

Breakout Sessions 2:15 pm – 3:00 pm

- ***Process and Technical Infrastructure for Data Science ROI. Case***
- ***Are You Vaccinated Against Risk? Cultural, Technological, and Process Tools,***

Process and technical infrastructure for Data Science ROI Case Study: Predicting and preventing clinic no shows

Tristan Markwell
Lindsay Mico
17 May 2018

AIRBNB ENGINEERING & DATA SCIENCE

Creative engineers and data scientists building a world
where you can belong anywhere.

Featured Projects



ReAir

Easy-to-use tools for replicating tables and partitions between Hive data warehouses.

[View Project](#)

Apache Superset (incubating)

A data exploration platform designed to be visual, intuitive, and interactive.

[View Project](#)

Enzyme

JavaScript Testing utilities for React.

[View Project](#)

Aerosolve

A machine learning package built for humans.

[View Project](#)

Apache Airflow (incubating)

Use Apache Airflow (incubating) to author workflows as directed acyclic graphs (DAGs) of tasks.

[View Project](#)

Airlpal

A web-based, query execution tool for Facebook's PrestoDB.

[View Project](#)

Applied Machine Learning

Our Applied Machine Learning team improves Facebook products and services through artificial intelligence. We develop and advance algorithms that rank feeds and search results, create new text understanding algorithms that keep spam and misleading content at bay, and automatically caption videos in your news feed through our speech recognition systems. We're also responsible for displaying billions of translated stories every day, developing computer vision algorithms that make images and videos accessible to the blind, and creating magical visual experiences such as turning panorama photos into fully interactive 360 images. Our efforts form the glue between science, research, and Facebook experiences.

PYTORCH **ONNX** **Caffe2**

AI at F8 2018: Open frameworks and responsible development

PyTorch 1.0

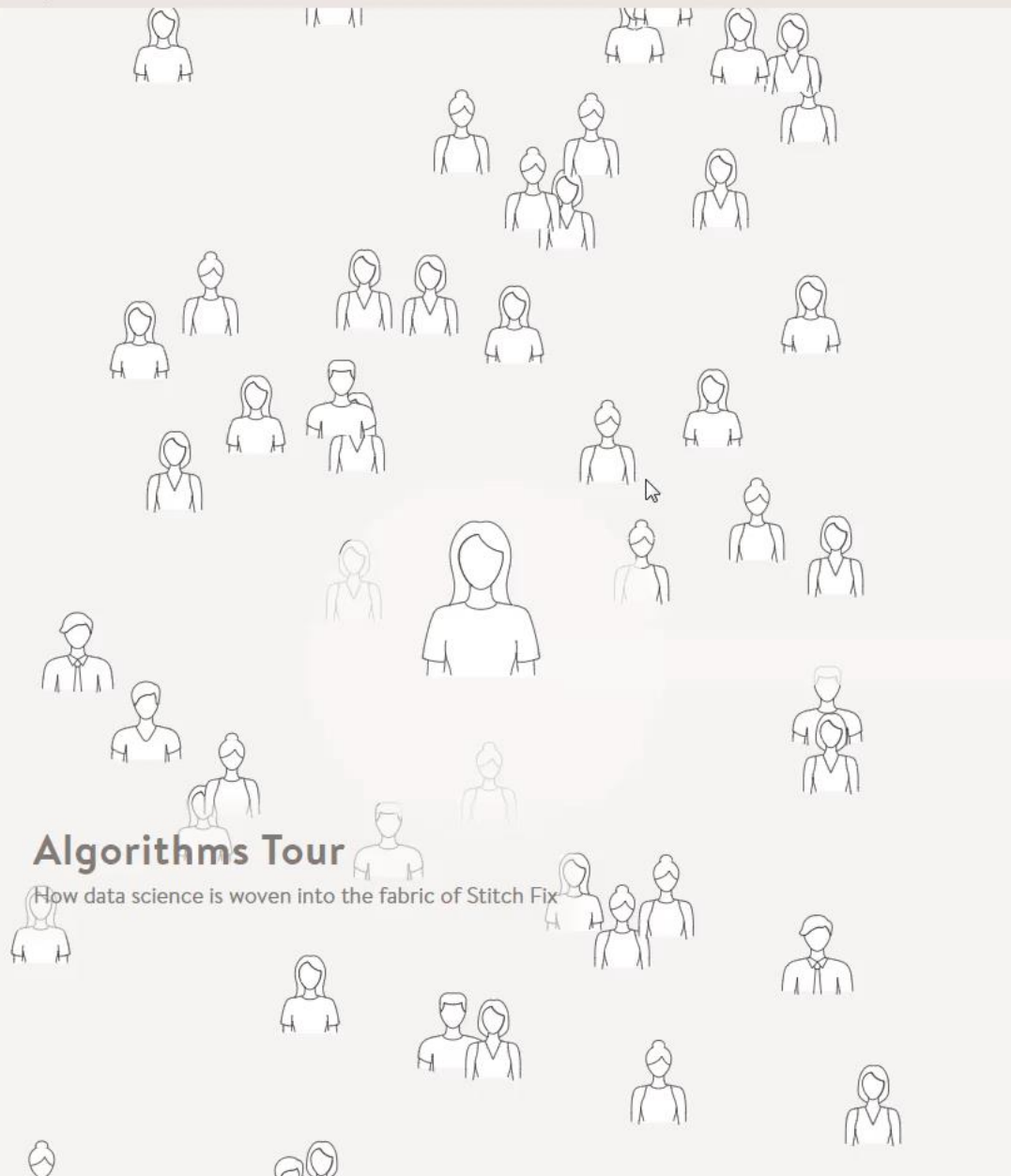
Announcing PyTorch 1.0 for both research and production

