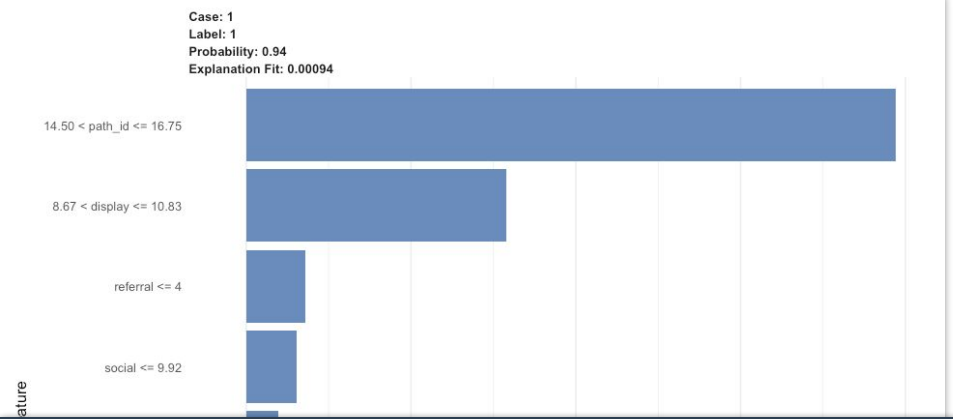
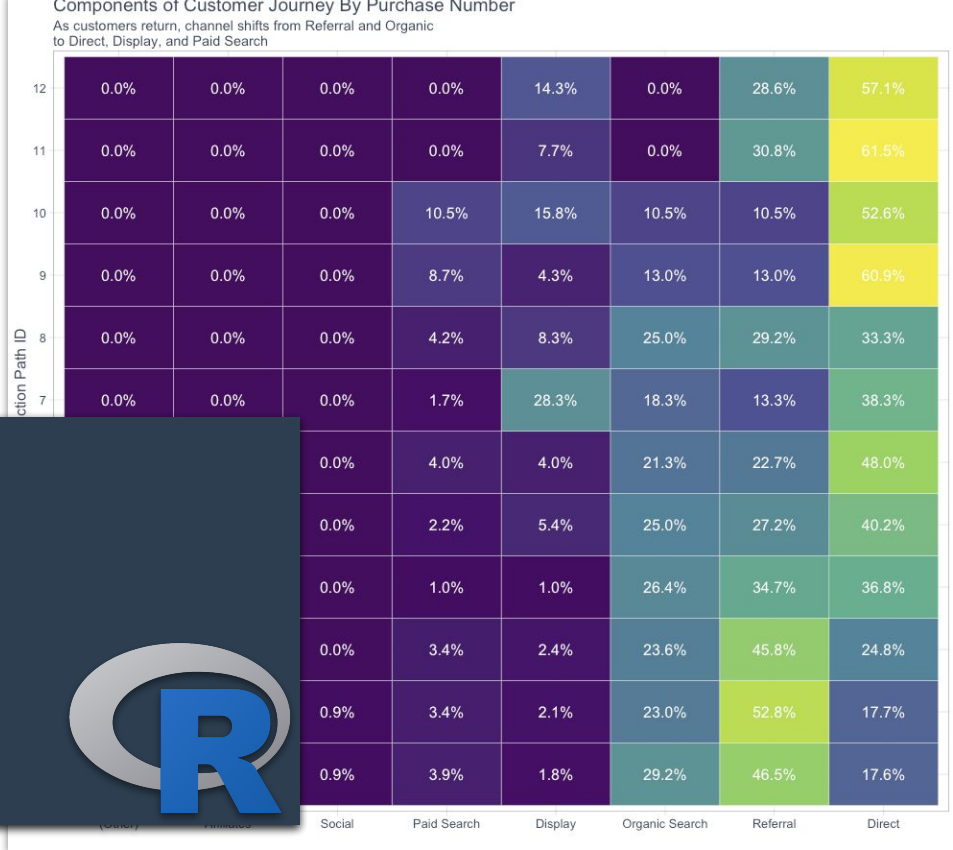




Machine Learning for Customer Journey

Using Google Analytics Data

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**.

Marketing Series

- **Lab 24 - A/B Testing**
  - Business Science's Website
  - Infer - Bootstrap & Permutation
- **Lab 25 - Multi-Channel Attribution (Part 1)**
  - Google Analytics Data
  - ChannelAttribution
- **Lab 26 - ML for Customer Journey (Part 2)**
  - Path Splitting
  - Applied ML for Conversion Probabilities
- **Lab 27 - Automated Prediction & Tracking Google Trends**
  - Google Trend Forecasting
  - gtrendsR, forecast
  - chronR, taskscheduleR

Learning Labs PRO

Every 2-Weeks

1-Hour Course

Recordings + Code + Slack

$19/month

university.business-science.io

Lab 25 *- Marketing Series*
Attribution with ChannelAttribution

Lab 24 *- Marketing Series*
A/B Testing with Infer

Lab 23 *- SQL Series*
SQL with BigQuery & Conversion Funnel

Lab 22 *- SQL Series*
SQL for Time Series

Lab 21 *- SQL Series*
SQL for Data Science

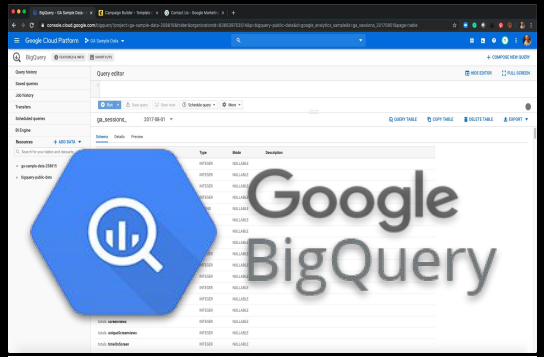
Lab 20 *- Machine Learning*
Explainable Machine Learning

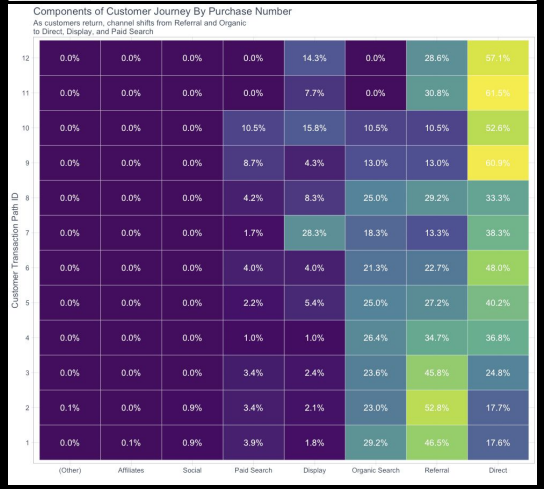
Lab 19 *- Network Analysis*
Using Customer Credit Card History for Networks Analysis

Lab 18 *- Anomaly Detection*
Time Series Anomaly Detection with anomalize

Continuous Learning
Advanced Topics

Agenda





- **Business Case Study**
  - Google Merchandise Store
  - Understand how customers buy
    - New Customer
    - Repeat Customer
- **Customer Journey**
  - Terminology
  - Conversion Paths
- **Tools & Process**
  - **Path Splitting**
  - **Large Data**
  - **Predicting & Explaining**
- **30-Min Demo**
  - dplyr
  - dtplyr
  - parsnip
  - lime
- **Pro-Tips & Learning Guide**

