Optimize, David works with businesses to help improve website performance and SEO using data science. His passion is **ethical Machine Learning initiatives**.

# Success Story

# Casper Craus

- Data Engineer - Keyphase
  - Started course 5 Weeks Ago
  - Got the job!



***“Before starting DS4B 101, I was in the middle of a job transition. I got the job, and I’m hired as a Data Engineer.”***



## Handling missing values and Outliers

CCrause

27/09/201

Loading the weather-data that is semi wrangled

Previously I wrangled a dataset that contained weather data. With this presentation I plan to check for outliers, look for missing value and explore the different ways of dealing with NA values and experiment with some basic functional programming and filtering time-series data.

```
library(tidyverse)
weather_data_pivot_tbl =
readr::read_rds("../7daysofdatascience/Data_wrangling/weather_data_pivoted.rds")
glimpse(weather_data_pivot_tbl)

## # Observations: 366
## # Variables: 23
## # date
## # Events
## # Max.TemperatureF
## # Mean.TemperatureF
## # Min.TemperatureF
## # Max.Dew.PointF
## # MeanDew.PointF
## # Min.DewpointF
## # Max.Humidity
## # Mean.Humidity
## # Min.Humidity
## # Max.Sea.Level.PressureIn
## # Mean.Sea.Level.PressureIn
## # Min.Sea.Level.PressureIn
<chr> "2014/12/1", "2014/12/2", "2014/12/3...
<chr> "Rain", "Rain-Snow", "Rain", "", "Ra...
<dbl> 64, 42, 51, 43, 42, 45, 38, 29, 49, ...
<dbl> 52, 38, 44, 37, 34, 42, 30, 24, 39, ...
<dbl> 39, 33, 37, 30, 26, 38, 21, 18, 29, ...
<dbl> 46, 40, 49, 24, 37, 45, 36, 28, 49, ...
<dbl> 40, 27, 42, 21, 25, 40, 20, 16, 41, ...
<dbl> 26, 17, 24, 13, 12, 36, -3, 3, 28, 3...
<dbl> 74, 92, 100, 69, 85, 100, 92, 92, 10...
<dbl> 63, 72, 79, 54, 66, 93, 61, 70, 93, ...
<dbl> 52, 51, 57, 39, 47, 85, 29, 47, 86, ...
<dbl> 30.45, 30.71, 30.40, 30.56, 30.68, 3...
<dbl> 30.13, 30.59, 30.87, 30.33, 30.59, 3...
<dbl> 30.01, 30.48, 29.87, 30.09, 30.45, 3...
<dbl> 10, 10, 10, 10, 10, 10, 10, 10, ...
<dbl> 10, 8, 5, 10, 4, 10, 8, 2, 3, ...
<dbl> 10, 2, 1, 10, 5, 0, 5, 2, 1, 1, 1, ...
<dbl> 22, 24, 29, 25, 22, 22, 25, 21, 38, ...
<dbl> 13, 15, 12, 12, 10, 8, 15, 13, 20, 1...
<dbl> 29, 29, 38, 33, 26, 25, 32, 28, 52, ...
<dbl> 0.01, 0.10, 0.04, 0.00, 0.11, 1.09, ...
<dbl> 6, 7, 8, 3, 5, 6, 8, 8, 8, 8, 7, ...
<dbl> 268. 62, 254. 292. 61. 313. 350. 354.
```

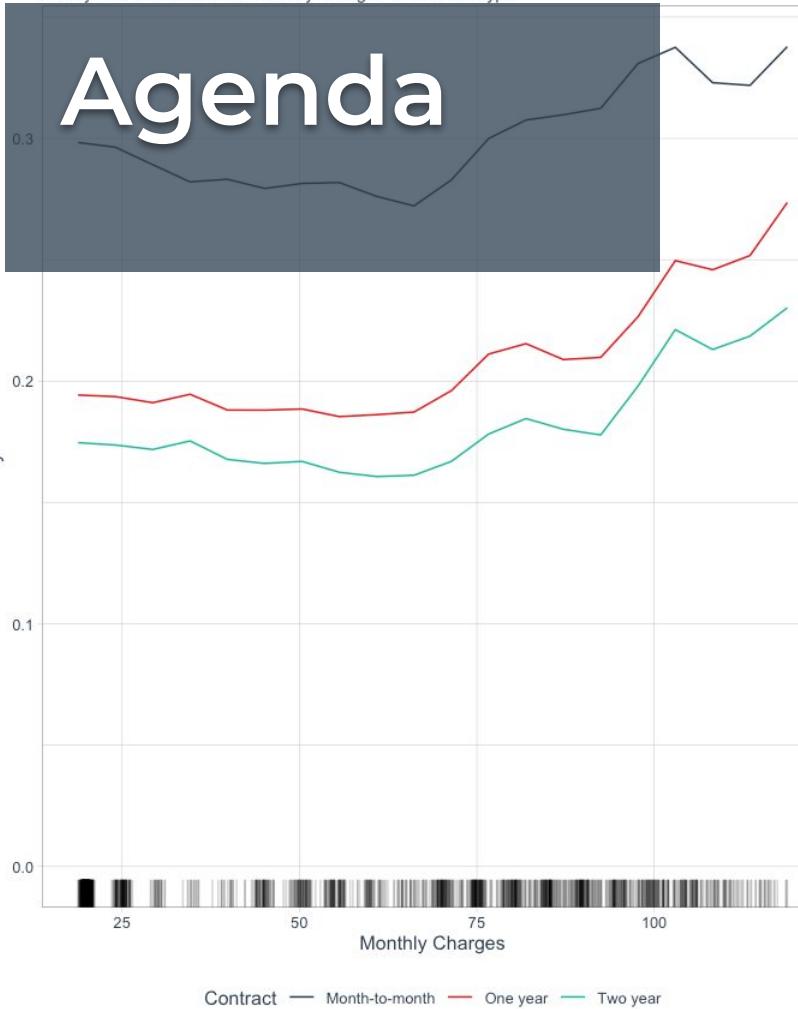
# #Business Science Success



Casper Crause 2:38 AM

Hi Matt, This is a word of thanks. Over the course of 5 weeks my data science skill set has shown tremendous growth. Before starting DS4B 101 I was in the middle of a job transition. I got the job and now I'm hired as a Data Engineer! Thank you so much for your hard work in creating course content that is second to none! I truly believe you have touched the lives of thousands of people like me! We will be working closely with a company that applies machine learning to estimate the potential yield of the harvests of their clients. One of the super cool perks is I get to work remotely. I have been assigned the role of project manager for this particular project! So I'm really keen to learn H2O\_AI in your 201 course!

# Agenda



- **Business Case Study**
  - Customer Churn
  - Why Explanations are CRITICAL
- **Explainable ML**
  - Key Concepts
- **R Packages**
  - IML
  - DALEX
- **30-Min Demo**
  - Telecom Customers
  - ML - Churn Prediction
  - ML - Churn Explanation
- **Pro-Tips:**
  - Tactics to **Deliver Stories** to Executives



# Learning Labs PRO

Every 2-Weeks

1-Hour Course

Recordings + Code + Slack

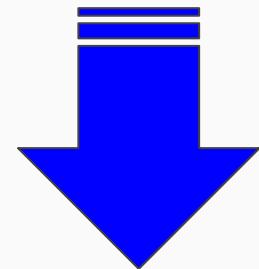
**\$19/month**

*university.business-science.io*

- Lab 19*  
**Using Customer Credit Card History for Networks Analysis**
- Lab 18*  
**Time Series Anomaly Detection with anomalize**
- Lab 17*  
**Anomaly Detection with H2O Machine Learning**
- Lab 16*  
**R's Optimization Toolchain, Part 2 - Nonlinear Programming**
- Lab 15*  
**R's Optimization Toolchain, Part 1 - Linear Programming**
- Lab 14*  
**Customer Churn Survival Analysis**



**Continuous Learning**  
Jet Fuel for your Brain



**Learning Labs Pro**

Community-Driven Data Science Courses

 Matt Dancho

**\$19/m**

# **Customer Churn**

## Business Case



# Why Explanations Matter

## Customer Churn

1. Subscriptions are a function of **inflow** and **outflow**
2. Outflow is called **churn**
3. If we can **explain** churn, we can **reduce** churn
4. Increases revenue, **improves** **customer experience**





# Telecommunications Subscriptions

## Understand Subscriber Behavior

1. Use **Random Forest** to model behavior
2. Use **Explainable ML** to understand what is causing RF to predict churn





# Customer Subscription History

## Descriptive Features

Customers

```
> customer_churn_raw_tbl
# A tibble: 7,043 x 21
  customerID gender SeniorCitizen Partner Dependents tenure PhoneService MultipleLines InternetService OnlineSecurity
    <chr>      <chr>     <dbl> <chr>      <chr>     <dbl> <chr>      <chr>      <chr>      <chr>
1 7590-VHVEG Female        0 Yes       No         1 No      No phone ser... DSL          No
2 5575-GNVDE Male         0 No        No         34 Yes     No           DSL          Yes
3 3668-QPYBK Male         0 No        No         2 Yes      No           DSL          Yes
4 7795-CFOCW Male         0 No        No         45 No      No phone ser... DSL          Yes
5 9237-HQITU Female       0 No        No         2 Yes      No           Fiber optic No
6 9305-CD SKC Female      0 No        No         8 Yes      Yes          Fiber optic No
7 1452-KIOVK Male         0 No        Yes        22 Yes     Yes          Fiber optic No
8 6713-OKOMC Female       0 No        No         10 No      No phone ser... DSL          Yes
9 7892-POOKP Female       0 Yes       No         28 Yes      Yes          Fiber optic No
10 6388-TABGU Male        0 No       Yes        62 Yes     No           DSL          Yes
# ... with 7,033 more rows, and 11 more variables: OnlineBackup <chr>, DeviceProtection <chr>, TechSupport <chr>,
#   StreamingTV <chr>, StreamingMovies <chr>, Contract <chr>, PaperlessBilling <chr>, PaymentMethod <chr>,
#   MonthlyCharges <dbl>, TotalCharges <dbl>, Churn <chr>
```

