





Hands-on Lab: Predictive Analytics with Looker and Amazon SageMaker Powered by AWS

looker Eric Carr

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Select the **Predictive Analytics with Looker and Amazon SageMaker Powered by AWS** lab in the drop-down





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Sales Engineer, Alliances



## Agenda

- 1. Data science workflow
- 2. Exploring the data
- 3. Training a model
- 4. Testing a model and analyzing performance
- 5. Questions



## Data science workflow



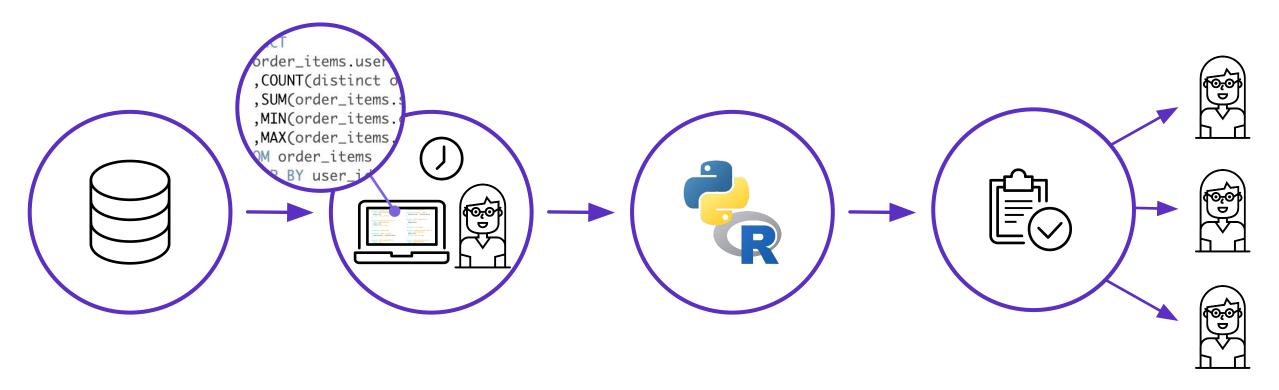
## **Data science**

Why is predictive analytics important?

- Forecasting, sales, events, volume
- Fraud detection
- Computing risk



## Workflow pre-Looker





## **Workflow with Looker**





## What is SageMaker?

Machine learning for every developer and data scientist

- Fully-managed service that covers the entire machine learning workflow
- Quickly build, train, and deploy machine learning models
  - Build and optimize a ML algorithm from the built-in marketplace
  - Train the model to optimize performance
  - Deploy to a fully managed environment with auto-scaling
- Use Looker's Action Hub integration with Amazon SageMaker to streamline the data science workflow by allowing model training and inference to be initiated directly from within the Looker Scheduler



# **Exploring the data**



## Will a customer enroll in a term deposit?

Make a prediction using bank client information

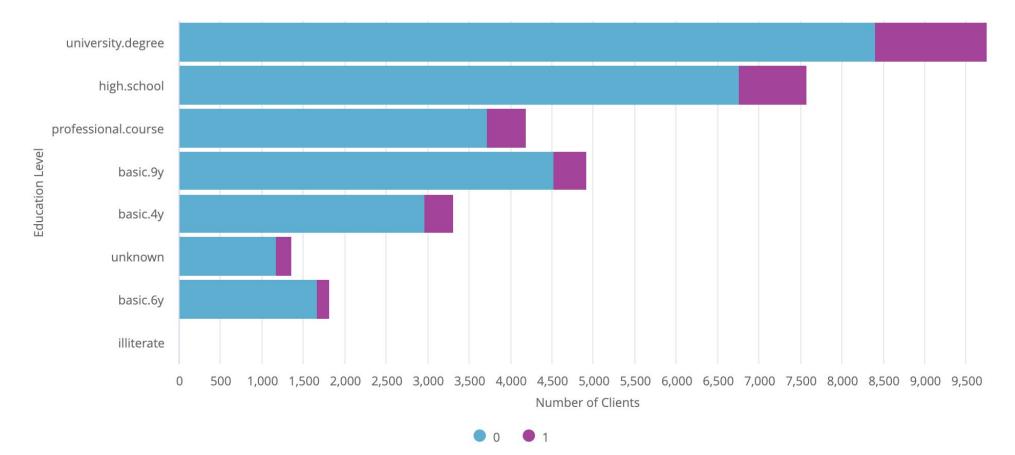
- The scenario: You work for the marketing department of a bank, and you need to predict if a customer will enroll in a term deposit using the client data that you have available.
  - Client demographics
  - Responses to prior marketing events
  - External environment factors
- Explore the data and identify client variables that you think will help predict whether or not a client enrolls in a term deposit.



## **Explore the data**

What variables will influence a client's behavior the most?