Google Merchandise Store

Business Case

Business Case

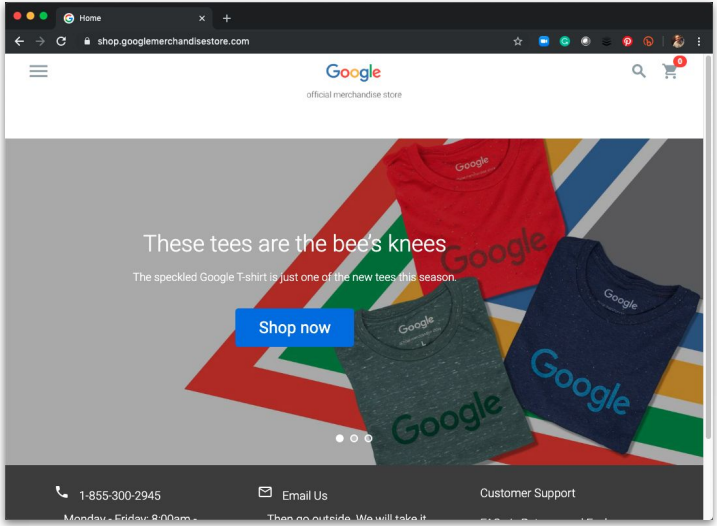
Google Merchandise Store

Customers can purchase t-shirts, gear, etc

Google Analytics tracks **channel sources** leading into the website.

We are interested in **Channels that lead to Transactions.**

Often called **Customer Journey.** We seek to understand this. The make actions to increase conversion.



https://shop.googlemerchandisestore.com/

Business Case

```
> query_tbl
# A tibble: 847,224 x 6
   fullVisitorId           date channelGrouping traffic_source   total_transactions total_transaction_revenue
   <chr>                  <dbl> <chr>           <chr>                        <dbl>                      <dbl>
 1 4702386946621457676 20170103 Organic Search  (direct)                        NA                         NA
 2 2087993472864421231 20170103 Organic Search  (direct)                        NA                         NA
 3 0577469839995590230 20170103 Organic Search  (direct)                        NA                         NA
 4 7618446014168949772 20170103 Paid Search     (direct)                        NA                         NA
 5 4837057017588527755 20170103 Paid Search     (direct)                        NA                         NA
 6 1555778933169102070 20170103 Direct          (direct)                        NA                         NA
 7 1116770359875973709 20170103 Organic Search  (direct)                        NA                         NA
 8 5465941681642086837 20170103 Direct          (direct)                        NA                         NA
 9 2383851094930392840 20170103 Direct          (direct)                        NA                         NA
10 6589579712030812313 20170103 Referral        sites.google.com                NA                         NA
# … with 847,214 more rows
```

850K Rows

700K Visitor ID’s

8 Channel Groups

Time Series

Customer Journey

Concepts & Business Goals

Touch Points

User interacts with media, website, referral, social, and search.

Tracked in **Google Analytics:**

- User ID
- Session ID
- Channel Group

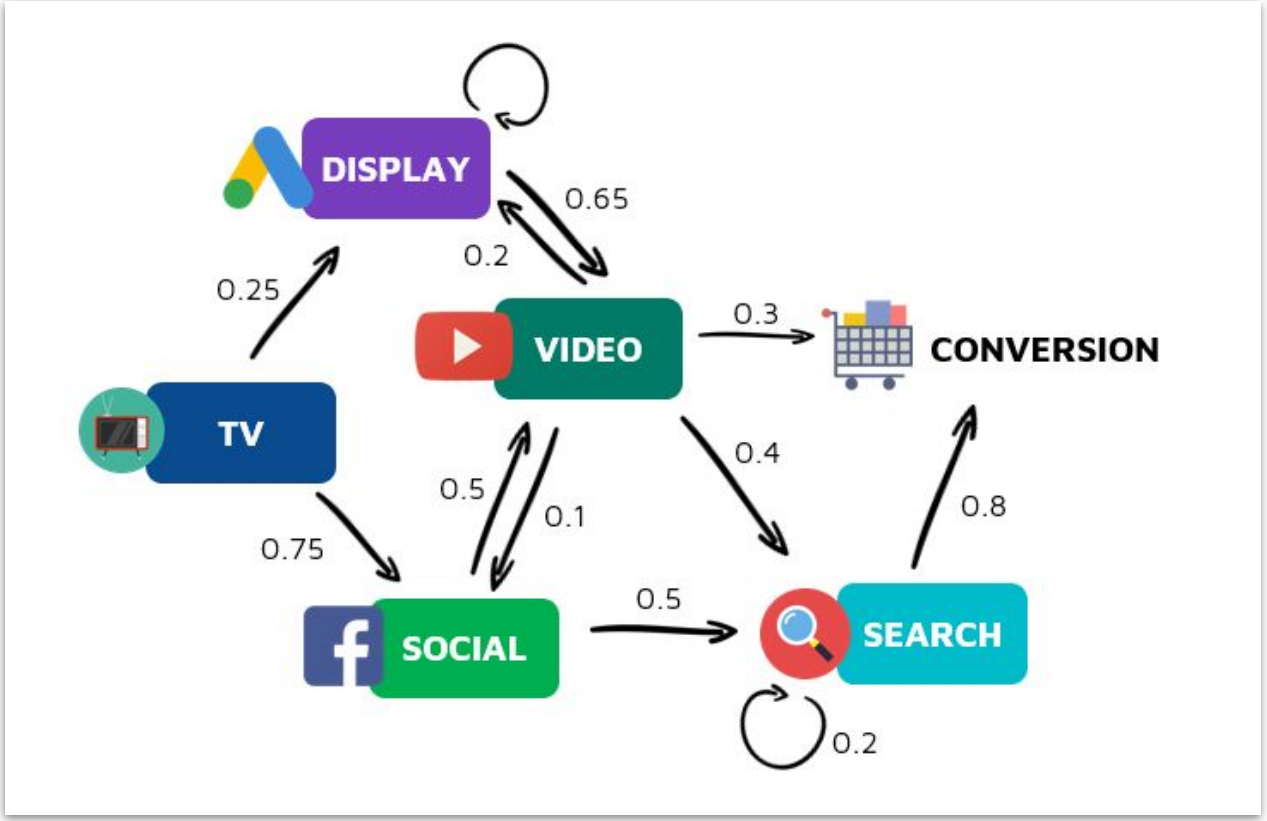
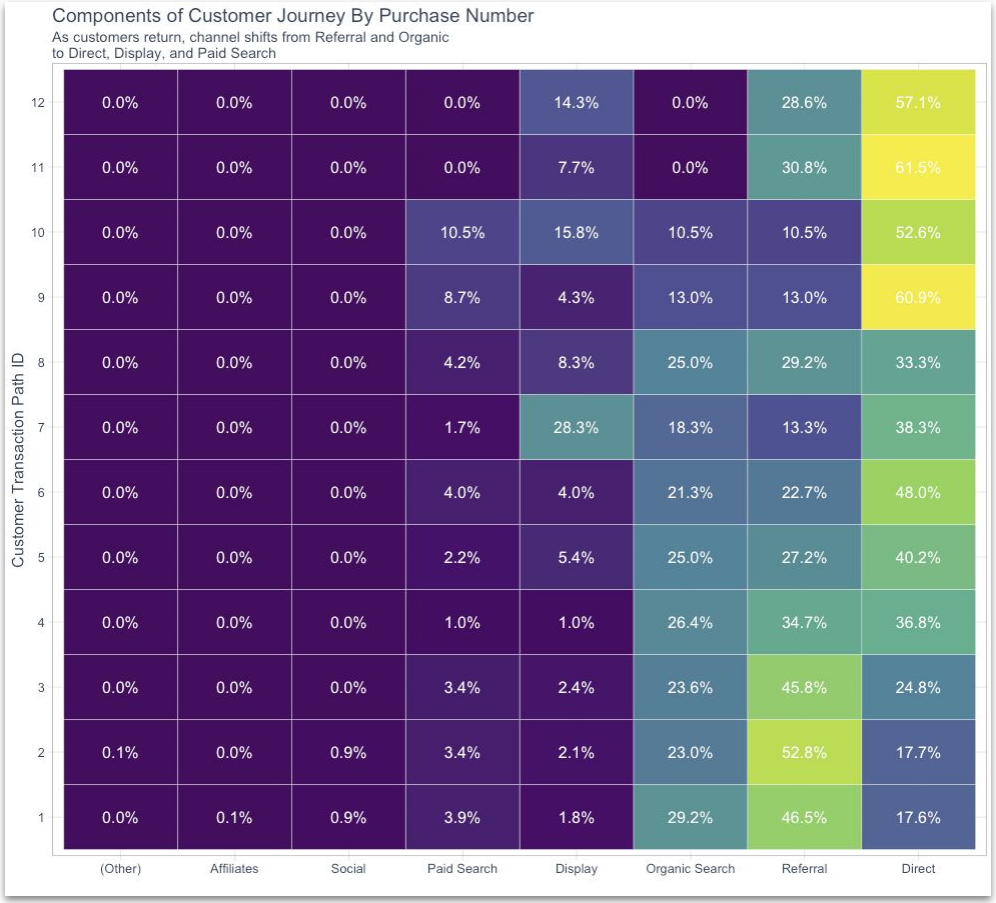