Advancing state-of-the-art image recognition with deep learning on hashtags

ONNX

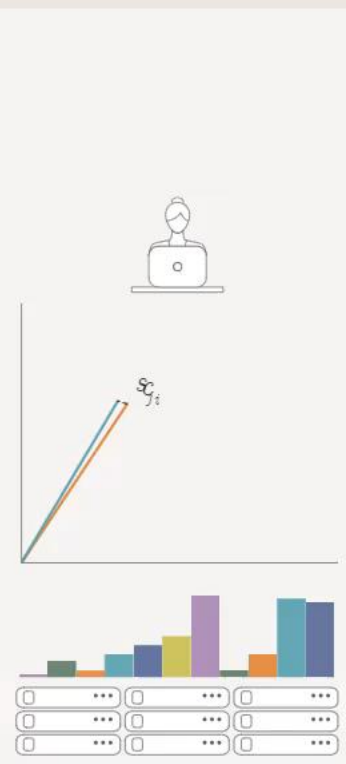
ONNX expansion speeds AI development

Embodied Question Answering: A goal-driven approach to autonomous agents



Algorithms Tour

How data science is woven into the fabric of Stitch Fix



$$\log \frac{p}{1-p} = a + X\beta + Zb$$

...

$$\min_a \sum_i \sum_j a_{ij} q_{ij}$$

$$s.t. a_{ij} \in \{0, 1\}, \forall i, j$$

$$\sum_j a_{ij} = 1 \forall i$$

$$\sum_i a_{ij} < k_j \forall j$$

...

$$\frac{\partial x}{\partial t} = f(x_t, u_t, w_t)$$



Awareness of the gap

Do we know

- How many patients will admit tomorrow?
- Which providers will retire next year?
- Which patients in the facility/community need the most attention?
- Which surgery method is best?

A large fire is burning in a field, producing thick, dark black smoke that rises into the sky. Several firefighters in orange gear are visible in the foreground, some standing near a fire hydrant and others near a ladder. A stream of water is being sprayed from the ladder towards the fire. The scene is set in a field with tall grass and a fence in the background.

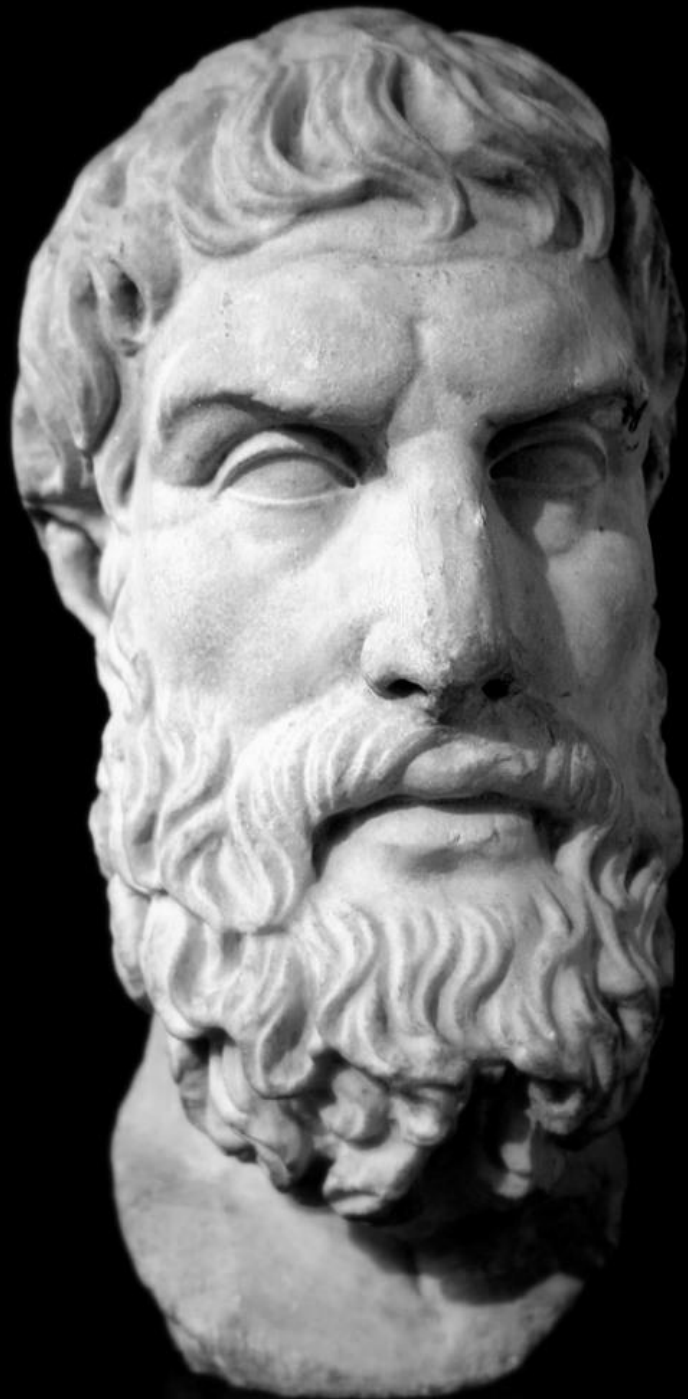
current cost reduction efforts

data teams

declining reimbursement



data science is a journey



**If you want to improve,
be content to be thought
foolish and stupid.**

Epictetus

Level 1: Business Intelligence



 **50**
HOSPITALS

 **829**
CLINICS

 **90**
NON-ACUTE
SERVICES

 **14**
SUPPORTIVE
HOUSING
PROGRAMS

 **111k**
CAREGIVERS

 **38k**
NURSES

 **20k**
PHYSICIANS

 HIGH SCHOOL,
NURSING
SCHOOLS
AND UNIVERSITY

 **2**
HEALTH
PLANS

 **1.9m**
COVERED LIVES

 **\$1.6b**
COMMUNITY
BENEFIT

Picking a Great First Project

- Problem with lots of examples and a clear target
- Demonstrable return from Data Science
 - Concrete costs
 - Are you trying to demonstrate that something isn't happening?
- Minimal integration needed
 - Likely not clinical
- Do you have an area where X intervention works but you don't have enough of it for everyone?
- Do you have a situation where you're already using a predictive model (LACE for readmission, etc)?

PMG No-Show Analysis

Lists no-shows as a count and a percentage of no-shows and arrived/completed appointments. Example: 2 (20%)
 Immediate Care / Urgent Care departments are excluded.

