



Your Model Will Probably Fail

AND HOW TO PREVENT IT

Alyssa Peck
Data Scientist
Tableau Software

Data Scientist

National Parks Enthusiast

Hobbyist cyclist, gardener, and more



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National Parks Enthusiast

Hobbyist cyclist, gardener, and more

Triplet



Your Model Will Probably Fail

Statistics show that your data science model won't make it into production

87% of data science projects never make it into production

- VentureBeat Al

77% of businesses say that business adoption of big data and Al initiatives represent a challenge for their organizations

- NewVantage

80% of Al projects will remain alchemy, run by wizards whose talents will not scale in the organization

- Gartner

Sometimes they should fail

Sometimes they should fail

Data issues

Sometimes they should fail

Data issues

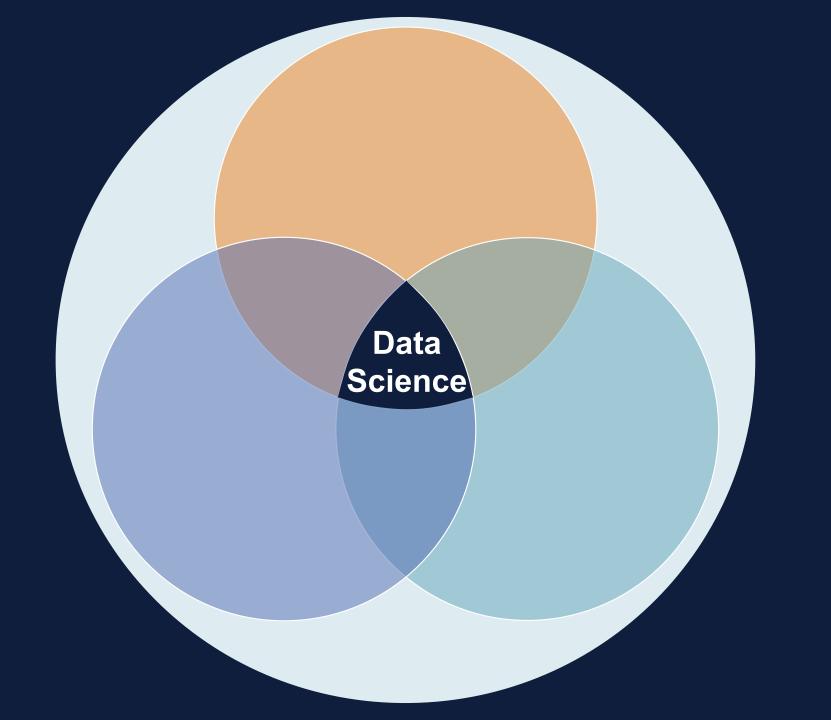
Lack of leadership buy-in/understanding

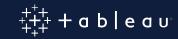
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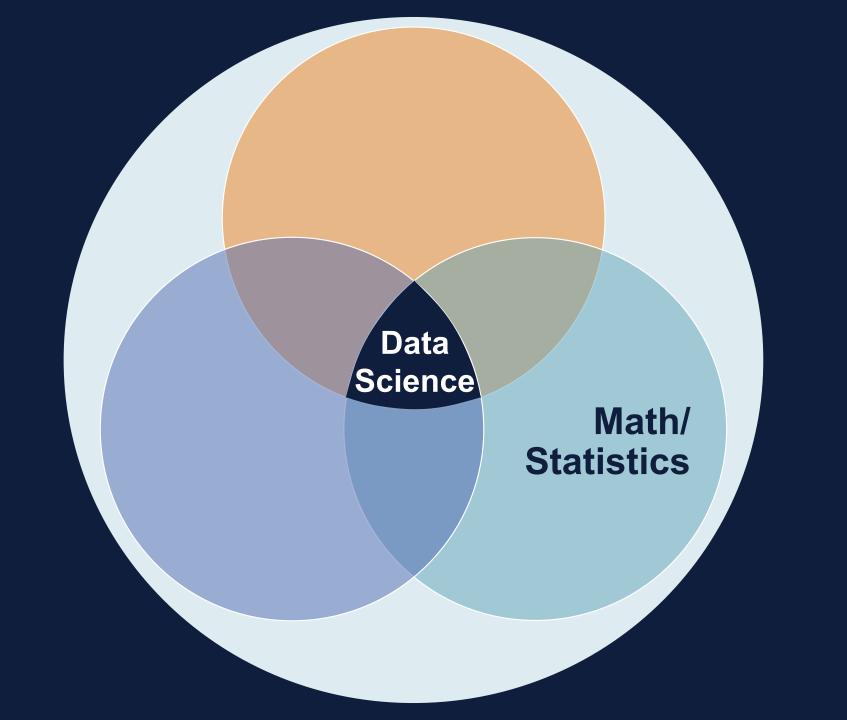
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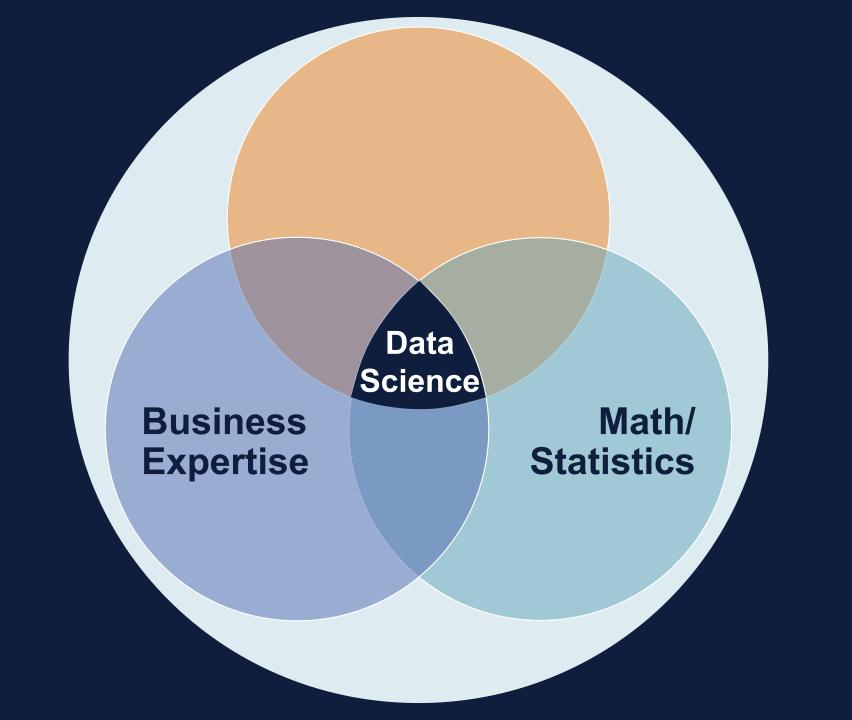
Can't get model into production