# Explainable ML Basics

## 80/20 Concepts

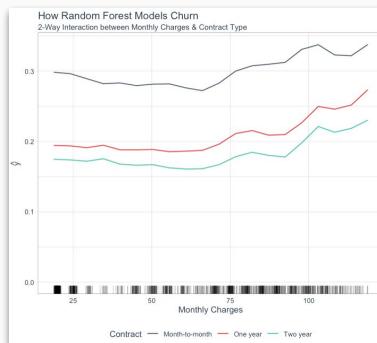


# Types of Explanations

1

Global

1 or 2 Features, All Observations

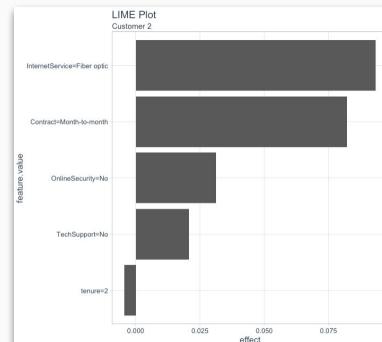


What is the  
Churn Effect for  
Contract Type?

2

Local

1 Observation, Many Features

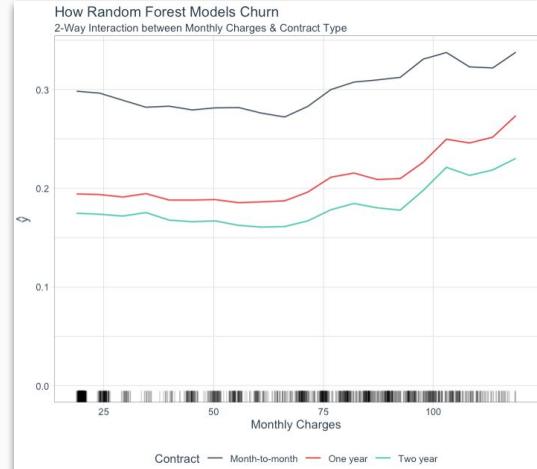


What is causing  
Customer ID 5575-GNVDE  
to Churn?

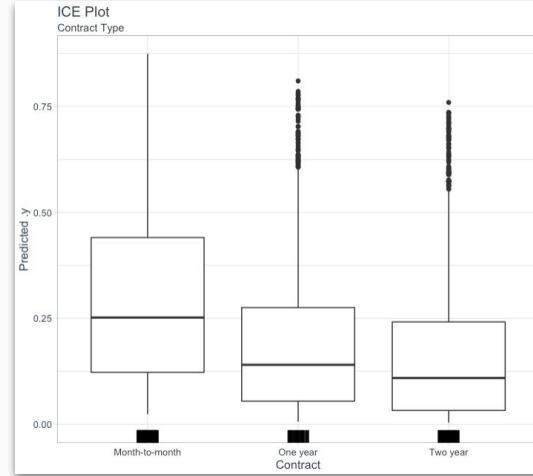
# Explainable ML Methods

Critical explanations that matter to the business

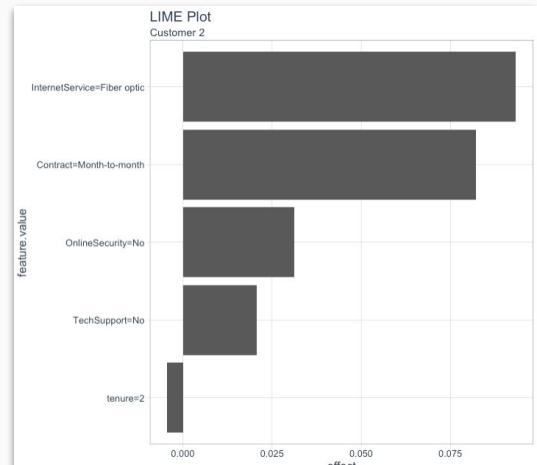
- GLOBAL - PDP & ICE
- LOCAL - LIME & Shapley



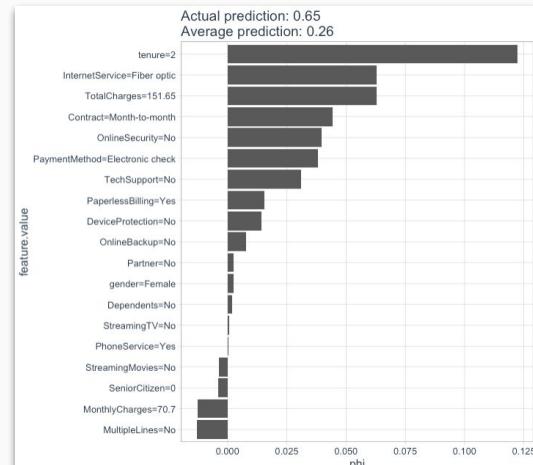
PDP



ICE



LIME

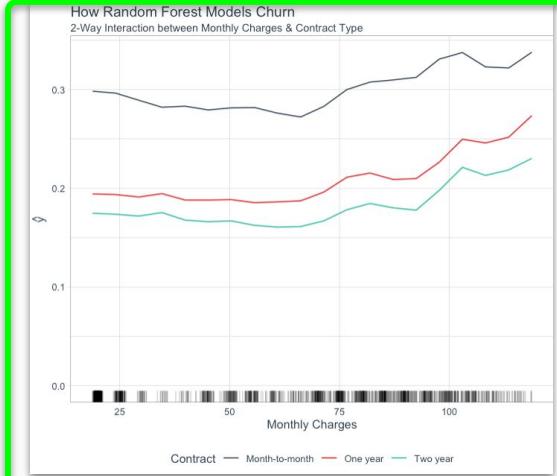


Shapley

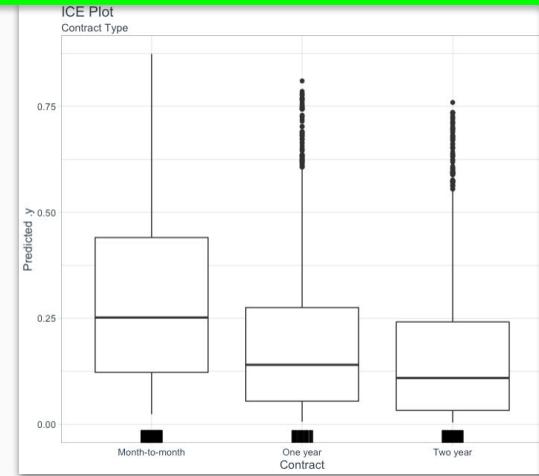
# Explainable ML Methods

Critical explanations that matter to the business

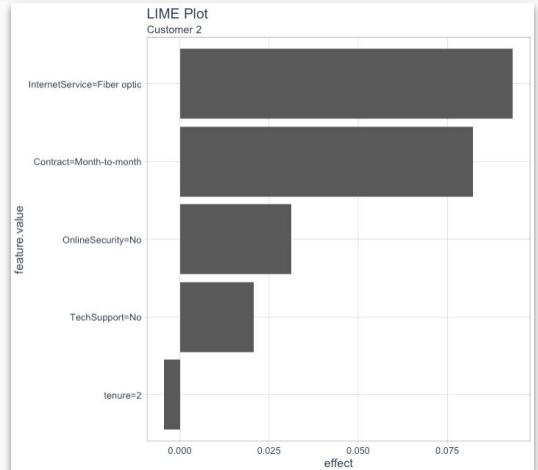
- **GLOBAL - PDP & ICE**
- LOCAL - LIME & Shapley