Clinic(s) selected: All

Hospital clinic(s) selected: None

No-Show Rates 04/01/2018 to 04/30/2018: Enterprise

Percentages are based on the specific payor class, confirmation status, or appointment lag sub totals and not the overall total.

	Total	Appointment Type					
		OVR	OVE	NP	WE	PX	C
Total	10,885 (6.3%)	3,236 (7.1%)					
Payor Class							
Capitation	302 (9.4%)	86 (5.3%)	15 (5.7%)		10 (5.0%)	1 (3.6%)	181 (20.0%)
Commercial							
Managed Care	829 (7.4%)	406 (6.9%)	46 (6.8%)		115 (7.8%)	4 (5.0%)	195 (9.9%)
Medicaid	1,689 (13.0%)	398 (12.3%)	151 (14.5%)		64 (13.8%)	16 (8.3%)	906 (12.2%)
Medicaid HMO	7,938 (11.9%)	3,154 (11.4%)	863 (14.1%)		789 (14.3%)	119 (10.9%)	2,193 (10.0%)
Medicare	4,673 (4.5%)	1,589 (4.1%)	574 (4.9%)		64 (2.3%)	35 (3.1%)	2,128 (4.4%)
Medicare HMO							
Other	31 (3.9%)	12 (5.4%)	3 (2.8%)		2 (2.4%)	0 (0.0%)	11 (3.0%)
OTHER GOVERNMENT	566 (6.3%)	180 (5.9%)	62 (7.8%)		24 (4.9%)	3 (2.1%)	236 (6.6%)
Uninsured	7,526 (12.5%)	536 (19.8%)	242 (17.3%)		209 (17.4%)	12 (9.2%)	6,170 (11.1%)
Worker's Comp	390 (5.2%)	40 (2.2%)	6 (2.9%)		1 (25.0%)	2 (6.3%)	337 (6.0%)
Confirmation Status							
Confirmed	4,109 (4.3%)	1,422 (4.1%)	500 (4.5%)		260 (3.8%)	38 (2.3%)	1,390 (4.4%)
Removed	1,753 (11.3%)	644 (10.4%)	226 (12.0%)		236 (9.3%)	18 (5.6%)	338 (14.0%)
Appointment Lag							
0	3,281 (2.7%)	671 (1.9%)	116 (2.2%)		54 (3.4%)	19 (1.2%)	2,327 (3.0%)
1	2,151 (6.1%)	741 (4.8%)	189 (5.1%)		63 (6.1%)	12 (5.6%)	1,043 (8.8%)
8-14	5,809 (8.4%)	1,652 (8.0%)	573 (8.2%)		292 (6.6%)	51 (5.9%)	2,741 (9.9%)
15-30	7,354 (8.2%)	2,044 (7.9%)	662 (8.3%)		461 (6.8%)	82 (7.0%)	3,379 (8.8%)
31+	11,886 (10.0%)	3,373 (8.2%)	877 (8.2%)		859 (7.4%)	90 (7.2%)	5,656 (13.0%)

Level 2: Building Models



Browse > Computer Science > Software Development



JOHNS HOPKINS
UNIVERSITY

#1 Specialization

Data Science Specialization

Launch Your Career in Data Science. A nine-course introduction to data science, developed and taught by leading professors.