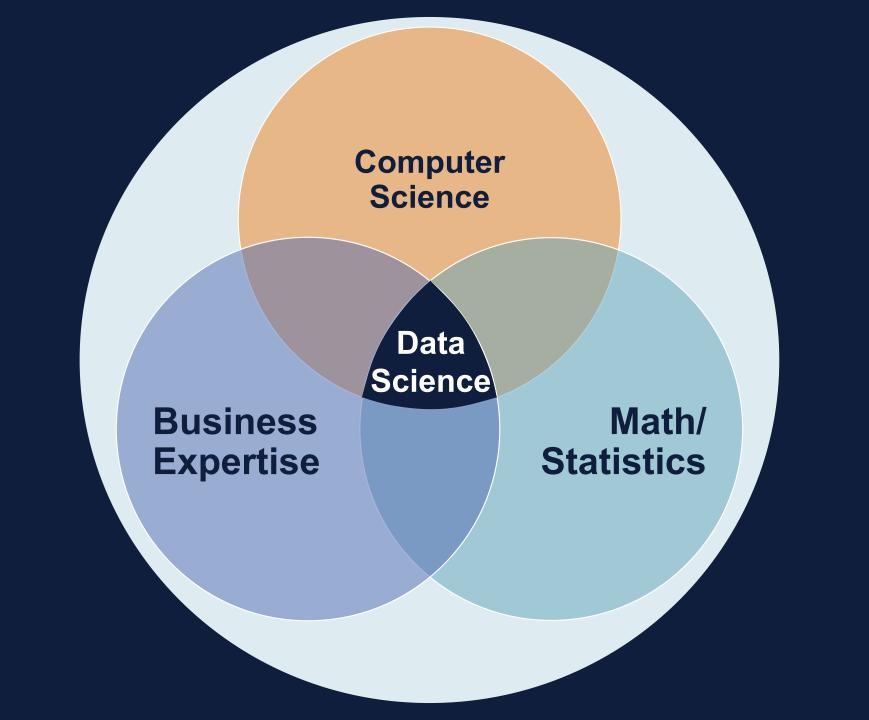




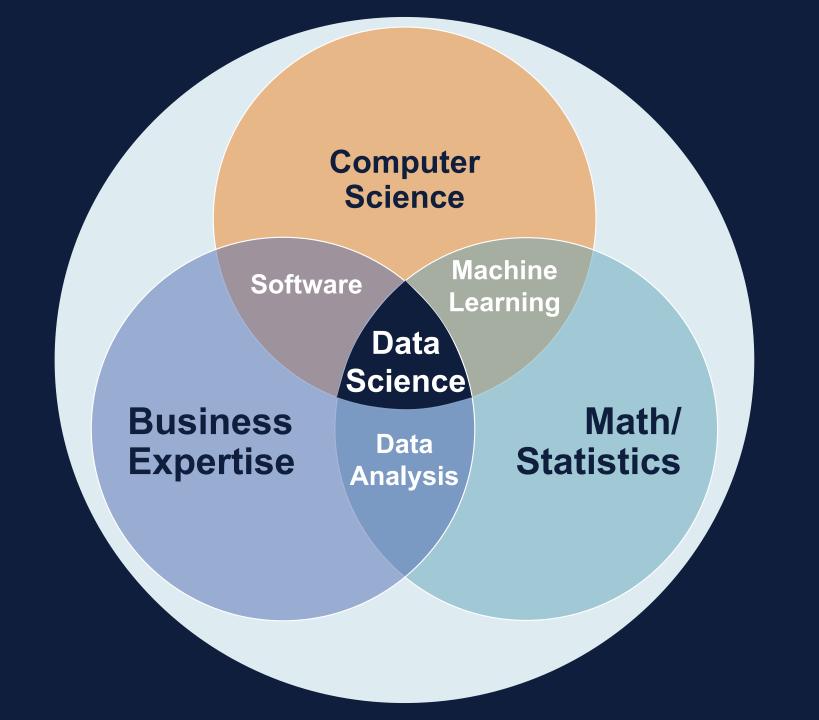














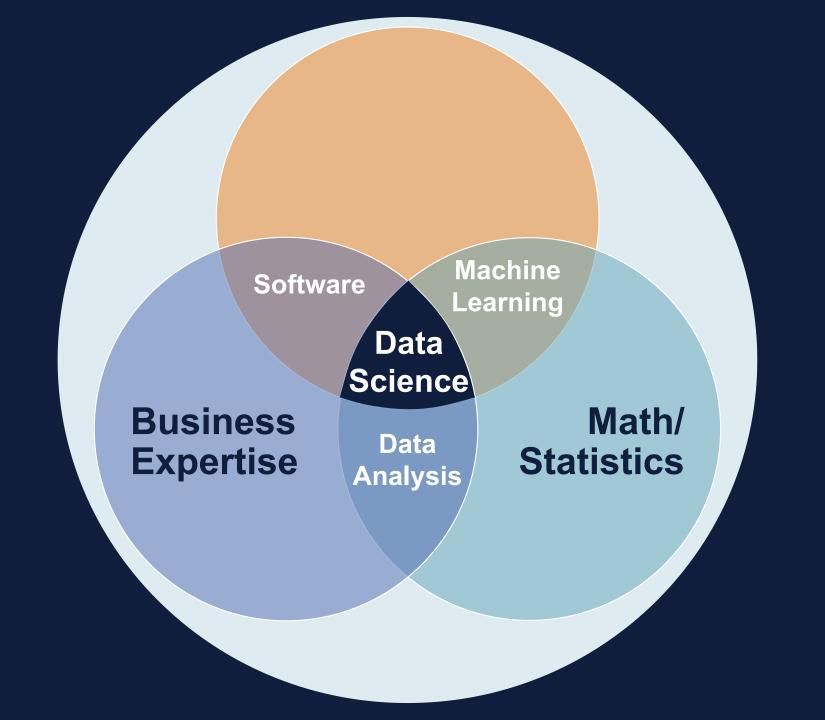




Tableau Prep

Machine Learning

Data Science

Business Expertise

Software

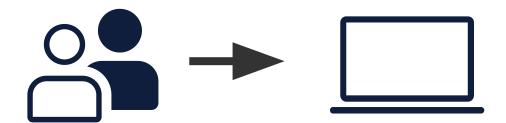
Data Analysis Math/ Statistics





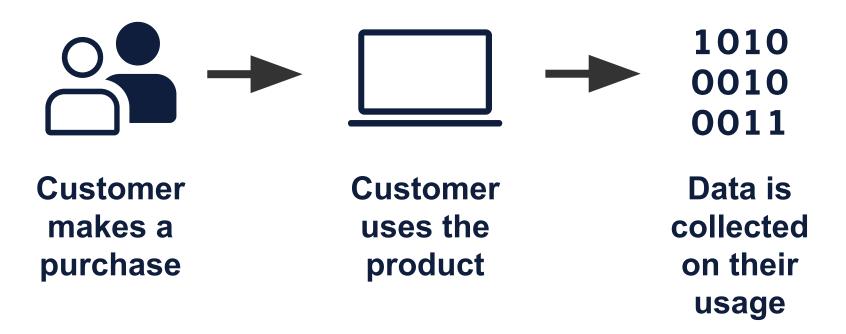


Customer makes a purchase



Customer makes a purchase

Customer uses the product





Predicting The Future



Predicting The Future with 3 Simple Ingredients

Predicting The Future ... with 3 Simple Ingredients

Data about the past

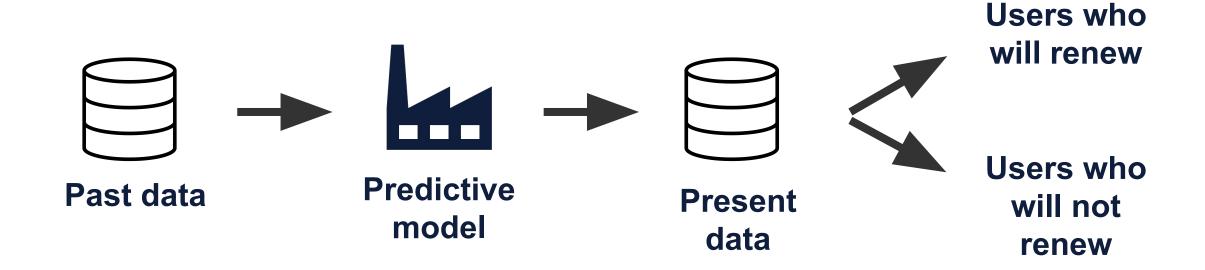
Predicting The Future ... with 3 Simple Ingredients

- Data about the past
- Data about the present

Predicting The Future ... with 3 Simple Ingredients

- Data about the past
- Data about the present
- Predictive model

Predicting The Future with 3 Simple Ingredients



- Data about the past
- Data about the present
- Predictive model



Past Data

# Customer ID	Abc Outcome	# Pct Active Days	# ¥ Watch Hours	# Profiles	# Years Customer
7	Did not Renew	70%	146.622	2	6
14	Did not Renew	59%	258.284	1	7
33	Did not Renew	67%	166.236	1	1
37	Renewed	100%	384.249	4	2
86	Did not Renew	64%	131.440	1	3
100	Did not Renew	71%	110.971	2	1
110	Did not Renew	65%	149.879	1	4
136	Did not Renew	68%	155.361	2	1
138	Did not Renew	66%	251.167	2	5
154	Renewed	71%	94.895	1	1