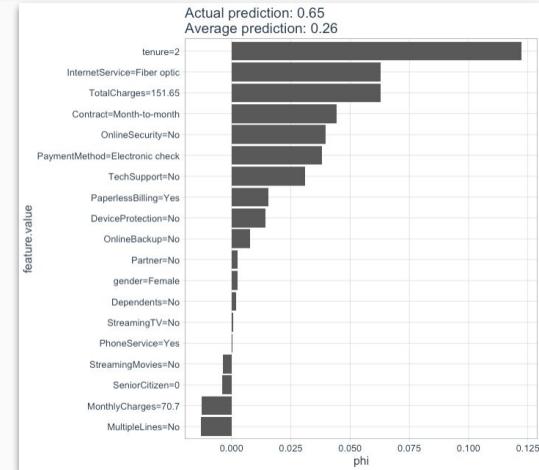
PDP



ICE



LIME

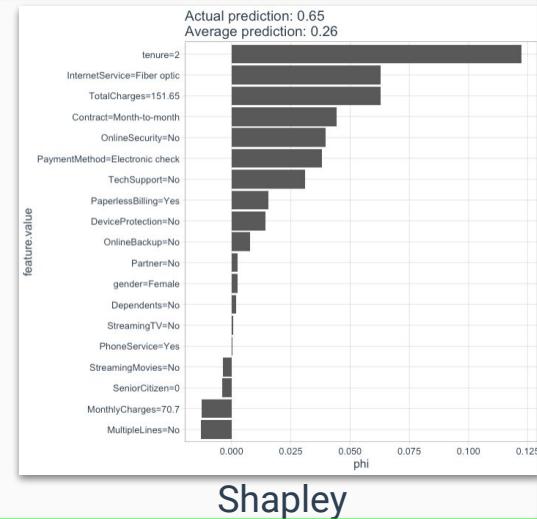
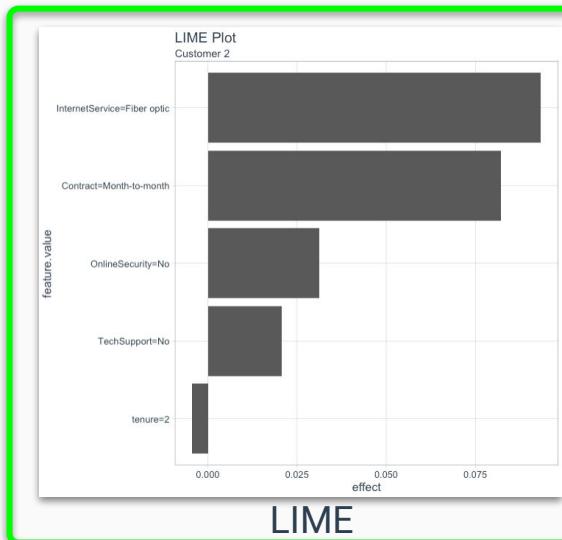
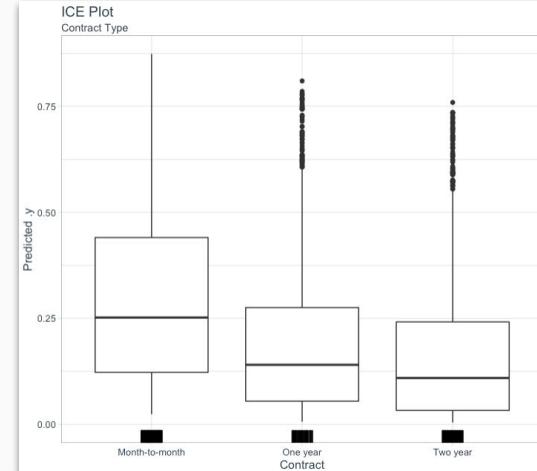
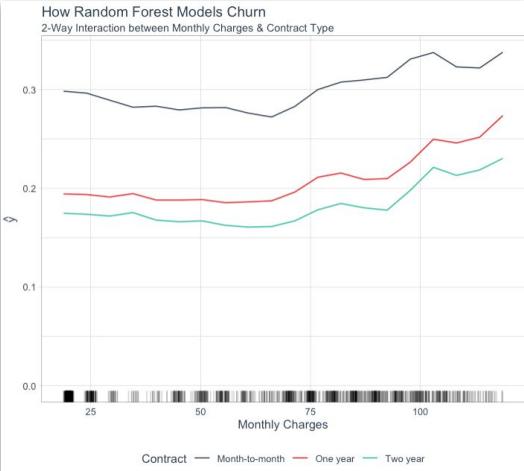


Shapley

# Explainable ML Methods

Critical explanations that matter to the business

- GLOBAL - PDP & ICE
- LOCAL - LIME & Shapley



# Core Concepts

## 80/20 Theory



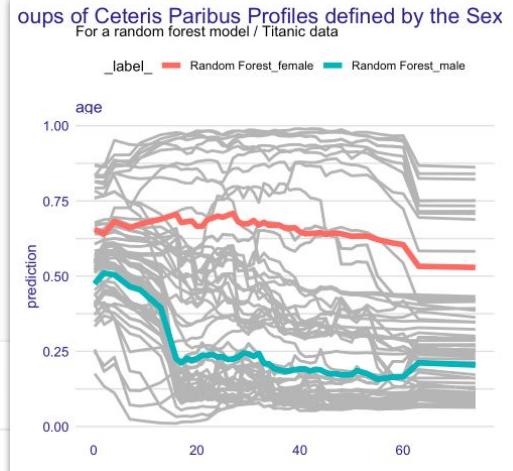
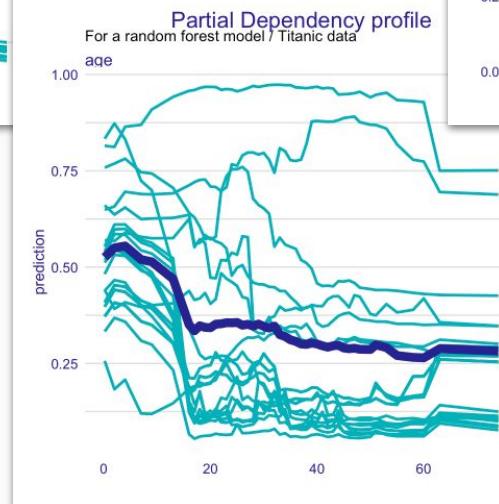
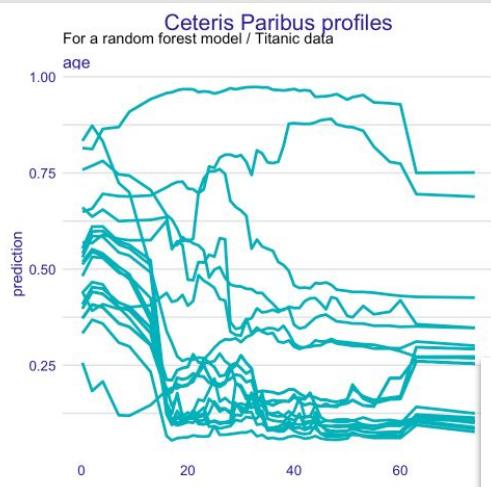
# Partial Dependence Plots (PDP) - Global

## Key Concept

Show how the expected model response for random observations.

Hold all other features constant & **vary feature** of interest.

Then **Average Results**.



# Individual Conditional Expectation (ICE) Plot - Global



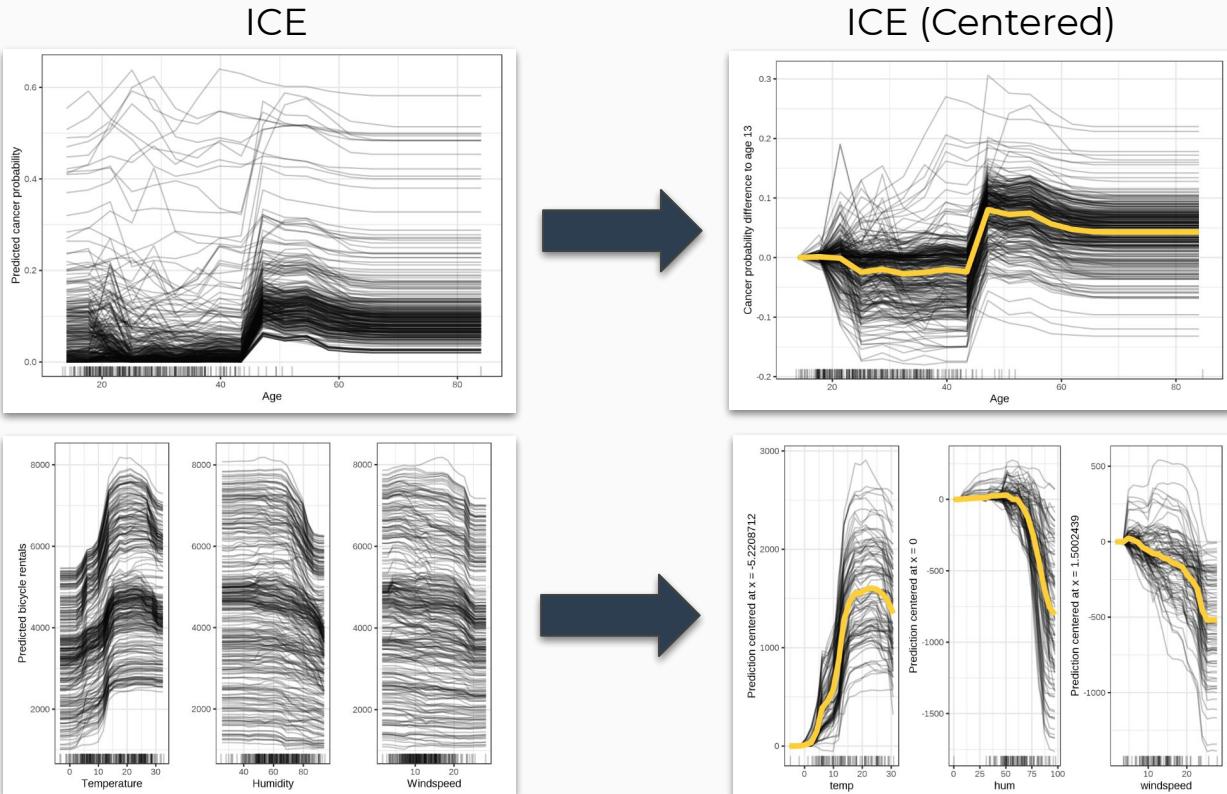
## Key Concept

Same as PDP,  
except:

**Don't Average  
(unlike PDP).**

**Center** (if desired).

**Show Trend Line**  
(if desired).



# Local Interpretable Model-Agnostic Explanation (LIME) Plot - Local



## Key Concept

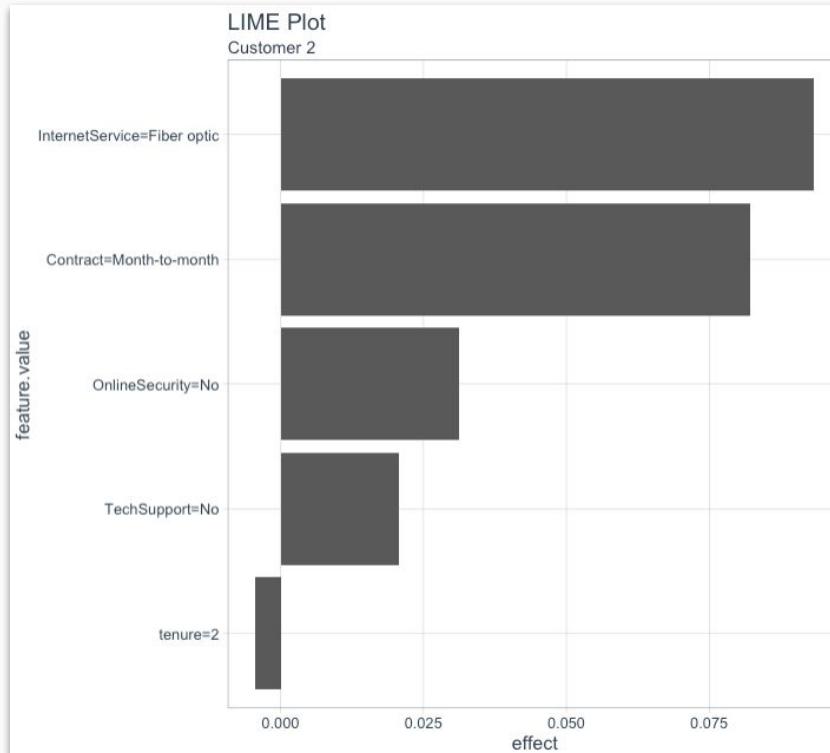
Select observation of interest

Probe the Black Box with **permuted** samples of training data.

Weight sample by proximity to sample of interest.

Train an interpretable model on weighted:

- Lasso
- Decision Tree





# Shapley Value Plot - Local

## Key Concept

Each Feature is Player in Game

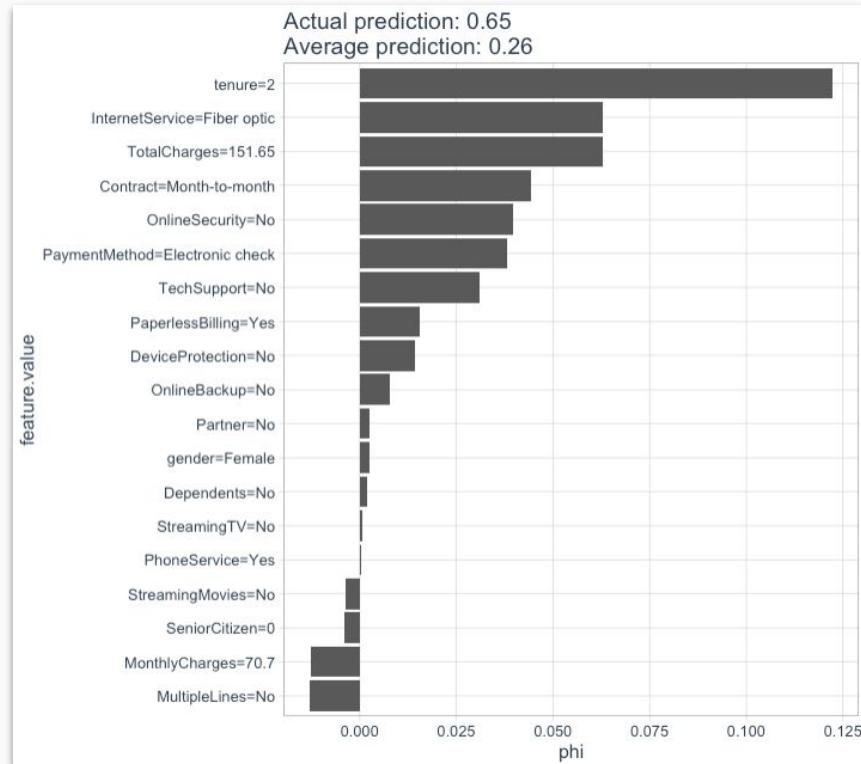
Prediction is Payout

How much has each feature contributed to the prediction?

**Coalition** - Features that work together to make prediction

**Gain** - The actual prediction minus the average for all features

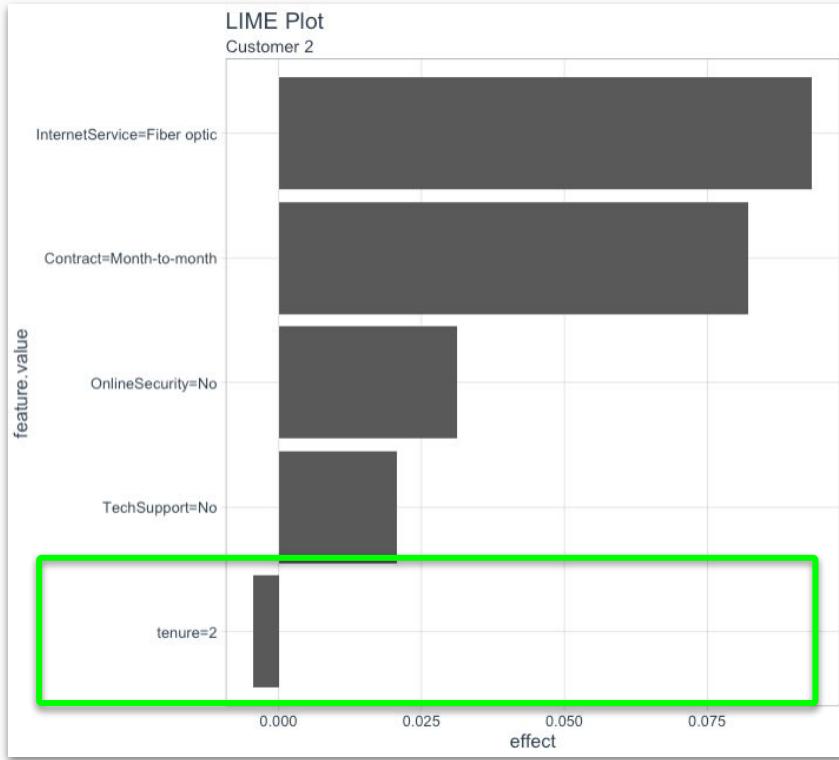
**Shapley Value** - Average Contribution to the prediction in different coalitions