Image Credit: https://github.com/MatCyt/Markov-Chain

Customer Journey



Transaction Path Patterns

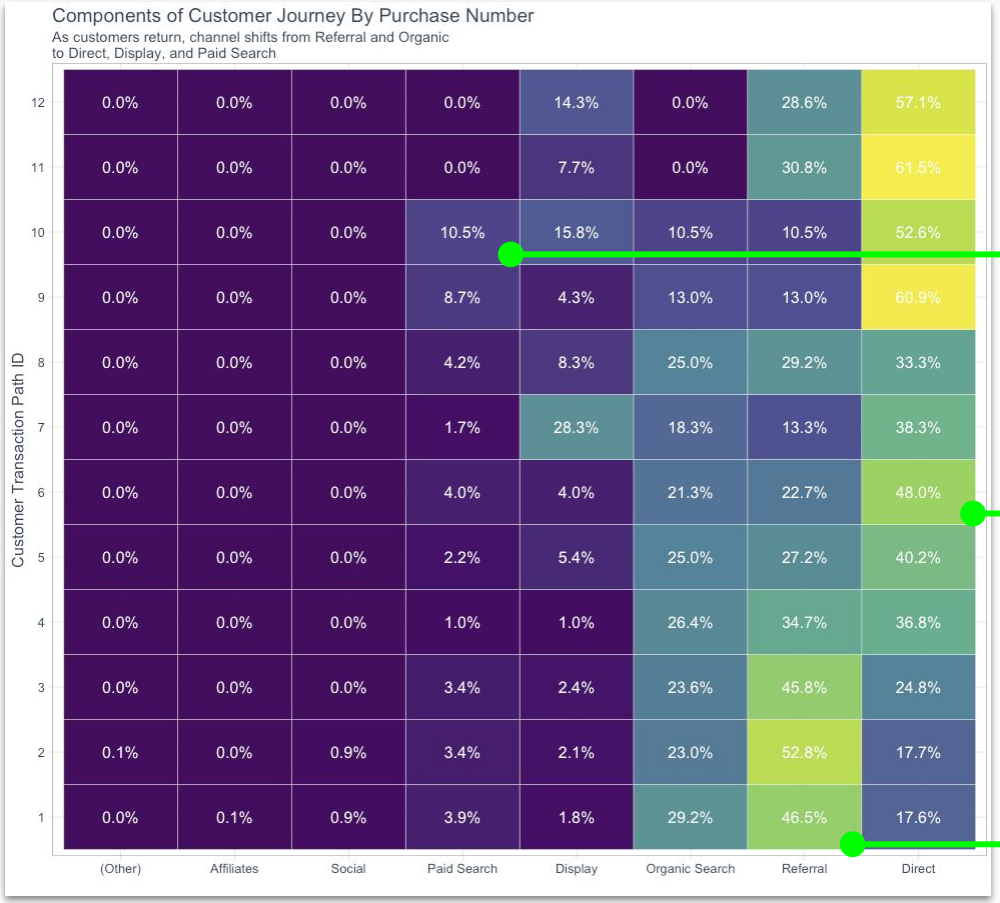
Each transaction is part of a path.

New Customers have only one transaction path.

Returning Customers have multiple transaction paths.

Patterns for New vs Returning are different.

Customer Journey Composition



Path 10
Customers making their **10th purchase** come composed of **Direct** and **Paid Search / Display (Adwords)**

Path 6
Customers making their **6th purchase** comes through **Direct (Email)**

Path 1
Customers that are making their **first purchase** come through **Referral (Hyperlinks on websites) & Organic Search (Googling)**.

Goal

Create an actionable marketing plan

Path 10
Customers making their **10th purchase** come composed of **Direct** and **Paid Search / Display**

Path 6
Customers making their **6th purchase** comes through **Direct (Email)**

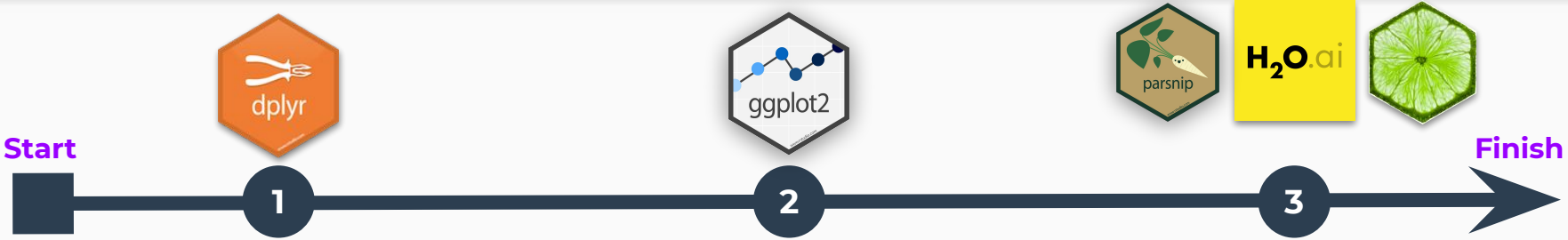
Path 1
Customers that are making their **first purchase** come through **Referral (Hyperlinks on websites) & Organic Search (Googling)**.