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Predicting Customer Renewal

- Data about the past
- Data about the present
- Predictive model



# Customer ID	# Pct Active Days	# Watch Hours	# Profiles	# Years Customer
14	71%	82.81	1	5
35	60%	318.66	1	6
62	66%	283.33	1	4
97	61%	259.84	2	5
110	64%	304.36	2	3
133	100%	54.30	2	3
140	60%	159.85	1	3
147	56%	126.04	2	10
160	64%	172.31	2	1
165	70%	420.44	2	1

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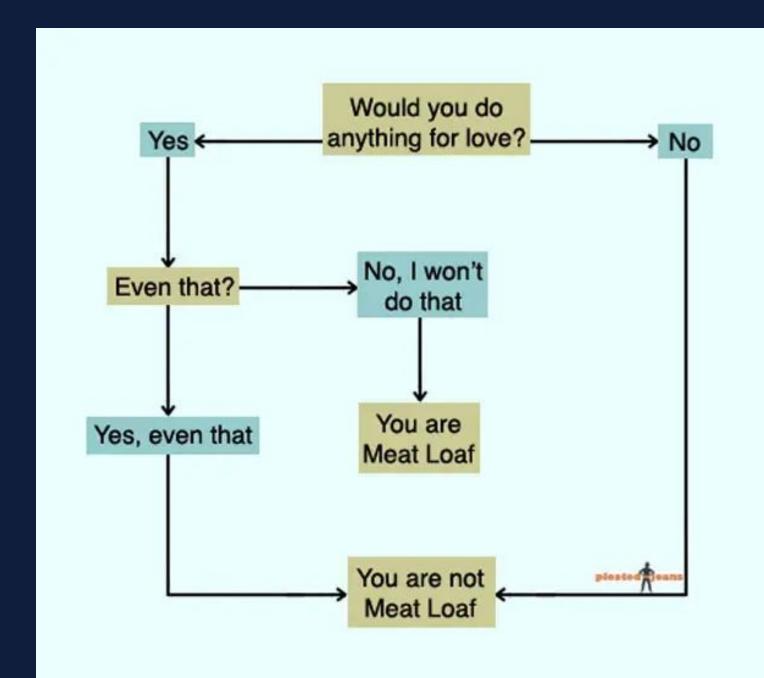
Predicting Customer Renewal

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- Data about the present
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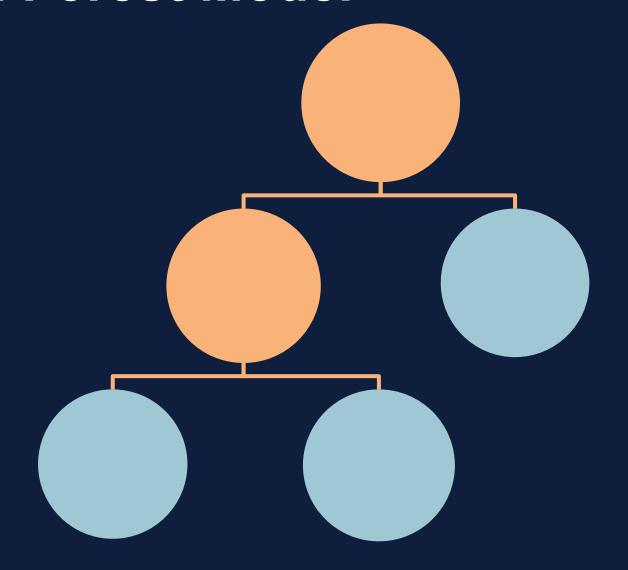