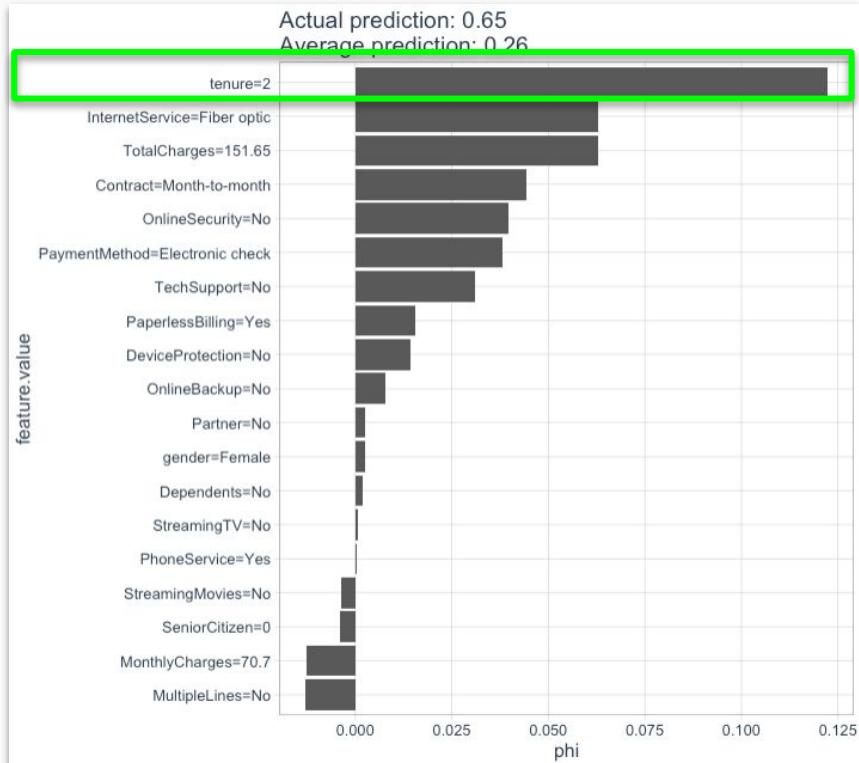
# LIME vs Shapley



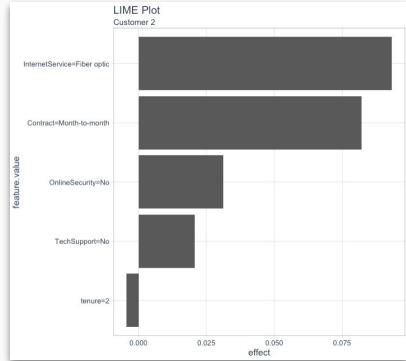
## LIME



## Shapley

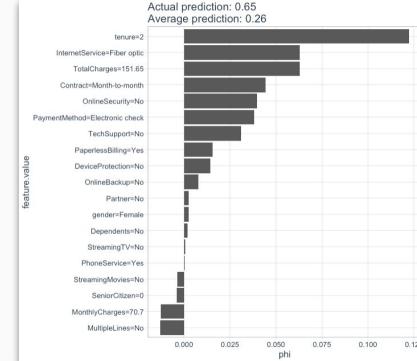


# LIME vs Shapley



## LIME

- Con - Does not guarantee a fair distribution
- Con - Assumes Linear Behavior
- **Pro - Very Fast**
- **Pro - Effect is Weight x Feature Value = Impact to Linear Model**



## Shapley

- **Pro - Guarantees a fair distribution of feature values**
- **Pro - Models explanations as a game**
- Con - Can be very slow as coalitions of features increase
- Con - Phi not easily interpreted



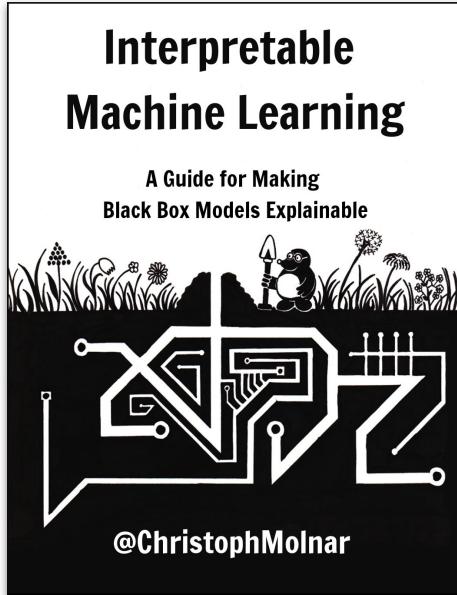
# SHAP (SHapley Additive exPlanations)

The goal of SHAP is to explain the prediction of an instance  $x$  by computing the contribution of each feature to the prediction.

More interpretable than Shapley - SHAP is additive & closer to LIME's "Effect"

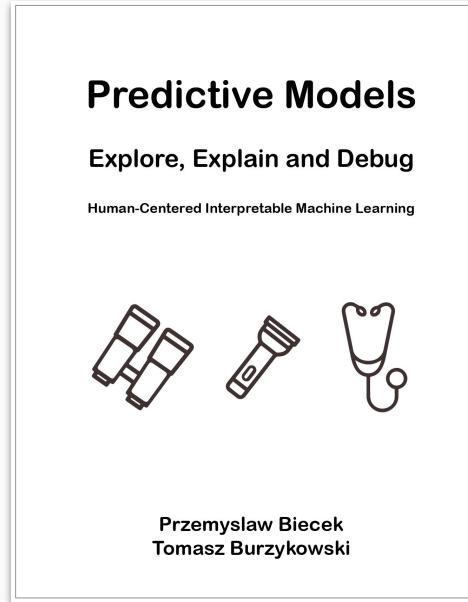
Still slow - KernelSHAP is extremely slow, TreeSHAP is faster

Implemented in DALEX



**CREATOR OF IML**

<https://christophm.github.io/interpretable-ml-book/>



**CREATORS OF DALEX**

[https://pbiecek.github.io/PM\\_VEE/](https://pbiecek.github.io/PM_VEE/)

# Explainable ML Software



christophM/iml: iml: interpreta | Descriptive mACHINE Learning | +

← → C 🔒 github.com/christophM/iml

build passing CRAN 0.9.0 downloads 39K codecov 91% JOSS 10.21105/joss.00786

## iml: interpretable machine learning

iml is an R package that interprets the behaviour and explains predictions of machine learning models. It implements model-agnostic interpretability methods - meaning they can be used with any machine learning model.

Currently implemented:

- Feature importance
- Partial dependence plots
- Individual conditional expectation plots (ICE)
- Accumulated local effects
- Tree surrogate
- LocalModel: Local Interpretable Model-agnostic Explanations
- Shapley value for explaining single predictions

Read more about the methods in the [Interpretable Machine Learning book](#)

## Tutorial

Start an interactive notebook tutorial by clicking on the badge: [launch binder](#)

## Installation

The package can be installed directly from CRAN and the development version from github:

<https://github.com/christophM/iml>



Descriptive mAchine Learning x +

modeloriented.github.io/DALEX/

DALEX part of the DrWhy.AI developed by the MIA2 DataLab 0.4.8

Reference Articles Changelog

# Descriptive mAchine Learning EXplanations



## Overview

The DALEX package (Descriptive mAchine Learning EXplanations) helps to understand how complex models are working. The main function `explain()` creates a wrapper around a predictive model. Wrapped models may then be explored and compared with a collection of local and global explainers. Recent developments from the area of Interpretable Machine Learning/explainable Artificial Intelligence.

The philosophy behind DALEX explanations is described in the [Predictive Models: Explore, Explain, and Debug](#) e-book. The DALEX package is a part of DrWhy.AI universe.

## Installation

```
# the easiest way to get DALEX is to install it from CRAN:  
install.packages("DALEX")  
  
# Or the development version from GitHub:  
# install.packages("devtools")  
devtools::install_github("ModelOriented/DALEX")
```

Links

Download from CRAN at <https://cloud.r-project.org/package=DALEX>

Browse source code at <https://github.com/ModelOriented/DALEX>

Report a bug at <https://github.com/ModelOriented/DALEX/issues>

License

GPL

Community

[Contributing guide](#)

Citation

[Citing DALEX](#)

Developers

Przemyslaw Biecek  
Author, maintainer 

[All authors...](#)