Tools & Process

Cutting-edge

Customer Journey Workflow

Step-By-Step



Large Data ETL

Biggest Challenge
Transformation to split paths
Time Series Data
Grouped Lag & Cumulative Sums
using **dtplyr**

Channel Path Visualization

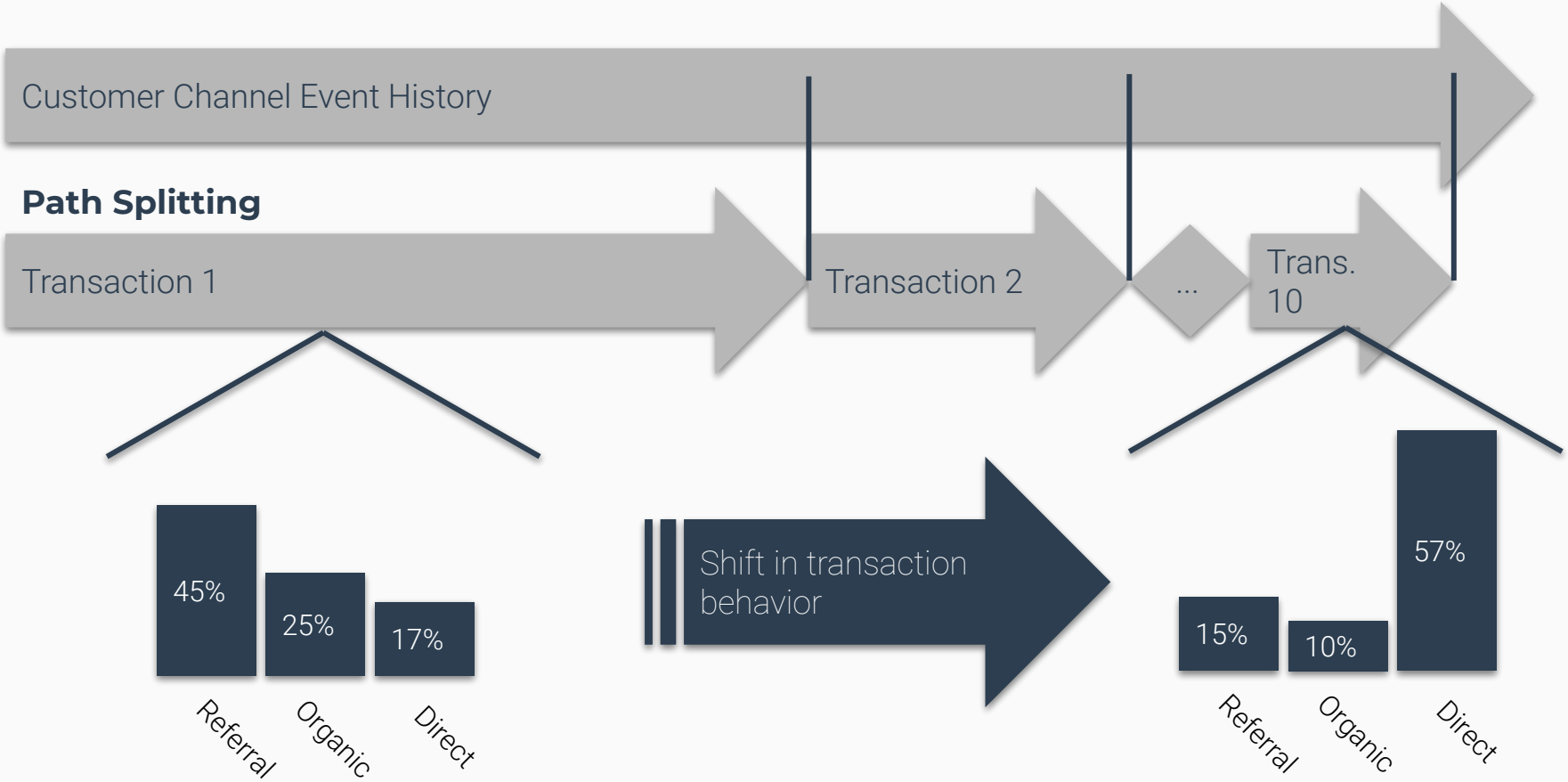
Most important step
Can make strategies.

Problem
Strategies don't incorporate probability.

Machine Learning

Model all conversion paths with tools like **Parsnip (XGBoost) & H2O.**
Paths scored using probability.
Explain a collection of paths using **LIME.**

Path Splitting



Path splitting with dplyr

800K+ unique sessions

700K+ unique users (groups)

Tools (learn these)

- Big Data (dtplyr)
- ETL (dplyr)