Enroll

Financial aid available

About
Data Science
Specialization

Course 1
The Data Scientist's
Toolbox

Course 2
R Programming

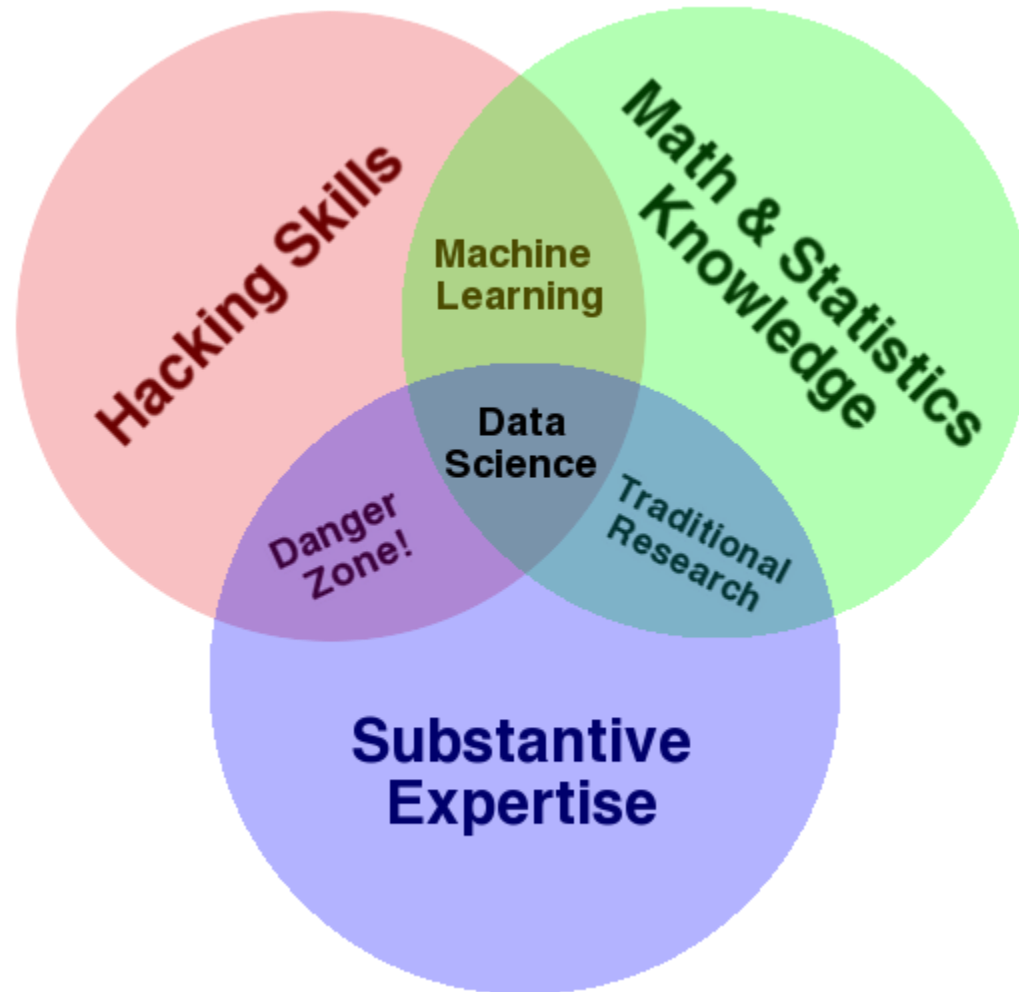
Course 3
Getting and Cleaning
Data

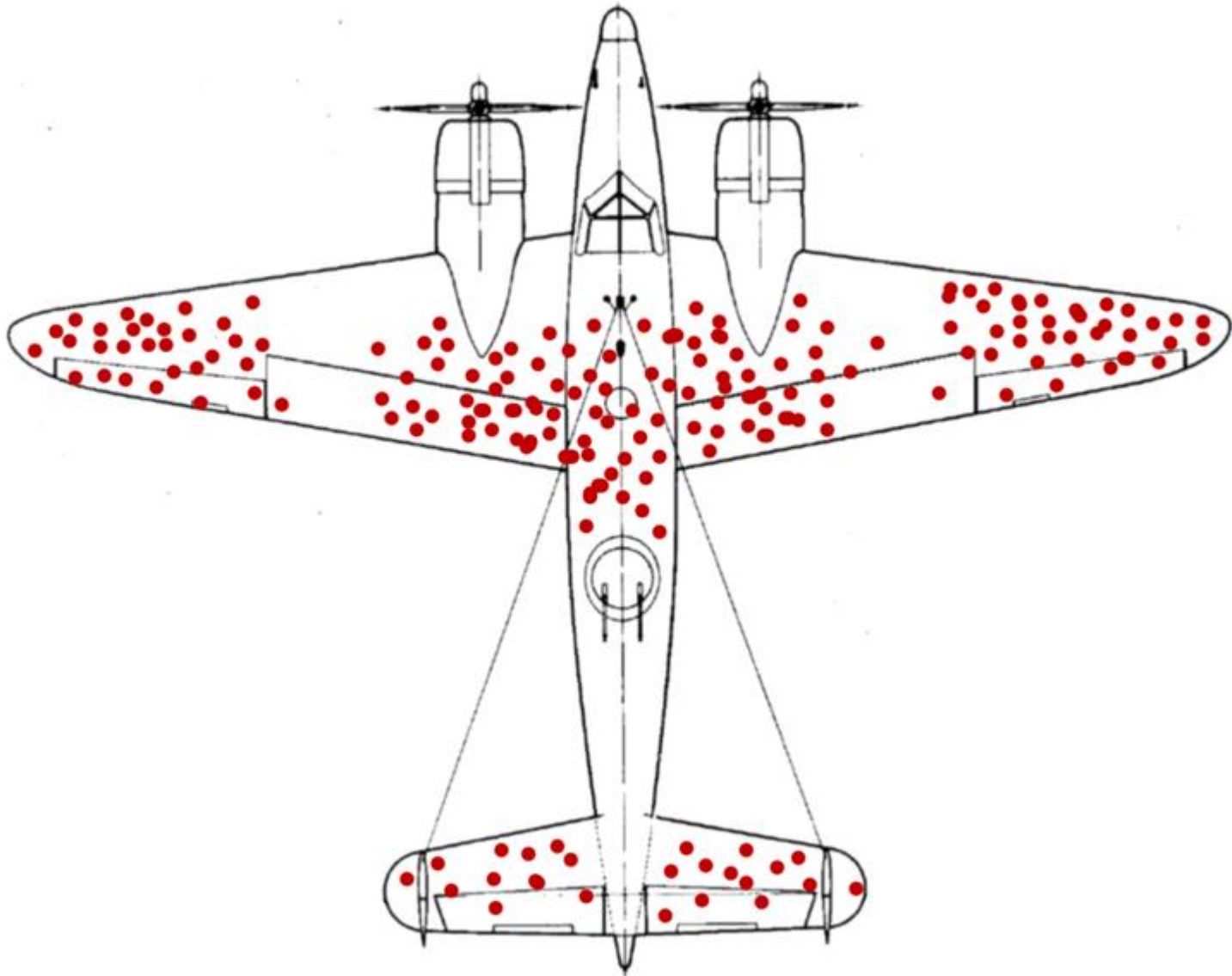
Course 4
Exploratory Data
Analysis

About this Specialization

Ask the right questions, manipulate data sets, and create visualizations to communicate results.

This Specialization covers the concepts and tools you'll need throughout the entire data science pipeline, from asking the right kinds of questions to making inferences and publishing results. In the final Capstone Project, you'll apply the skills learned by building a data product using real-world data. At completion, students will have a portfolio demonstrating their mastery of the material.







Computers are useless;
they can only give answers.

Pablo Picasso

```

1 require(httr)
2 require(jsonlite)
3 require(dplyr)
4 require(magrittr)
5 require(xml2)
6
7 headlines <- GET(url = 'https://newsapi.org/v1/articles?source
8 headlines$content %>% rawToChar %>% fromJSON %>% extract2(4) -
9
10 NYThealth <- GET(url = 'https://api.nytimes.com/svc/topstories
11 NYThealth$content %>% rawToChar %>% fromJSON %>% extract2('res
12

```

Environment History

Global Environment

Data

- covData 5610473 obs. of 97 variables
- inTextData 2000 obs. of 4 variables
- perChargeCat 232 obs. of 4 variables

Values

aftervisits	19060L
beforevisits	24518L
connStr	"Driver=SQL Server;Server=WN34069.wa. ..."

Files Plots Packages Help Viewer

R: Cross Tabulation and Table Creation Find in Topic

table {base} R Documentation

Cross Tabulation and Table Creation

Description

table uses the cross-classifying factors to build a contingency table of the counts at each combination of factor levels.