Predictive Model

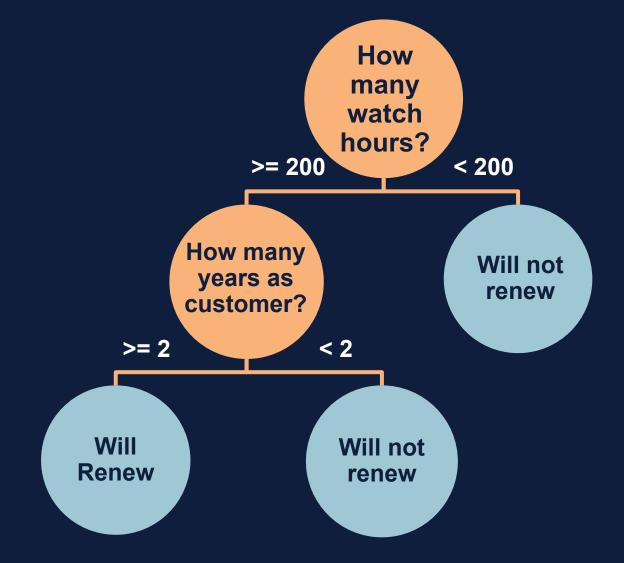






































































































































Predicting Customer Renewal

- Data about the past
- Data about the present
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BuildData





ScoreData





```
fit_predict <- function(full_data){</pre>
 library(randomForest)
 full_data$outcome <- as.factor(full_data$outcome)</pre>
 build rf <- randomForest(outcome ~ pct active days + watch hours + profiles +
       years customer,
                          data = full_data[full_data$Purpose == 'Model Building',])
 full data$churn probs[full data$Purpose == 'Scoring'] <-
   predict(build_rf, full_data[full_data$Purpose == 'Scoring',], type = "prob")[,1]
 full_data$Predicted <- ifelse(full_data$churn_probs >= 0.5,
                                 'Predict_NoRenew', ifelse(full_data$churn_probs < 0.5,
                                                        'Predict Renew', NA))
 output_data <- subset(full_data, Purpose == 'Scoring',
                        select = c(customer_id, pct_active_days, watch_hours, profiles,
              years customer, churn probs, Predicted))
 return(output_data)
```

RCode fit_predict <- function(full_data){

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library(randomForest)



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full_data\$outcome <- as.factor(full_data\$outcome)</pre>



```
build rf <- randomForest(outcome ~ pct_active_days + watch_hours +</pre>
              profiles + years_customer,
      data = full data[full data$Purpose == 'Model Building',])
```

```
full data$churn probs[full data$Purpose == 'Scoring'] <-
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++++ + a b | e a u

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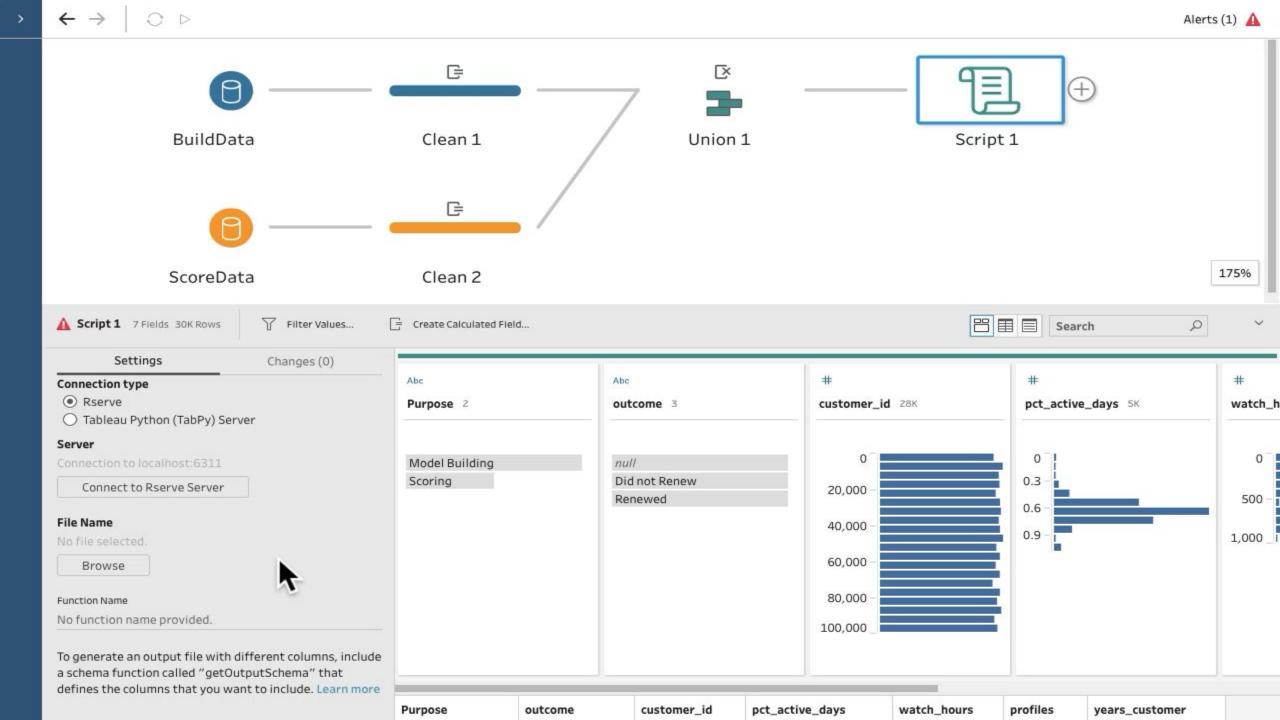
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              years customer, churn probs, Predicted))
 return(output data)
```