Dev status

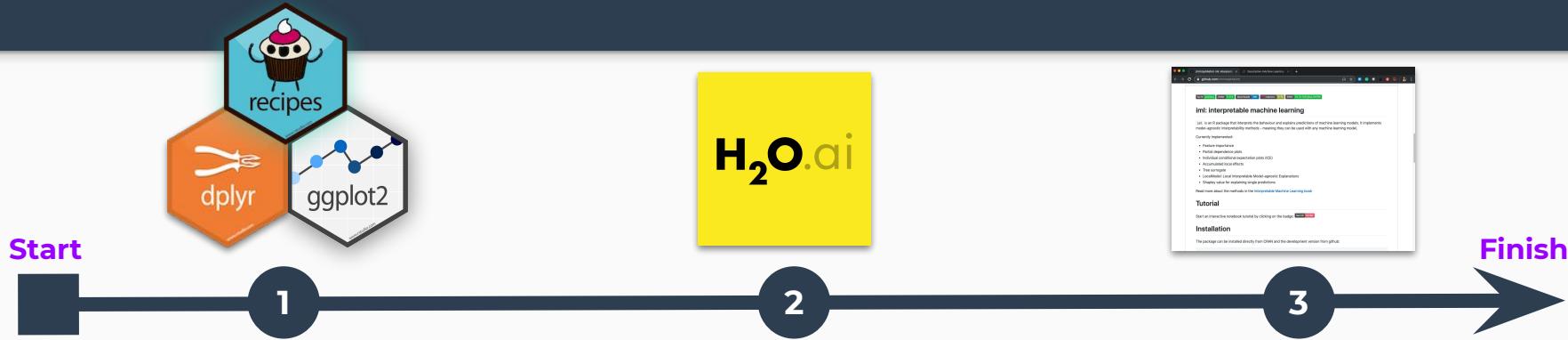
 build passing

<https://github.com/ModelOriented/DALEX>



# Customer Churn Workflow

## Step-By-Step



**Data Clean &  
Transform**

Exploratory Data Analysis

**Machine Learning**

Develop Segments

**IML**

Explain  
Customer Segments

# 30-Min Demo

## Analyze Customer Networks

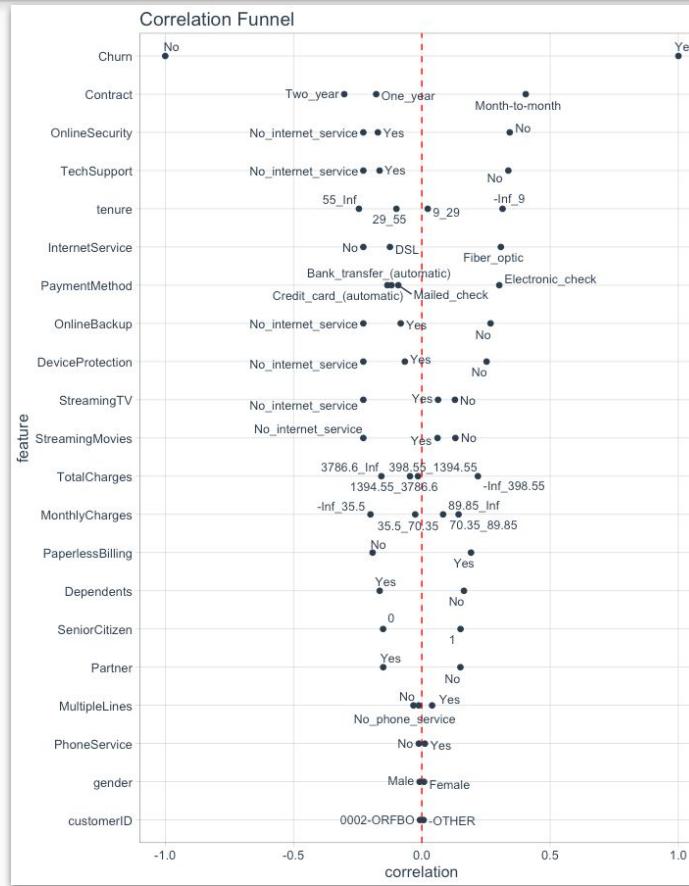
Secret Tactics for

# Explaining with Machine Learning

Use these tips to  
**increase help build a story**

## Pro Tip #1

# Make a correlation funnel

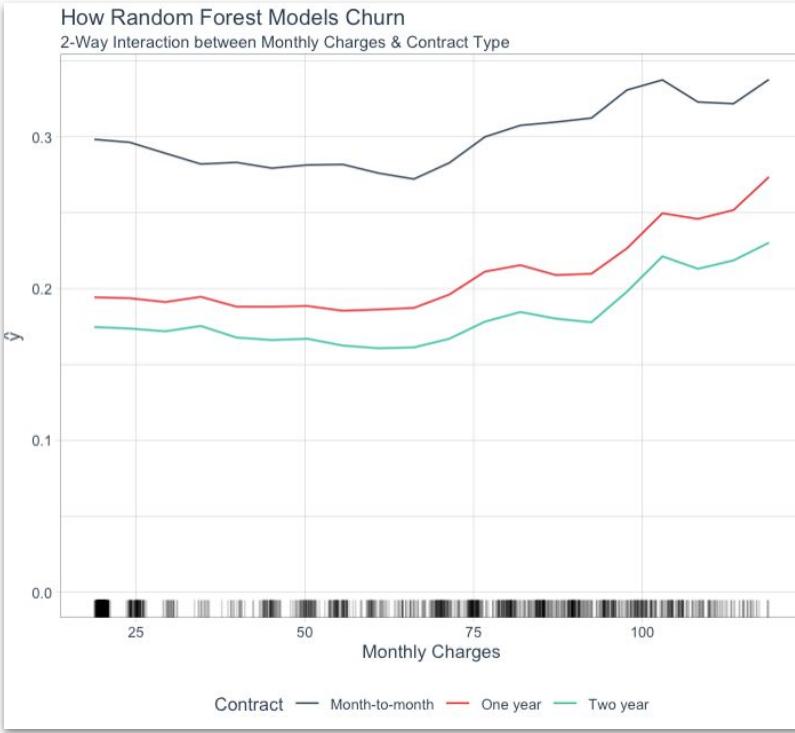


Get a general understanding of your model.