Usage

```

table(...,
  exclude = if (useNA == "no") c(NA, NaN),
  useNA = c("no", "ifany", "always"),
  dnn = list.names(...), deparse.level = 1)

as.table(x, ...)
is.table(x)

```

Console //phsorn154/users/p337683/

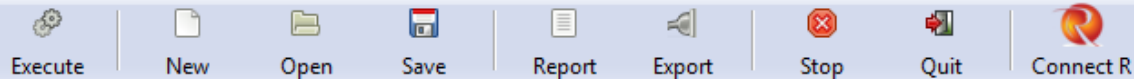
```

R version 3.4.3 (2017-11-30) -- "Kite-Eating Tree"
Copyright (C) 2017 The R Foundation for Statistical Computing
Platform: x86_64-w64-mingw32/x64 (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
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Type 'license()' or 'licence()' for distribution details.

R is a collaborative project with many contributors

```



Data: Explore Test Transform Cluster Associate Model Evaluate Log

Source: File ARFF ODBC R Dataset RData File Library Corpus ScriptFilename: (None) Separator: , Decimal: . Header Partition 70/15/15 Seed: 42 View Edit
 Input Ignore Weight Calculator: Target Data Type: Auto Categorical Numeric Survival
Welcome to Rattle (rattle.togaware.com).

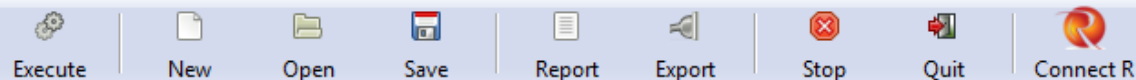
Rattle is a free graphical user interface for Data Science, developed using R. R is a free software environment for statistical computing, graphics, machine learning and artificial intelligence. Together Rattle and R provide a sophisticated environment for data science, statistical analyses, and data visualisation.

See the Help menu for extensive support in using Rattle. The books Data Mining with Rattle and R and Essential Data Science are available from Amazon. The Togaware Desktop Data Mining Survival Guide includes Rattle documentation and is available from datamining.togaware.com

Rattle works with open source R which is limited to datasets and processing that fit into your computers memory. Further details from <https://docs.microsoft.com/en-us/r-server/>

Rattle is licensed under the GNU General Public License, Version 2. Rattle comes with ABSOLUTELY NO WARRANTY. See Help -> About for details.

Rattle Version 5.1.0. Copyright 2006-2017 Togaware Pty Ltd. Rattle is a registered trademark of Togaware Pty Ltd. Rattle was created and implemented by Graham Williams with contributions as acknowledged in 'library(help=rattle)'.



Data Explore Test Transform Cluster Associate Model Evaluate Log

Type: Tree Forest Boost SVM Linear Neural Net Survival All

No Target Algorithm: Traditional Conditional

Model Builder: randomForest

Trees: 500 Sample Size:

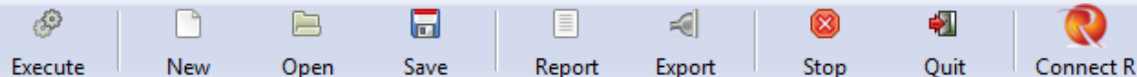
Variables: 10 Impute

Random Forest Model

A random forest is an ensemble (i.e., a collection) of un-pruned decision trees. Ensemble models are often robust to variance and bias.

Random forests are often used when we have large training datasets and particularly a very large number of input variables (hundreds or even thousands of input variables). The algorithm is efficient with respect to a large number of variables since it repeatedly subsets the variables available. Use the Importance button to view the relative importance of each variable.

A random forest model is typically made up of tens or hundreds of decision trees. Use the Errors button to view the rate of decrease of the model error as the number of trees increases.



Data Explore Test Transform Cluster Associate Model Evaluate Log

 Export Comments: Rename Internal Variables: From crs\$ to MY

```
# For repeatability export this log of all activity to a
# file using the Export button or the Tools menu. This
# script can serve as a starting point for developing your
# own scripts. Exporting to a file called 'model.R' will
# allow you to type into a new R Console the command
#"source('model.R')" and so repeat all actions. Generally,
# you will want to edit the file to suit your own needs.
# You can also edit this log in place to record additional
# information before exporting the script.

# Note that saving/loading projects retains this log.

# We begin most scripts by loading the required packages.
# Here are some initial packages to load and others will be
# identified as we proceed through the script. When writing
# our own scripts we often collect together the library
# commands at the beginning of the script here.

library(rattle) # Access weather dataset and utilities.
library(magrittr) # For the %>% and %<>% pipeline operators.

# This log generally records the process of building a model.
# However, with very little effort the log can also be used
# to score a new dataset. The logical variable 'building'
# is used to toggle between generating transformations,
# when building a model and using the transformations,
# when scoring a dataset.

building <- TRUE
scoring <- ! building

# A pre-defined value is used to reset the random seed
# so that results are repeatable.

crv$seed <- 42
```

Level 3: Deploying to Users



Medford Pilot Reduces No-Shows by 49%

Tristan Markwell, 22 September 2015

Background

From early July through early September 2015, two Providence clinics (Doctors Clinic Internal Medicine and Medford Neurology) called patients at 6% or higher risk of no-show as determined by a Providence-wide machine learning model built by the Providence Data Science team. Lists were distributed each morning to staff at the clinics, who called patients up to three times to confirm the appointments. 3,235 calls were made over the course of the 8-week pilot. Results were compared to those for the same clinics in May and June, before the pilot had started.