R Code

```
getOutputSchema <- function() {</pre>
  return (data.frame(
    Customer ID = prep string(),
    Percent_Active_Days = prep_decimal(),
    Watch Hours = prep decimal(),
    Profiles = prep decimal(),
    Years Customer = prep decimal(),
    Churn Probability = prep decimal(),
    Predicted Outcome = prep_string()));
```





Any library or model

- Any library or model
- Easy to schedule jobs

- Any library or model
- Easy to schedule jobs
- Fresh output data

Who is predicted to renew?





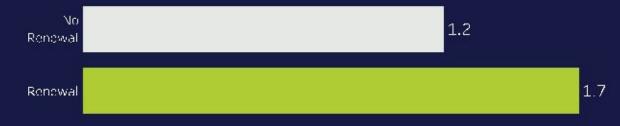
Those predicted to renew have a higher percentage of login days



Asia and Rest of World over-index on predicted non-renewals



... have more user profiles



... and have been customers for longer.



Customer ID	Predicted Outcome	Churn Probability	Percent Active Days	Profiles	Years Customer
14	Renewal	0.14	71%	1	-5
35	No Renewal	0.85	60%	1	6
62	Renewal	0.41	66%	1	4
97	No Renewal	0.77	61%	2	5
110	Renewal	0.35	64%	2	3
133	Renewal	0.34	100%	2	3
140	No Renewal	0.91	60%	1	3
147	Renewal	0.34	56%	2	10
160	No Renewal	0.76	64%	2	1
165	Renewal	0.00	70%	2	1
175	Renewal	0.29	75%	1	4
189	Renewal	0.10	73%	1	5

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160	No Renewal	0.76	64%	2	1
165	Renewal	0.00	70%	2	1
175	Renewal	0.29	75%	1	4
189	Renewal	0.10	73%	1	5

Over / Under based on global average

				r a
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110	Renewal			
133	Renewal	A		
110	No Renewal			
147	Renewal			
160	No Renewal			

Why Do Data Science Projects Fail?

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Sometimes they should fail

Data issues

Lack of leadership buy-in/understanding

Can't get model into production

Focus on impactful models

Focus on impactful models

Work as a data community to solve data issues

Focus on impactful models

Work as a data community to solve data issues

Effective communication and "selling" of models



Focus on impactful models

Work as a data community to solve data issues

Effective communication and "selling" of models

Use Tableau Prep + R/Python to get models into production

THANK YOU

Alyssa Peck apeck@tableau.com