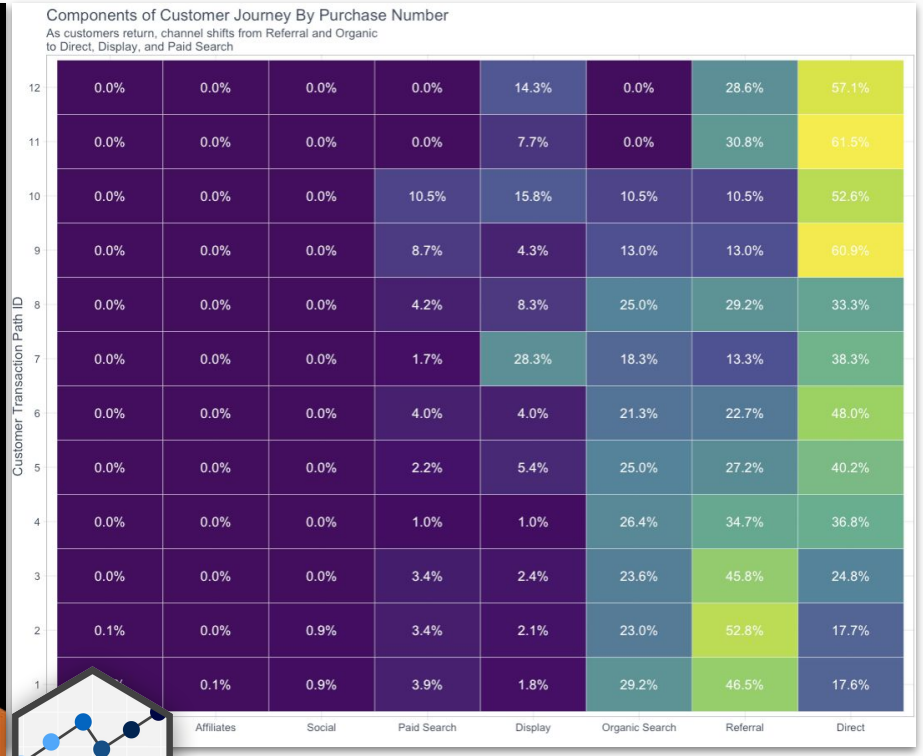
Data Skills Needed

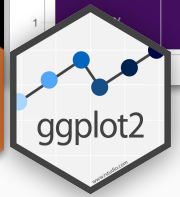
- Grouped calculations
- Time series - lag(), cumsum(), last()
- Started at 2-min per calc, **reduced to 17-sec**

```
query_paths_split_dt <- query_dt %>%

    # Format data
    mutate(date = ymd(date)) %>%
    select(fullVisitorId, date, channelGrouping, total_transactions) %>%

    # Create flag if transaction > 0
    mutate(flag = case_when(
        total_transactions > 0 ~ 1,
        TRUE ~ 0
    )) %>%

    # Group by full Visitor Id
    group_by(fullVisitorId) %>%

    # Order by date
    arrange(date) %>%

    # Add paths by group
    mutate(paths = cumsum(flag)) %>%
    mutate(path_id = lag(paths, n = 1)) %>%

    ungroup() %>% # End Group by Full Visitor ID

    # Fill path_id NA's
    mutate(path_id = ifelse(is.na(path_id), 0, path_id)) %>%

    # Move from 0-base to 1-base index
    mutate(path_id = path_id + 1) %>%

    # Create visitor-path ids
    mutate(visitor_path_id = str_c(fullVisitorId, "_", path_id)) %>%

    # Group By All Unique Visitor-Paths - Flag if full path has a transaction
    group_by(visitor_path_id) %>%
    mutate(transaction_flag = ifelse(last(flag) == 1, 1, 0)) %>%
    ungroup()
```

Visualize Customer Journey Composition

```
156 customer_journey_tbl <- query_paths_split_tbl %>%
157     select(visitor_path_id, transaction_flag, path_id, channelGrouping) %>%
158
159     # Only evaluate successful paths
160     filter(transaction_flag == 1) %>%
161
162     # Count successful channels by path id
163     group_by(channelGrouping, path_id) %>%
164     summarize(count = n()) %>%
165     ungroup() %>%
166
167     # Calculate successful channel composition by path id
168     group_by(path_id) %>%
169     mutate(prop = count / sum(count)) %>%
170     ungroup() %>%
171
172     mutate(channelGrouping = as_factor(channelGrouping) %>% fct_reorder(prop)) %>%
173     ungroup() %>%
174
175     # Filter out paths > 12 (few people have more than 12 transactions in 1 year)
176     select(-count) %>%
177     filter(path_id <= 12) %>%
178     mutate(path_id = as.factor(path_id)) %>%
179
180     # Trick to fill in missing observations with zeros
181     pivot_wider(names_from  = channelGrouping,
182                 values_from = prop,
183                 values_fill = list(prop = 0)) %>%
184     pivot_longer(cols = `(Other)`:Social, names_to = "channelGrouping", values_to = "prop") %>%
185
186     mutate(channelGrouping = as_factor(channelGrouping) %>% fct_reorder(prop))
187
188 customer_journey_tbl
189
```





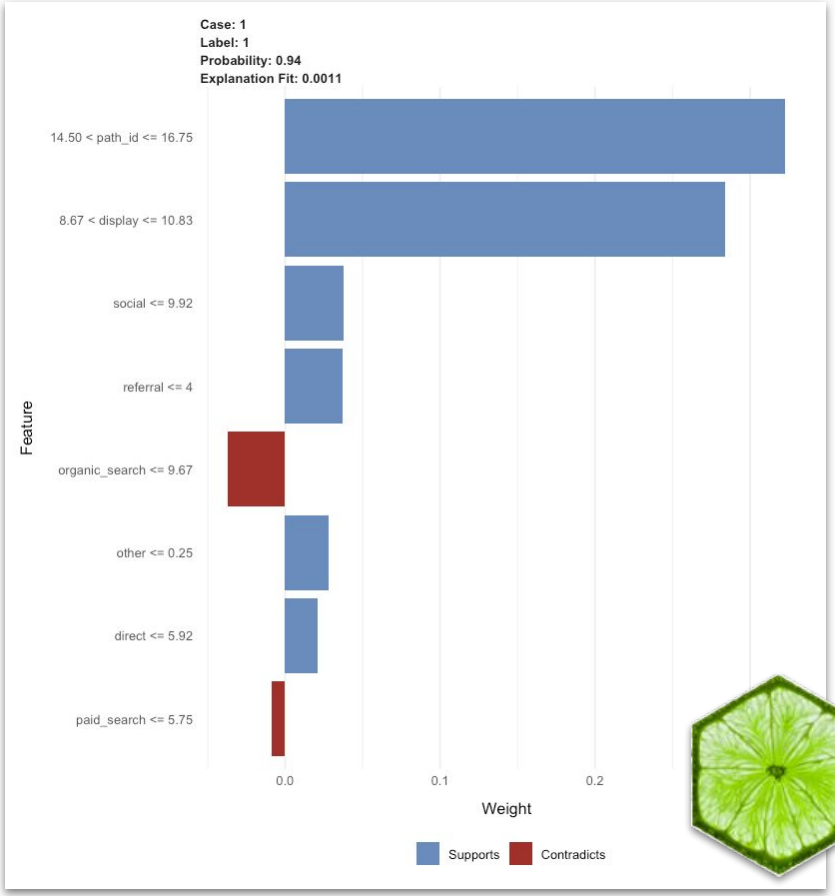
Machine Learning Model

```r
# 4.2 Modeling ----
# WARNING - LONG RUNNING SCRIPT - TAKES 7 MINUTES TO RUN ----
# > toc()
# 428.923 sec elapsed

tic()
model_xgboost <- boost_tree(mode = "classification",
                            mtry = 12,
                            trees = 1000,
                            min_n = 3,
                            tree_depth = 5,
                            learn_rate = 0.01,
                            loss_reduction = 0.01) %>%
    set_engine("xgboost") %>%
    fit.model_spec(transaction_flag ~ ., data = data_aggregated_tbl %>% select(-visitor_path_id))
toc()
```

Gives us conversion probabilities

```
> predictions_tbl %>% arrange(desc(.pred_1))
# A tibble: 719,113 x 13
   .pred_0 .pred_1 visitor_path_id       transaction_flag path_id other affiliates direct display organic_search paid_search referral social
     <dbl>   <dbl> <chr>                 <fct>              <dbl> <dbl>      <dbl>  <dbl>   <dbl>          <dbl>       <dbl>    <dbl>  <dbl>
 1  0.0624   0.938 1957458976293878100_… 0                     15     0          0      0       9              0           0        0      0
 2  0.0701   0.930 1957458976293878100_… 1                     12     0          0      0       2              0           0        0      0
 3  0.0713   0.929 1957458976293878100_… 1                     13     0          0      0       5              0           0        0      0
 4  0.0750   0.925 1957458976293878100_… 1                     10     0          0      0       3              0           0        0      0
 5  0.0808   0.919 7311242886083854158_… 1                     12     0          0      5       0              0           0        0      0
 6  0.0811   0.919 2402527199731150932_… 1                     15     0          0      3       0              0           0        0      0
 7  0.0811   0.919 7813149961404844386_… 1                     13     0          0      3       0              0           0        0      0
 8  0.0811   0.919 7813149961404844386_… 1                     16     0          0      3       0              0           0        0      0
 9  0.0811   0.919 7813149961404844386_… 1                     17     0          0      3       0              0           0        0      0
10  0.0811   0.919 7813149961404844386_… 1                     25     0          0      3       0              0           0        0      0
# … with 719,103 more rows
```

Explainable Machine Learning



Describe why ML Model concludes 94% Probability

Use **LIME Explainable Machine Learning** to interpret prediction for single observation.