Raw Results

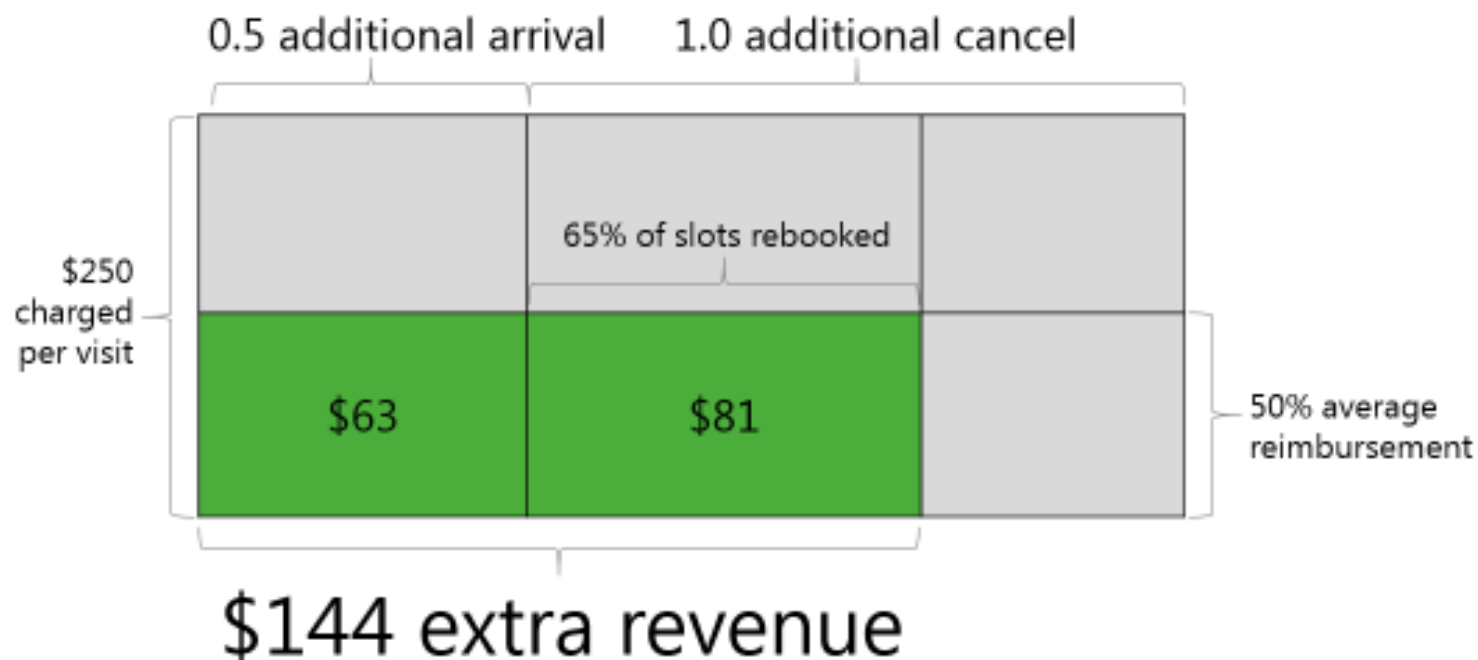
Usually the no-show rate is computed as the number of no-shows out of the number of appointments that weren't cancelled (that is, arrived and no-show). By this measure, **no-shows went down sharply – 8.6% for May-June but only 5.6% for the pilot, a 35% drop.** Considering cancellations within two days in both denominators, the rates are 7.6% for May-June and 4.7% for the pilot, a drop of 38%.

Calibration

terms of their likelihood to no-show. Indeed, the average no-show risk for the May-June patients was 10.2%, but 12.2% for the pilot group. That means that **the number of no-shows went down, even in an environment where we would have expected them to increase by 20%.** 46% of each group was classified as high-risk, but even with the reduction in no-shows, the high-risk group accounts for 77% of the no-shows for May-June and 75% of the no-shows for the pilot period. One way to better account for this mismatch between the pilot and control group is to calibrate the two time periods for specified bins of risk. Because no-shows are relatively rare events, for the bins to be similar in size they are much narrower at the low end of risk and wider at the high end. The cut points selected were 0%, 2%, 3%, 4%, 6%, 8%, 10%, 15%, 20%, 30%, 40%, and 100%. Comparing the two groups within each of these bins, the effects of the calls for patients at a given level of risk are clearer.

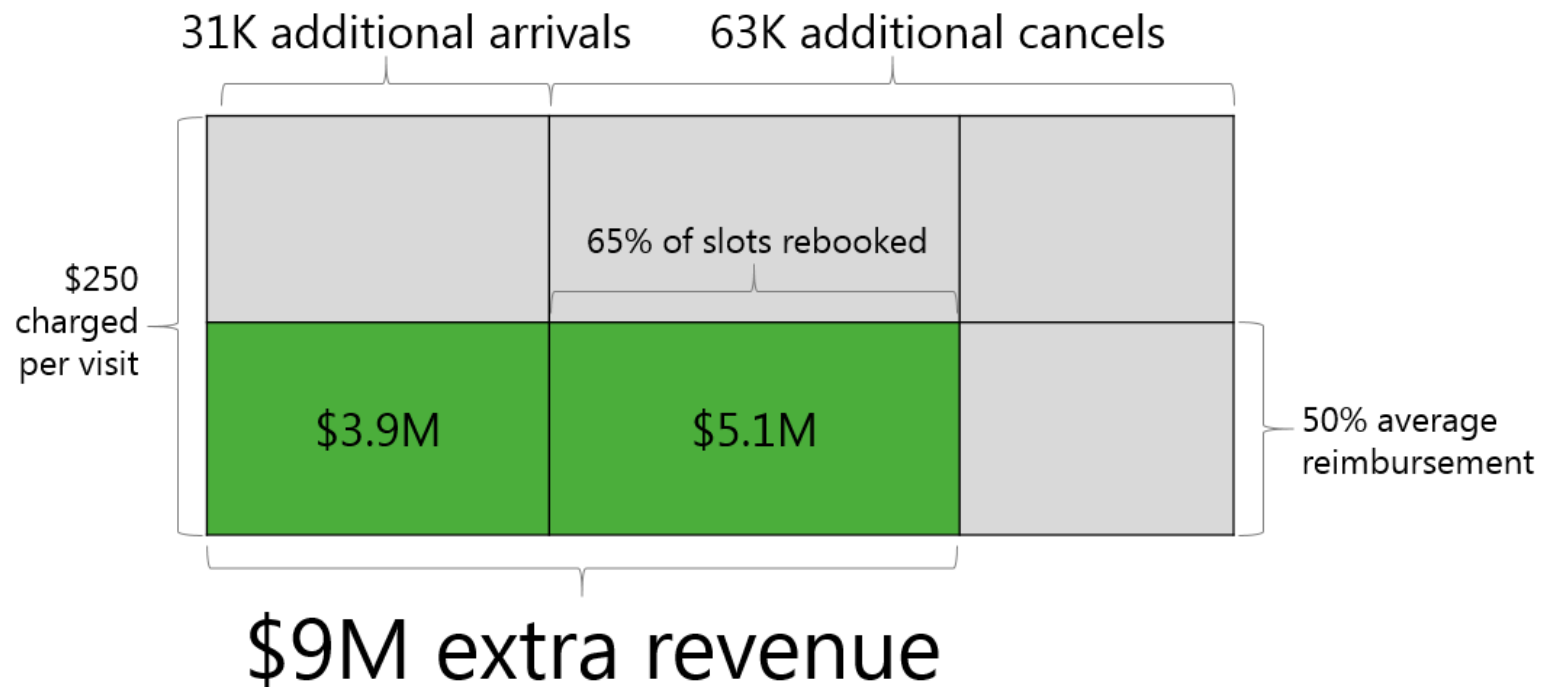
From Figure 1, it is clear that the group that was called had a much lower no-show rate (that is, the intervention pretty clearly bends the curve), but rather than those patients coming in it appears that most are being