Focus on explaining the top features

## Pro Tip #2

# Build a feature story



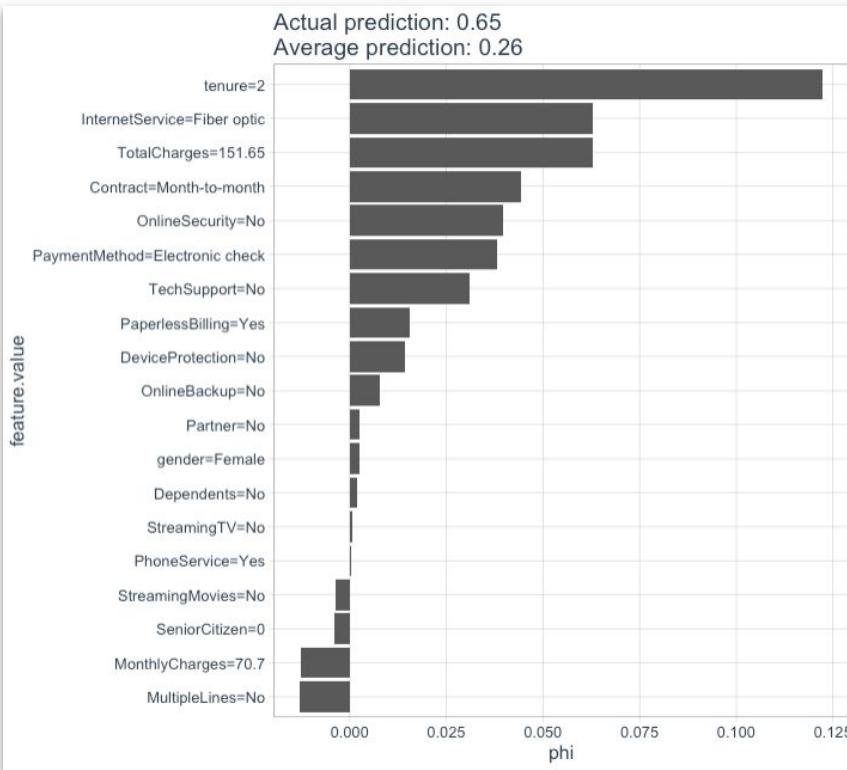
Use top features

Check interactions

Build a story

## Pro Tip #3

# Pick one customer, and explain her!



Talk about what **specifically** makes her susceptible to leaving

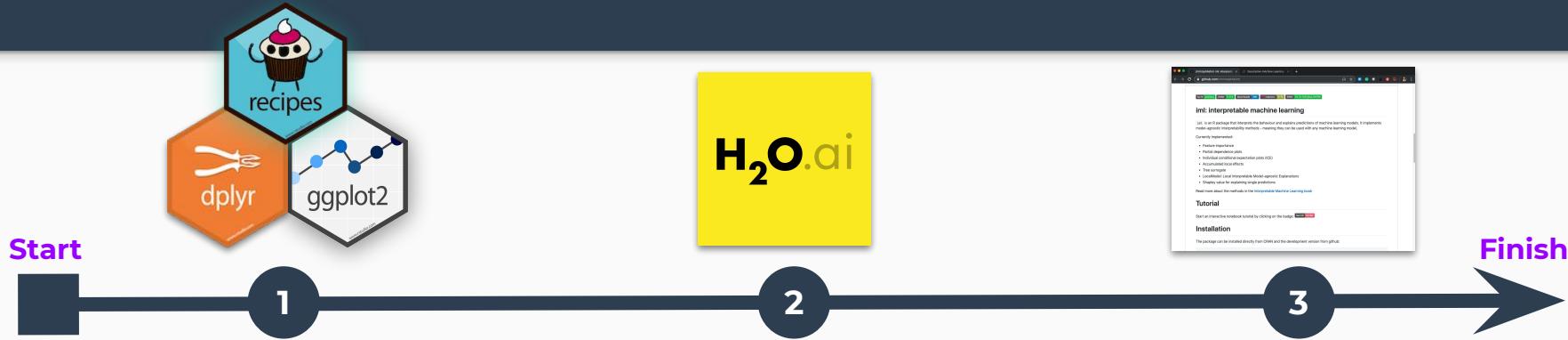
# Data Science Transformation

Skills that are needed to do what we just did



# Customer Churn Workflow

## Step-By-Step



**Data Clean &  
Transform**

Exploratory Data Analysis

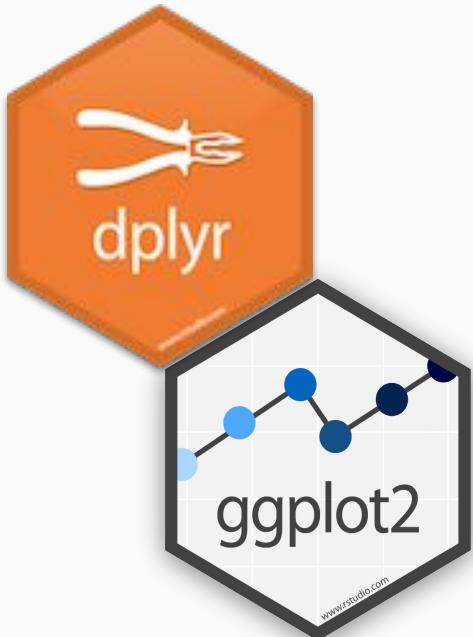
**Machine Learning**

Develop Segments

**IML**

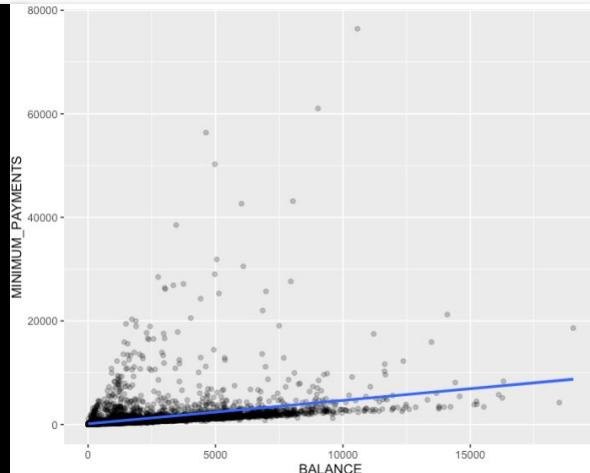
Explain  
Customer Segments

# dplyr, ggplot2



```
29
30 # 2.1 Minimum Payments has NA (missing data)
31
32 credit_card_tbl %>%
33   pull(MINIMUM_PAYMENTS) %>%
34   quantile(na.rm = TRUE)
35
36 credit_card_no_missing_tbl <- credit_card_tbl %>%
37   select_if(is.numeric) %>%
38   filter(!is.na(MINIMUM_PAYMENTS)) %>%
39   filter(!is.na(CREDIT_LIMIT))
40
41 credit_card_no_missing_tbl %>%
42   binarize() %>%
43   correlate(target = MINIMUM_PAYMENTS_825.49646275_Inf) %>%
44   plot_correlation_funnel()
45
46 credit_card_tbl %>%
47   ggplot(aes(BALANCE, MINIMUM_PAYMENTS)) +
48   geom_point(alpha = 0.25) +
49   geom_smooth(method = "lm")
```

## 101 & 201



# dplyr, ggplot2



## 101 & 201

```
63
64 # 3.1 Preprocessing ----
65 set.seed(123)
66 rsample_splits <- initial_split(customer_churn_raw_tbl, prop = 0.8)
67
68 rec_obj <- recipe(Churn ~ ., data = training(rsample_splits)) %>%
69   step_mutate(TotalCharges = ifelse(is.na(TotalCharges), 0, TotalCharges)) %>%
70   step_rm(customerID) %>%
71   step_string2factor(all_nominal()) %>%
72   prep()
73
74 train_tbl <- bake(rec_obj, training(rsample_splits))
75 test_tbl  <- bake(rec_obj, testing(rsample_splits))
76
77 train_tbl
```

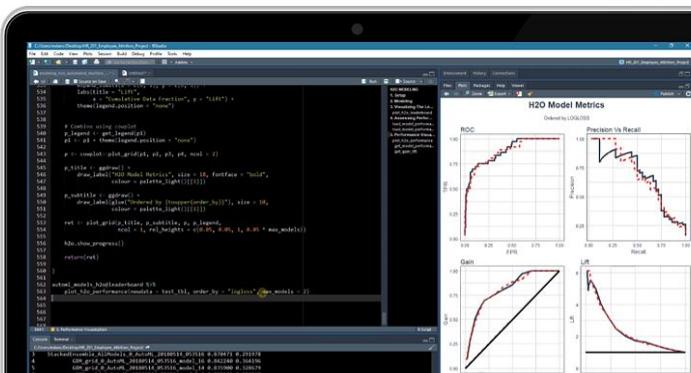
# ggplot2 & purrr



```

> h2o.predict(h2o_model, newdata = as.h2o(credit_card_group_tbl)) %>%
+   as_tibble()
|=====
|=====
# A tibble: 1,125 x 7
  predict      p1      p2      p3      p4      p5 Other
  <fct>     <dbl>    <dbl>    <dbl>    <dbl>    <dbl> <dbl>
1 Other      0.0000704 0.0228     0       0       0.977
2 Other      0.0232_  0.0000717 0.0000553 0       0.00376 0.973
3 Other      0       0.0000737 0.0238     0       0.000107 0.976
4 Other      0.00643_ 0.0000724 0.0000558 0.00343_ 0.000105 0.990
5 Other      0       0.0000720 0.0000555 0       0.000104 1.000
6 3          0       0.0000704 0.909      0       0.000102 0.0909
7 3          0       0.0000761 0.995      0       0.000110 0.00491
8 1          0.984   0.0000735 0.0000567 0.00349_ 0.000106 0.0127
9 Other      0.195   0.0000602 0.0000464 0.00285_ 0.0000870 0.802
10 Other     0       0.0000737 0.0000568 0       0       1.000
# ... with 1,115 more rows

```

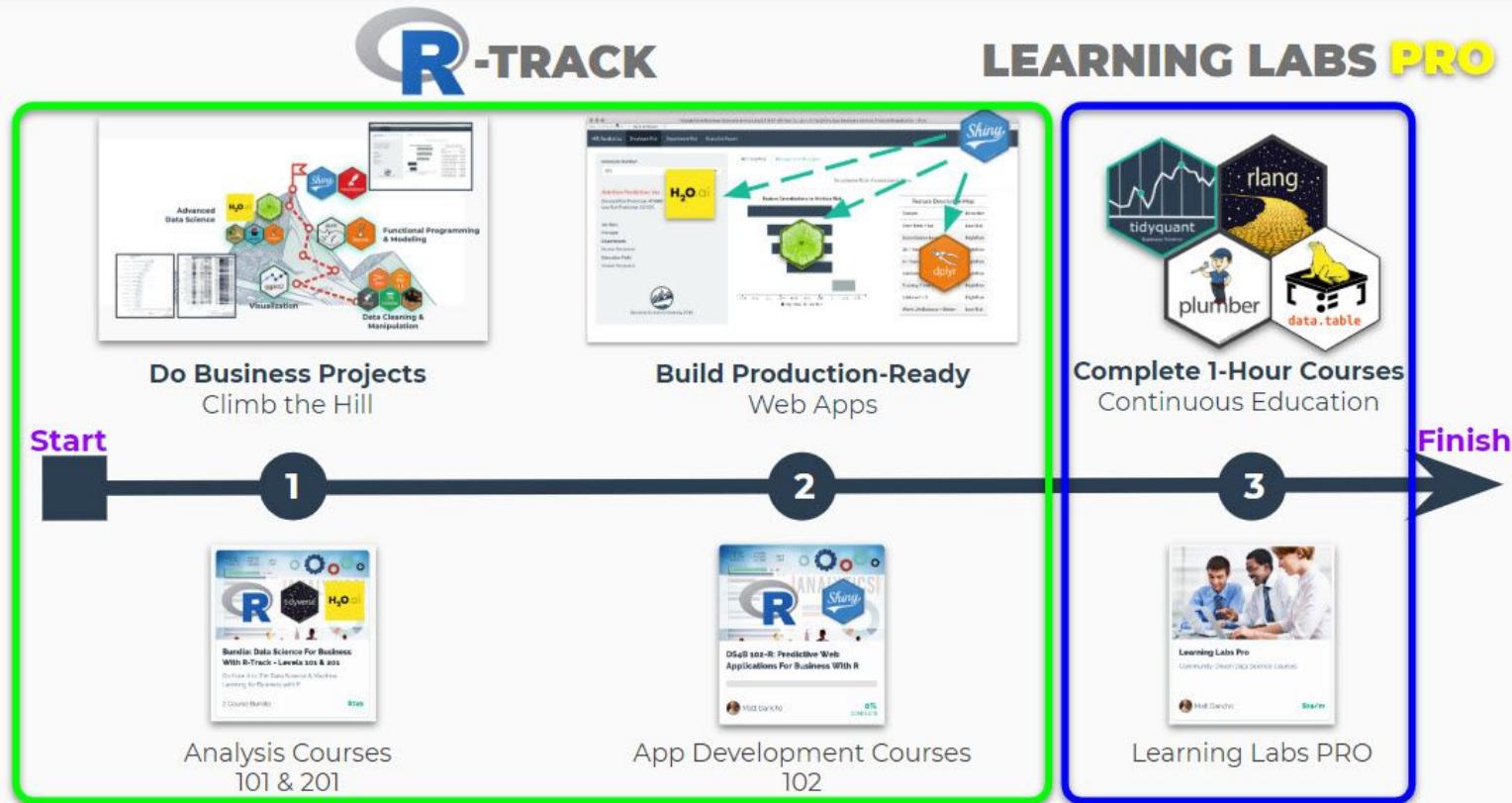


H2O AutoML

# **Business Science University**

Our program that will TRANSFORM YOU in weeks, not years.