- **94% Probability of Conversion**
- Customer has **purchase path count** is between 14.5 & 16.75
- **Display** links clicked between 8.7 and 10.8

Action: Send Email (Direct) to target person and gain conversion

30-Min Demo

Let’s do this!

PRO-TIPS

Yeahhhhhh!

Pro-Tip #1: We need to cross-validate model

We did not do Cross Validation

This is where H2O comes in.

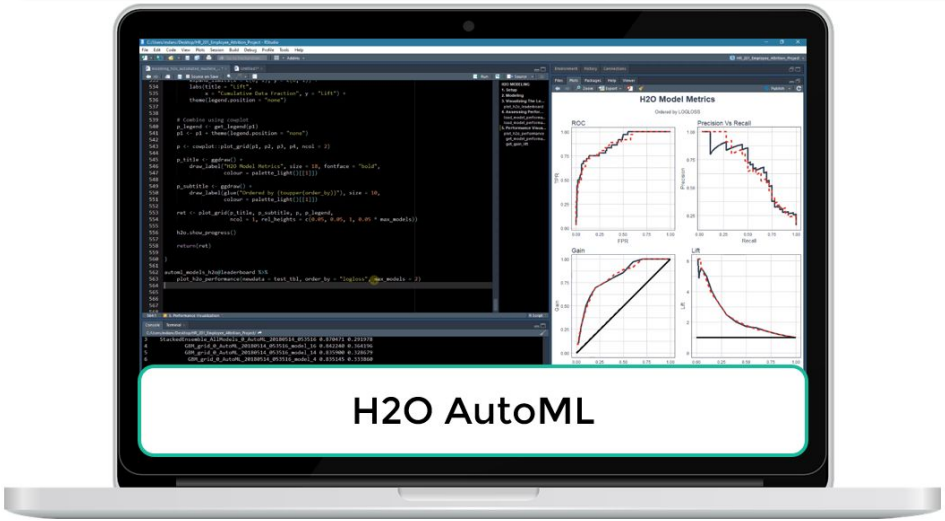
Run H2O AutoML overnight, come in the next day with **100+ models** that have been **5-Fold Cross Validated**.