Per hour of calls



Calling Patients at Risk for No-Show: Overall Providence Per Year

60-65K hours of calls (31 FTE, ≈\$1.5M wages and benefits?)



Two days out patients most likely to no-show

Minimum Risk

Market(s)

Department

Department	Patient Name	Phone 1	Phone 2	Provider	Appointment Time	No-show Risk
PMG GLISAN FAMILY MEDICINE				ROSENFELD, SHAI DAN	3/22/2017 15:00	38%
				WHITE, CHARLES THAYER	3/22/2017 13:40	36%
				ESKESEN, STACI JOANNA	3/22/2017 18:20	31%
				GLISAN MA	3/22/2017 15:40	29%
				RODGERS-ROBEY, MELISSA D..	3/22/2017 13:20	28%
				ROSENFELD, SHAI DAN	3/22/2017 15:20	28%
				WHITE, CHARLES THAYER	3/22/2017 14:20	27%
				GLISAN FM RN	3/22/2017 13:00	24%
				RODGERS-ROBEY, MELISSA D..	3/22/2017 14:40	21%
				WHITE, CHARLES THAYER	3/22/2017 11:20	21%
				GRAVES, RACHEL SINEX	3/22/2017 11:00	18%
				ROSENFELD, SHAI DAN	3/22/2017 10:40	17%
				ESKESEN, STACI JOANNA	3/22/2017 17:40	16%
				RODGERS-ROBEY, MELISSA D..	3/22/2017 17:00	15%
				WHITE, CHARLES THAYER	3/22/2017 13:00	15%
				GRAVES, RACHEL SINEX	3/22/2017 09:00	15%
				RODGERS-ROBEY, MELISSA D..	3/22/2017 15:20	14%
				WHITE, CHARLES THAYER	3/22/2017 10:00	13%
				ESKESEN, STACI JOANNA	3/22/2017 17:20	12%
				WHITE, CHARLES THAYER	3/22/2017 15:00	12%
			WHITE, CHARLES THAYER	3/22/2017 08:20	12%	
			ESKESEN, STACI JOANNA	3/22/2017 15:20	12%	
			ROSENFELD, SHAI DAN	3/22/2017 11:40	11%	
			WHITE, CHARLES THAYER	3/22/2017 15:40	11%	
			ESKESEN, STACI JOANNA	3/22/2017 13:00	10%	

Level 4: App Development



IBM

Vijay Venkatesan
PSJH Chief Data Officer

myHI way



My Saved Searches

Click the heart in the Search Box, and save it with a Search name to see it here...



My Bookmarks

Bookmark a search result to see it here ...



Showing 1 - 50 of 486 (372)ms

Sort by
relevance ▾

breast cancer ×

All 486 APIs 0 Apps 0 Data 2 Metrics 58 Reports 425 Terms 1 Training

TOPICS

- ▶ Business Operations 7
- ▶ Clinical Performance Groups 4
- ▶ Institutes 9
- ▶ Quality 2

ENVIRONMENT

- PHS Epic Hyperspace 204
- Tableau 78
- SHS Epic Hyperspace 52
- Providence InfoView 44
- Population Health 32

Show more

BUSINESS ENTITY

- Providence Health & Services 240
- Swedish 59
- Kadlec 38

PRODUCT TYPE

- Reporting Workbench Report 283
- Crystal Report 62
- Tableau View 49



Breast Cancer Workbook (Reports)

<https://tableauserver.providence.org/#/workbooks/34265>

System-wide Breast Cancer Volume, Treatment, and Quality Indicators



More

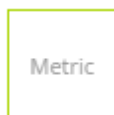


Breast Cancer Screening (Metrics)

This measure is available in the report(s) listed in the "Measure", "Measure Alias", "Measure(s)" or "You Have Selected (one of three dropdowns)" dropdown menus.
Definition: ...



More



Breast Cancer Screening (Metrics)

Breast cancer screening is checking for cancer before there are signs or symptoms of the disease. All women need to be informed by their health care provider about the best screening options for them...



More



MSSP 2015: Breast Cancer (Metrics)

This measure is available in the report(s) listed in the "You Have Selected (one of three dropdowns)" dropdown menu.
Definition: Percentage of women 52 through 74 years of ag...



More

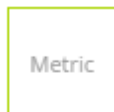


MSSP: NQF0031: Breast Cancer Screening (Metrics)

This measure is available in the report(s) listed in the "Measure", "Measure(s)" or "You Have Selected (one of three dropdowns)" dropdown menus.
Definition: Percentage of wom...



More



Preoperative Diagnosis of Breast Cancer (Metrics)

The percent of patients undergoing breast cancer operations who obtained the diagnosis of breast cancer preoperatively by a minimally invasive biopsy method



More

breast cancer x

Showing 1 - 50 of 486 (372)ms

All 486 APIs 0 Apps 0 Data 2 Metrics

Daily St...

Denials ...

iSurvey

No Show

Provider...