# The program that will deliver YOUR Transformation



Everything is **Taken Care of** For You in Our Platform

# 3-Course R-Track System



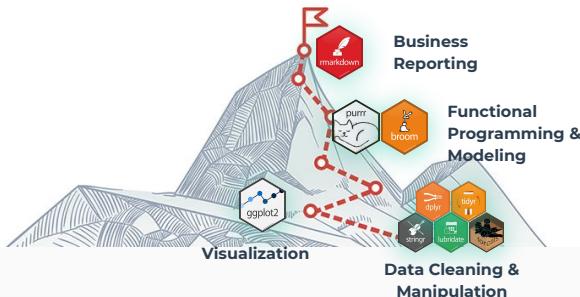
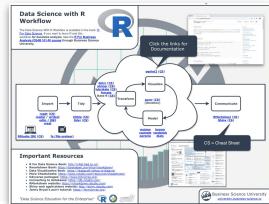
## Business Analysis with R (DS4B 101-R)

## Data Science For Business with R (DS4B 201-R)

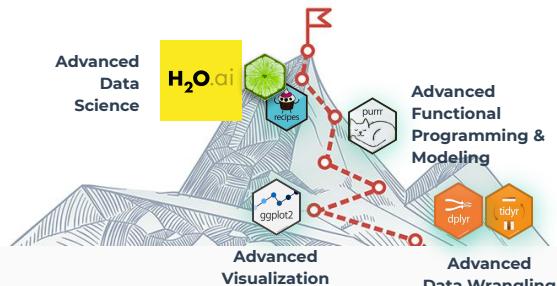
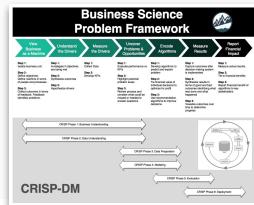
## R Shiny Web Apps For Business (DS4B 102-R)

### Project-Based Courses with Business Application

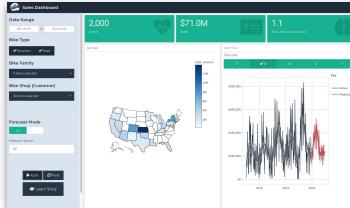
Data Science Foundations  
**7 Weeks**



Machine Learning & Business Consulting  
**10 Weeks**



Web Application Development  
**4 Weeks**

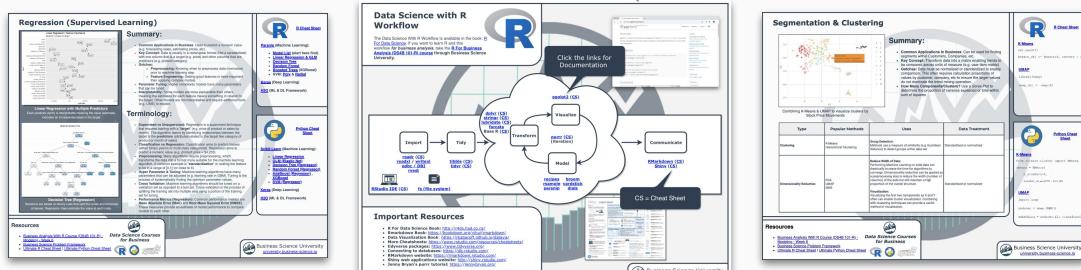


# Key Benefits

- Fundamentals - Weeks 1-5 (25 hours of Video Lessons)
  - Data Manipulation (dplyr)
  - Time series (lubridate)
  - Text (stringr)
  - Categorical (forcats)
  - Visualization (ggplot2)
  - Programming & Iteration (purrr)
  - 3 Challenges
- **Machine Learning - Week 6 (8 hours of Video Lessons)**
  - Clustering (3 hours)
  - Regression (5 hours)
  - 2 Challenges
- Learn Business Reporting - Week 7
  - RMarkdown & plotly
  - 2 Project Reports:
    1. Product Pricing Algo
    2. Customer Segmentation

# Business Analysis with R (DS4B 101-R)

Data Science Foundations  
**7 Weeks**



# Key Benefits

## End-to-End Churn Project

Understanding the Problem & Preparing Data - Weeks 1-4

- Project Setup & Framework
- Business Understanding / Sizing Problem
- Tidy Evaluation - rlang
- EDA - Exploring Data -GGally, skimr
- Data Preparation - recipes
- Correlation Analysis
- 3 Challenges

## Machine Learning - Weeks 5, 6, 7

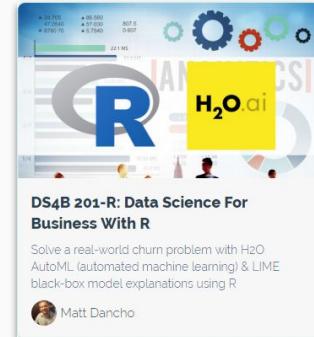
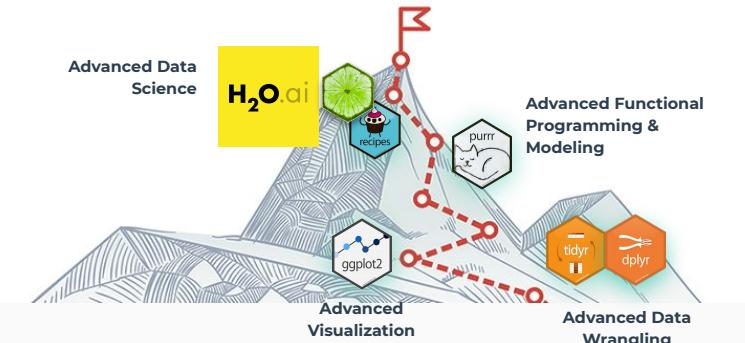
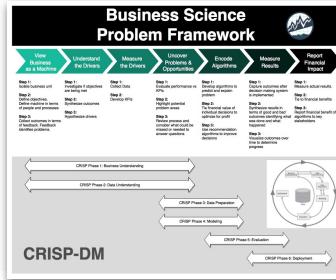
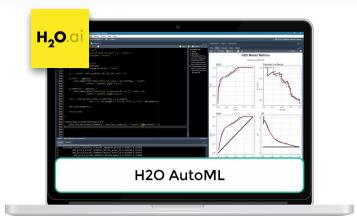
- H2O AutoML - Modeling Churn
- ML Performance
- LIME Feature Explanation

## Return-On-Investment - Weeks 7, 8, 9

- Expected Value Framework
- Threshold Optimization
- Sensitivity Analysis
- Recommendation Algorithm

# Data Science For Business (DS4B 201-R)

Machine Learning & Business Consulting  
**10 Weeks**



# Key Benefits

## Learn Shiny & Flexdashboard

- Build Applications
- Learn Reactive Programming
- Integrate Machine Learning

## App #1: Predictive Pricing App

- Model Product Portfolio
- XGBoost Pricing Prediction
- Generate new products instantly

## App #2: Sales Dashboard with Demand Forecasting

- Model Demand History
- Segment Forecasts by Product & Customer
- XGBoost Time Series Forecast
- Generate new forecasts instantly

# Shiny Apps for Business (DS4B 102-R)



Web Application Development  
**4 Weeks**

The collage includes:

- A "Data Science with R" dashboard showing a map of the US with state-level data, a bar chart for 'Blue Type' (2,000), a line chart for 'Sales Total' (\$71.0M), and a scatter plot for 'Avg Price' (1.1).
- A flowchart titled "Data Science with R Web Applications & the 'Shinyverse'" showing the process from "Start" through "Components", "Advanced Frontend Development", "Testing", and "Publish". It highlights "Shiny" and "Flexdashboard" as key components.
- A "Sales Dashboard" showing various charts and filters for sales data.
- A "Demand Forecasting" dashboard with multiple time-series plots and controls.



The collage includes:

- A "Shiny" logo with a large blue "R" and the word "ANALYTICS!".
- A "DS4B 102-R: Shiny Web Applications for Business (Level 1)" page.
- A "Matt Dancho" profile picture.

The "DS4B 102-R" page text:

Build a predictive web application using Shiny, Flexdashboard, and XGBoost.

# Success Story

## Masatake Hirono

- Took DS4B 201-R
- Completed the 10-Week Course
- **Landed a Job at one of the most Prestigious Management Consulting Firms**



***"This course showed me how to place data analytics in real business settings."***



Masatake Hirono • 1st  
Data Scientist at 株式会社進研アド  
4d

After struggling to balance with my work for many months, I've finally completed the Business Science University DS4B 201-R: Data Science For Business With R, taught by [Matt Dancho](#). Unlike other MOOCs, this course showed me how to place data analytics in real business settings. Without this course, I would have never attempted to pay attention to business/financial impacts, generated through my analysis. His instruction turned me a more advanced data scientist and helped me find a new career opportunity. I will start to work at one of the most prestigious management consulting firms in October as a cognitive & analytics consultant. Highly recommended if you would like to use R as a professional business person!

#business\_science\_success #dataanalysis #machinelearningtraining

2d ...

How did it help you find another career opportunity? Did he place you in touch with hiring firms?

1 Reply

Masatake Hirono • 1st  
Data Scientist at 株式会社進研アド  
1d ...

Of course not. In a job interview, I was able to draw interviewer's attention because of my experiences to formulate some insight from analytics for driving business, which I had developed through his course.

**#Business  
Science  
Success**

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## R-TRACK BUNDLE

**R-TRACK BUNDLE**

**DS4B 101-R: Business Analysis With R**  
Your Data Science Journey Starts Now! Learn the fundamentals of data science for business with the tidyverse.

**DS4B 201-R: Data Science For Business With R**  
Solve a real-world churn problem with H2O AutoML (automated machine learning) & LIME black-box model explanations using R

**DS4B 102-R: Shiny Web Applications For Business (Level 1)**  
Build a predictive web application using Shiny, Flexdashboard, and XGBoost

**Bundle - DS For Business + Web Apps (Level 1): R-Track - Courses 101, 102,**

3 Course Bundle

0% COMPLETE

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<input checked="" type="radio"/>	Paid Course 15% COUPON DISCOUNT	\$149 \$976.65	<a href="#">Enroll</a>
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<input type="radio"/>	6 Low Monthly Payments 15% COUPON DISCOUNT 6X Payment Plan	6 payments of \$24.99/m	6 payments of \$198.90/m
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# Begin Learning Today

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