Learn H2O AutoML in

- **Advanced ML & Business Consulting**
  DS4B 201-R

```
> 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       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.ai



Pro-Tip #2: Explain Results Locally

Executives need strategies to target a single customer

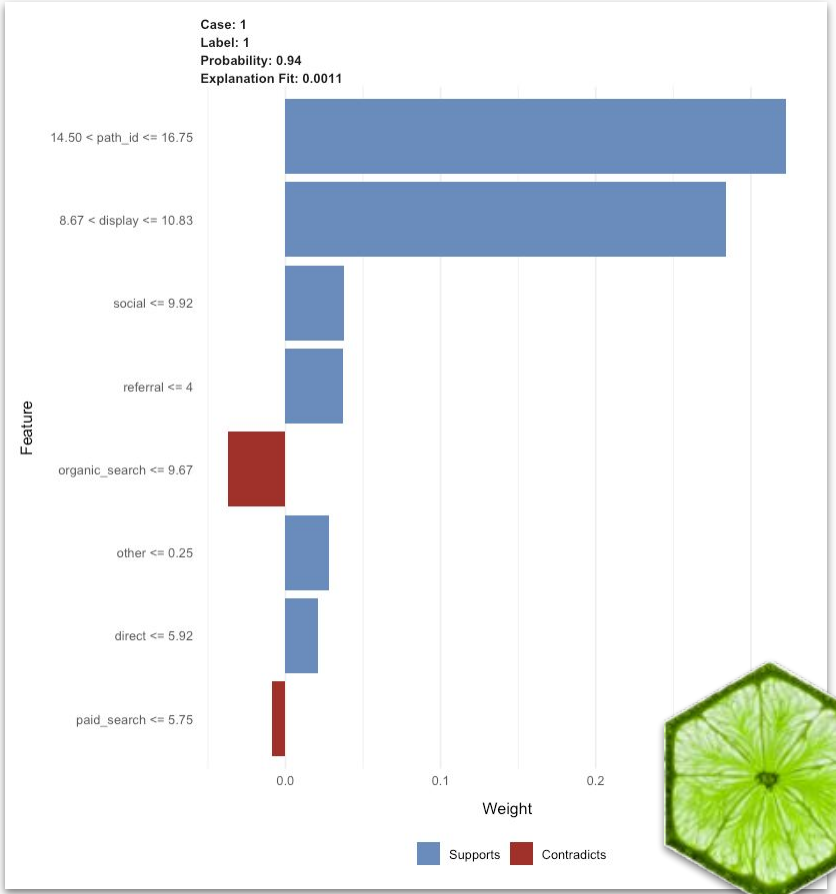
This is where **LIME** comes in.

Explain why an individual is high likelihood of converting.

Develop strategies your organization can use to target high probability customers and convert them.

Learn LIME in

- **Advanced ML & Business Consulting**
  DS4B 201-R



Pro-Tip #3: Productionalize the Results

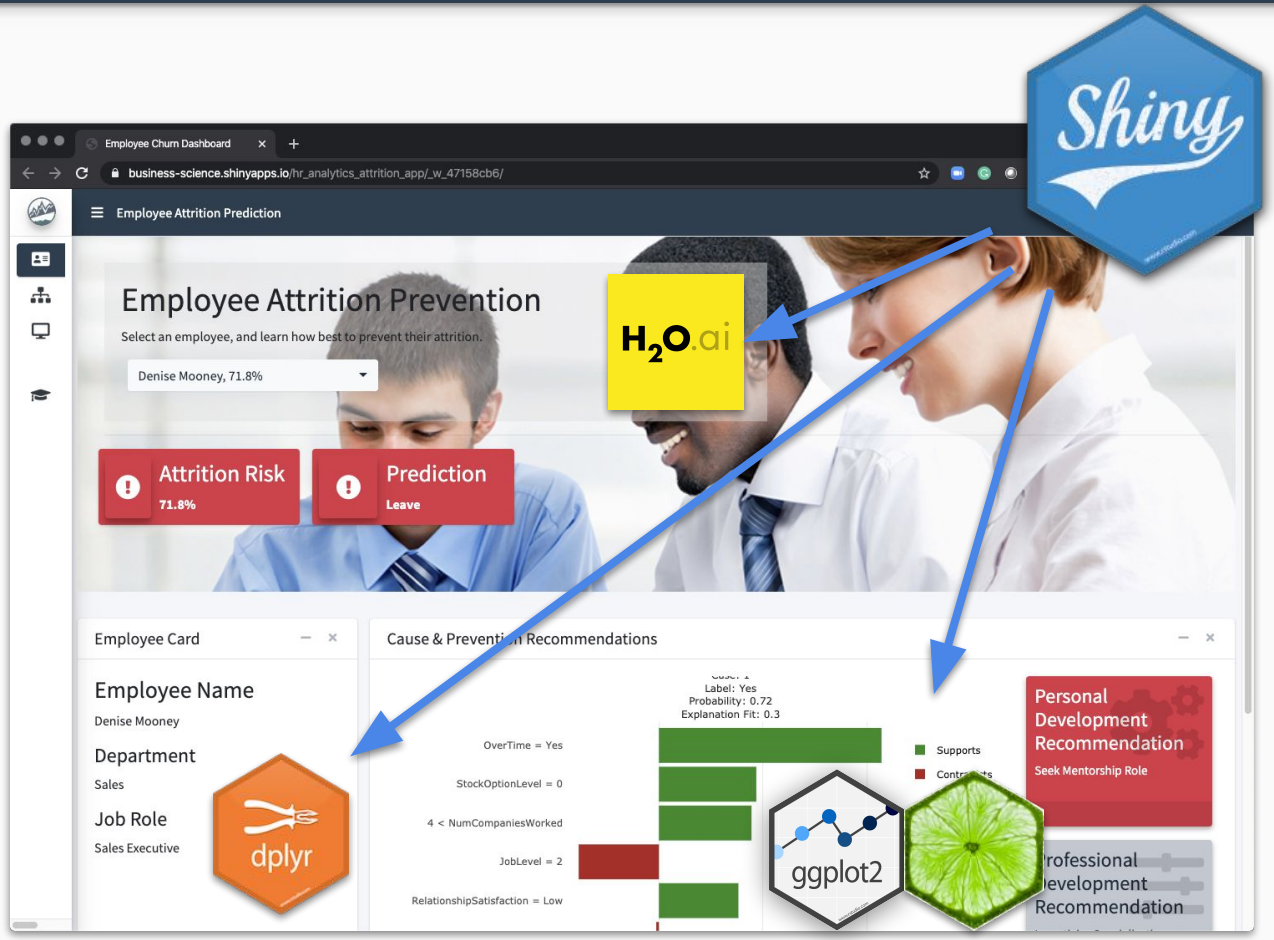
Businesses need apps

This is where **Shiny** comes in.

Make a shiny app to enable others to use your work.

Learn SHINY in:

- **Shiny Dashboards**
  DS4B 102-R
- **Shiny Developer w/ AWS**
  DS4B 202-R



4-Course R-Track System

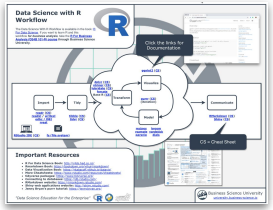
Business Analysis with R
(DS4B 101-R)

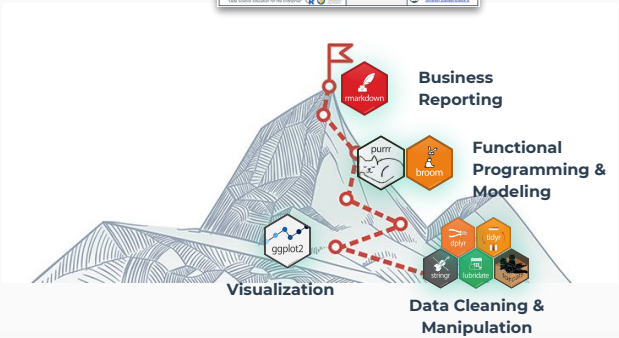
Data Science For Business with R
(DS4B 201-R)

Web Apps & Shiny Developer
(DS4B 102-R + DS4B 202A-R)

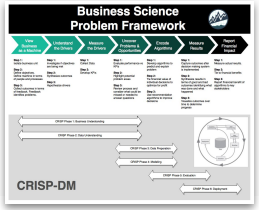
Project-Based Courses with Business Application

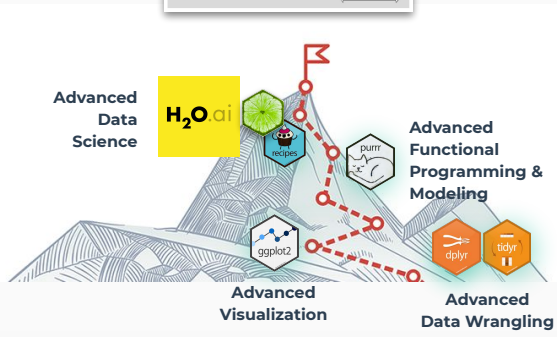
Data Science Foundations
7 Weeks



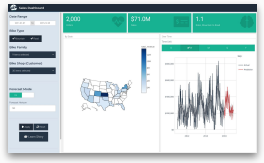


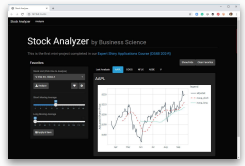
Machine Learning & Business Consulting
10 Weeks

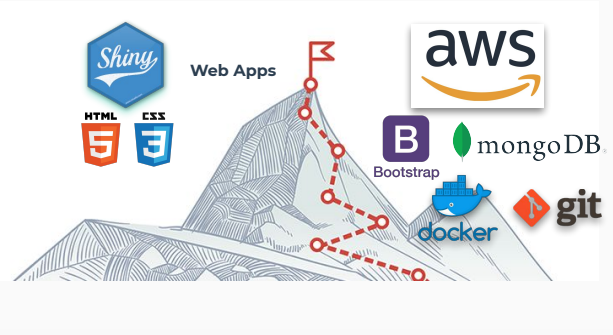




Web Application Development
12 Weeks







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

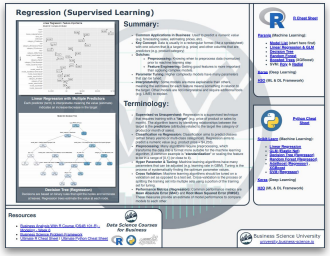
- **Machine Learning - Week 6 (8 hours of Video Lessons)**
  - **Clustering (3 hours)**
  - **Regression (5 hours)**
  - **2 Challenges**

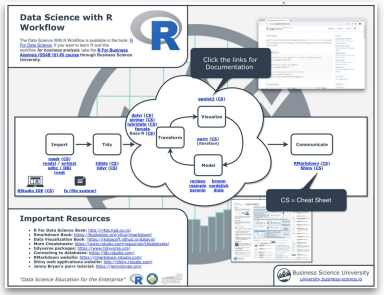
- Learn Business Reporting - Week 7
  - RMarkdown & plotly
  - 2 Project Reports:
    1. Product Pricing Algo
    2. Customer Segmentation

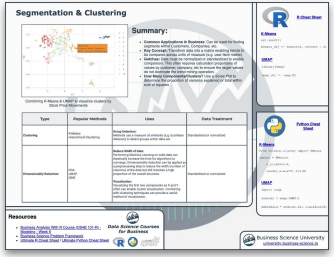
Business Analysis with R (DS4B 101-R)