Spider

Vantage

TOPICS

- ▶ Business Operations 7
- ▶ Clinical Performance Groups 4
- ▶ Institutes 9
- ▶ Quality 2

ENVIRONMENT

- PHS Epic Hyperspace 204
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- Population Health 32

Show more

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- Providence Health & Services 240
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- Kadlec 38

PRODUCT TYPE

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- Crystal Report 62
- Tableau View 49



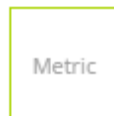
Breast Cancer Workbook (Reports)

<https://tableauserver.providence.org/#/workbooks/34265>
System-wide Breast Cancer Volume, Treatment, and Quality Indicators



Breast Cancer Screening (Metrics)

This measure is available in the report(s) listed in the "Measure", "Measure Alias", "Measure(s)" or "You Have Selected (one of three dropdowns)" dropdown menus.
Definition: ...



Breast Cancer Screening (Metrics)

Breast cancer screening is checking for cancer before there are signs or symptoms of the disease. All women need to be informed by their health care provider about the best screening options for them...



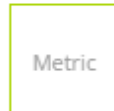
MSSP 2015: Breast Cancer (Metrics)

This measure is available in the report(s) listed in the "You Have Selected (one of three dropdowns)" dropdown menu.
Definition: Percentage of women 52 through 74 years of ag...



MSSP: NQF0031: Breast Cancer Screening (Metrics)

This measure is available in the report(s) listed in the "Measure", "Measure(s)" or "You Have Selected (one of three dropdowns)" dropdown menus.
Definition: Percentage of wom...



Preoperative Diagnosis of Breast Cancer (Metrics)

The percent of patients undergoing breast cancer operations who obtained the diagnosis of breast cancer preoperatively by a minimally invasive biopsy method





Data Refreshed: Tue 04/17/2018 6:06 AM

Cancelled appointments removed by



KADLEC, ...

KC RICHLAND PRIMARY CARE

2 Days Out (04/19/2018)

Sort by:

No Show Risk (high to low)

Include all appointments with no show risk at least:



Hide confirmed/cancelled

Exclude EPIC confirmation

<p>▼ Kobe Vandenberg</p> <p>MRN: 22700251 DOB: 03/09/1996 Provider: HUYNH, TONY HUU Appt Type: OB FIRST Appt Time: 04/19/2018 01:30 PM</p>	<p>No Show 69% Show 31%</p> <p>(478) 837-1226 (803) 899-1994</p>
<p>▼ Pris Lasky</p> <p>MRN: 22461126 DOB: 12/14/1996 Provider: SCHEVE, DAWN A Appt Type: PULM FOLLOW UP Appt Time: 04/19/2018 09:00 AM</p>	<p>No Show 55% Show 45%</p> <p>(561) 712-2312 (650) 524-9323</p>
<p>▼ Sharon Gotcher</p> <p>MRN: 91926828 DOB: 03/07/1964</p>	<p>No Show 45% Show 55%</p> <p>(281) 199-2016</p>





Data Refreshed: Tue 04/17/2018 6:06 AM

Cancelled appointments removed by



KADLEC, ...

KC RICHLAND PRIMARY CARE

2 Days Out (04/19/2018)

Sort by:

No Show Risk (high to low)

Include all appointments with no show risk at least:



Hide confirmed/cancelled

Exclude EPIC confirmation

▼ Kobe Vandenberg No Show 69% Show 31%

MRN: 22700251
 DOB: 03/09/1996
 Provider: HUYNH, TONY HUU
 Appt Type: OB FIRST
 Appt Time: 04/19/2018 01:30 PM

(478) 837-1226
 (803) 899-1994

📞 Call in progress: (478) 837-1226

Confirmed Patient
Cancelled Patient
Rescheduled Patient
Left Msg for Patient
Other (enter Note)

Confirmed Patient.

Done
Cancel



No Show Value Estimate

Tristan Markwell

January 17, 2018

Executive Summary

Use of the No Show app by a few clinics in Oregon, fed by a predictive algorithm from the Data Science team, had a net positive impact of about \$8K in December 2017 (annual rate of \$96K), with a net value of nearly \$5 per call. If scaled to all PHS, SHS and KHS, this equates to \$8.5M annually due to reduced no shows and earlier cancels. The app already contains all these clinics, so implementation would be purely organizational.

Situation

The No Show app has been in production since March 2017. Various clinics in multiple regions have tried it in different iterations, but its use has never been required, and at present almost all use is concentrated in the clinics in Oregon, which has a history of and central support for initiatives supporting improved access, and which held optional trainings in 2017 for all the clinics.

Background

Healthcare Intelligence first took up the question of predicting clinic no shows using machine learning in 2013. Over time this has evolved from a technical demonstration, to a 2015 pilot in Southern Oregon, to a Tableau dashboard, and finally to a myHIway app that automatically tracks how users are interacting with it. The Medford pilot was used a two-month test period compared to the two months prior, and estimated that an hour of calls could generate \$144 in additional revenue through reduced no-show rates and earlier cancels (enough time to rebook the slot); this scaled to about \$9M per year for all of PHS, for something like \$1.5M in wages for the callers. A more formal study of the effect of the calls on no show was undertaken in early 2017 and didn't replicate this finding; however, analysis showed that patients in the treatment and control arms were contacted at almost exactly the same rate (ie massive non-compliance), so there was no way to tease out the effect. Looking at the patients naturally contacted by clinics using the myHIway app is a way to estimate the effect of the calls in the wild, and a proper method of finding appropriate cases to match against should help mitigate issues with using a convenience sample.

Analysis

Exclusions

Since the app has gained traction in the clinics in the Oregon Region, the analysis is restricted to clinics and hospital clinics in the various Oregon markets in December 2017. Of the 107,068 encounters from that time period that were scored (the system automatically ignores new patient appointment types and weekend appointments), 87,314 (82%) had an associated two-business-day prediction, which is what the app would use to





Level 5: Operationalizing



Data Science Infrastructure POC



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Key Lessons from the POC

- Need for an integrated team to develop shared vocabulary
 - Architects
 - System administrators
- Data Science team needs expansive database privileges
- Open-source without vendor solutions don't scale well with complexity
- Too easy for people to get pulled off for production support



Photo by Alexander Mills on Unsplash

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Refreshment Break in Foyer 3:00 – 3:20

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