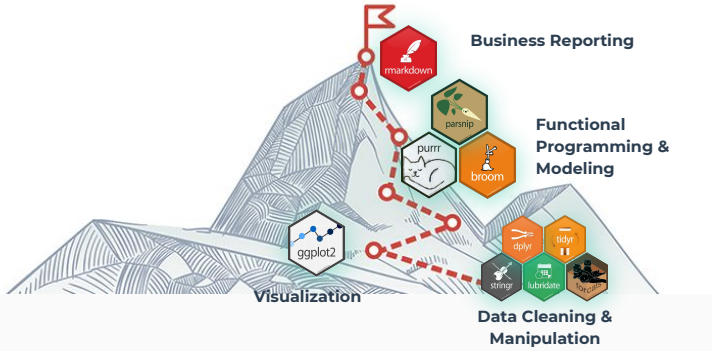
Data Science Foundations

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**

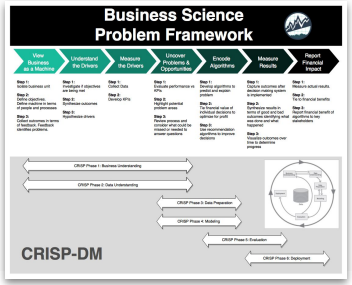
Return-On-Investment - Weeks 7, 8, 9

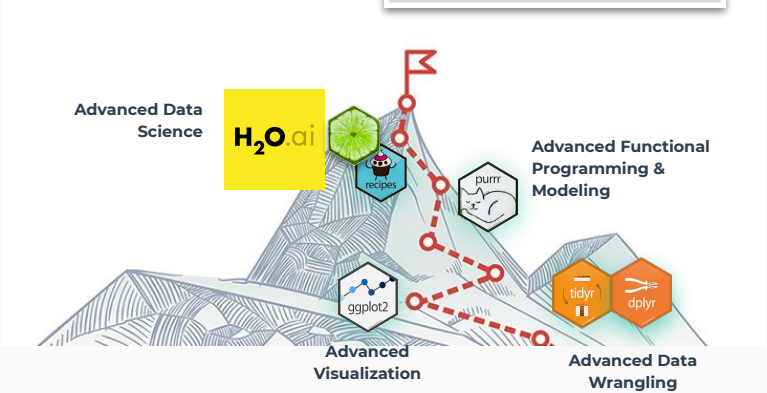
- **Expected Value Framework**
- **Threshold Optimization**
- **Sensitivity Analysis**
- **Recommendation Algorithm**

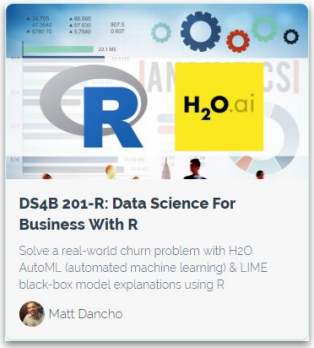
Data Science For Business (DS4B 201-R)

Machine Learning & Business Consulting

10 Weeks







Key Benefits

Learn Shiny & Flexdashboard
- Build Applications
- Learn Reactive Programming
- Integrate Machine Learning

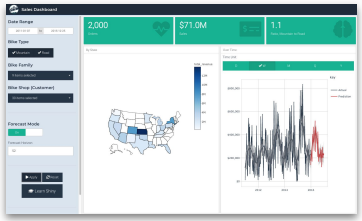
App #1: Predictive Pricing App
- Model Product Portfolio
- XGBoost Pricing Prediction
- Generate new products instantly

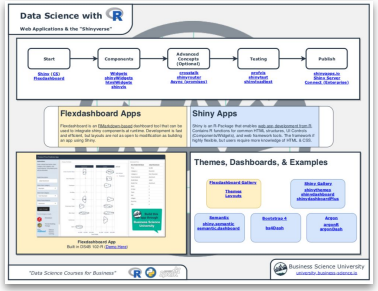
App #2: Sales Dashboard with Demand Forecasting
- Model Demand History
- Segment Forecasts by Product & Customer
- XGBoost Time Series Forecast
- Generate new forecasts instantly

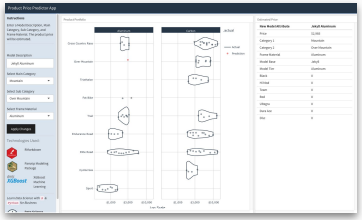
Shiny Apps for Business (DS4B 102-R)

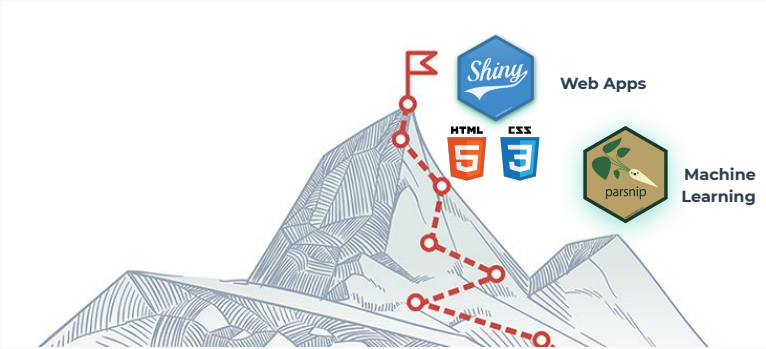
Web Application Development

4 Weeks









Key Benefits

Frontend + Backend + Production Deployment

Frontend for Shiny
- Bootstrap

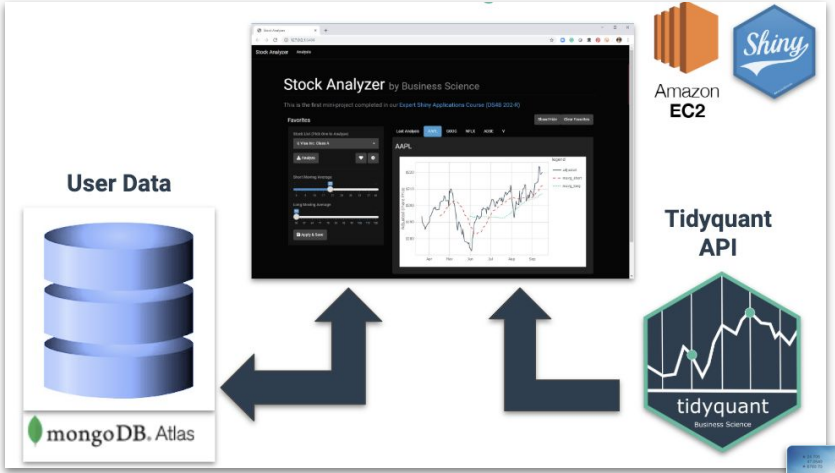
Backend for Shiny
- MongoDB
- Dynamic UI
- User Authentication
- Store & Write User Data

Production Deployment
- AWS
- EC2 Server
- VPC Connection
- URL Routing

Shiny Apps for Business (DS4B 202A-R)

Web Application Development

6 Weeks



aws

docker git Bootstrap mongoDB.

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Matt Dancho

DS4B 102-R: Shiny Web Applications For Business (Level 1)

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

Matt Dancho

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

Matt Dancho

DS4B 202A-R: Expert Shiny Developer with AWS

Learn how to build Scalable Data Science Applications using R, Shiny, and AWS Cloud Technology.

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