#### Education level:

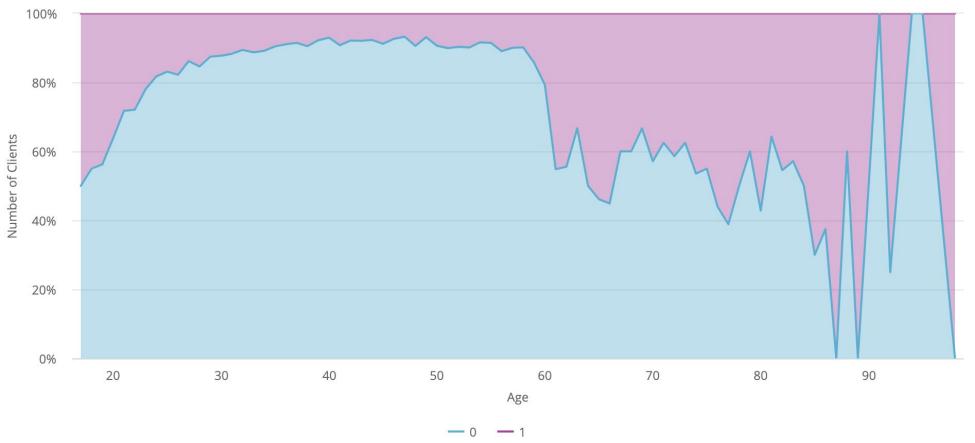




## **Explore the data**

What variables will influence a client's behavior the most?

#### Age:





# Training a model



## How to train your model

- 1. Create a dataset that includes the predictive variables and prediction target for a portion (commonly 70%) of your existing data using munged data
- 2. Make this data set available to an analytical tool
  - a. Amazon SageMaker via direct Looker integration
  - b. Python or R via the Looker SDK
- 3. Apply a training algorithm to the training data set to create a model that can be tested using the remaining data (and then applied to future data to make predictions)



## Create a training dataset

#### Include key variables identified via exploration

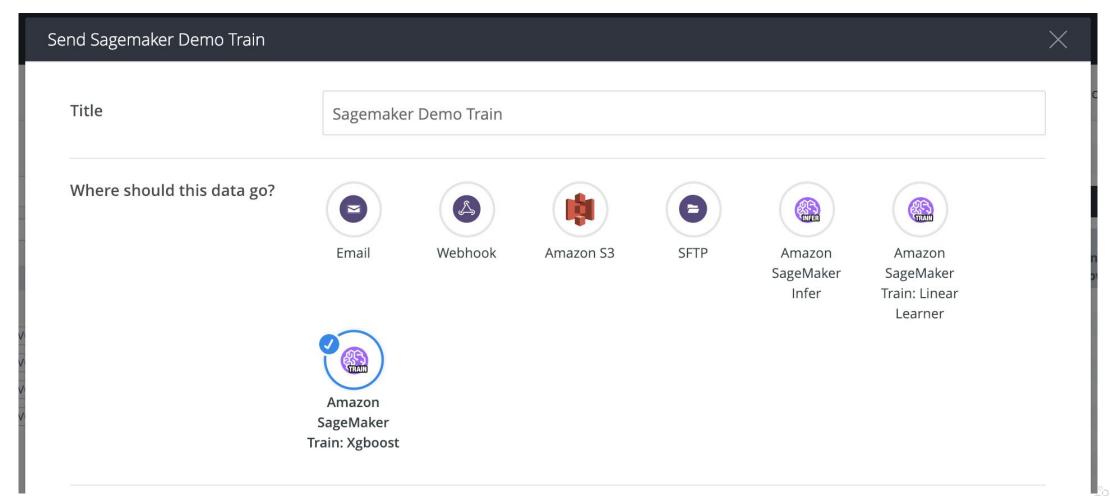
1	Data to Explore <b>Did</b> <b>Subscribe</b> ^	Data to Explore Age	Data to Explore Campaign Touches	Data to Explore Days Since Last Contact	Model Training Data <b>Has</b> <b>Housing</b> <b>Loan</b>	Model Training Data Unknown Housing Loan	Model Training Data No Housing Loan	Model Training Data Has Personal Loan	Model Training Data No Persona Loan		Model Training Data Unknown Personal Loan	Model Training Data Credit Default Status Unknown	Model Training Data Is In Credit Default	Model Training Data Is Not In Credit Default	
1	0	33	5	-999	0		1	0	0	0	1		0	0	1
2	0	38	4	-999	1		0	0	1	0	C		1	0	0
3	0	55	3	-999	1		0	0	1	0	C		1	0	0
4	0	34	19	-999	0		0	1	1	0	C		1	0	0
5	0	35	3	-999	1		0	0	0	1	C	)	0	0	1
6	0	59	2	-999	1		0	0	0	1	0		1	0	0
7	0	53	11	-999	0		0	1	0	1	0		0	0	1
8	0	42	19	-999	1		0	0	0	1	0		0	0	1
9	0	68	4	-999	1		0	0	0	1	0		0	0	1
0	0	56	1	2	0		0	1	0	1	0		0	0	1
1	0	38	8	-999	1		0	0	0	1	C		0	0	1
2	0	41	2	-999	0		0	1	0	1	0		0	0	1
3	0	57	2	-999	1		0	0	1	0	0		0	0	1
4	0	55	5	-999	0		0	1	0	1	0		0	0	1
5	0	25	4	-999	0		0	1	1	0	0		0	0	1
6	0	52	4	-999	1		0	0	1	0	0		0	0	1
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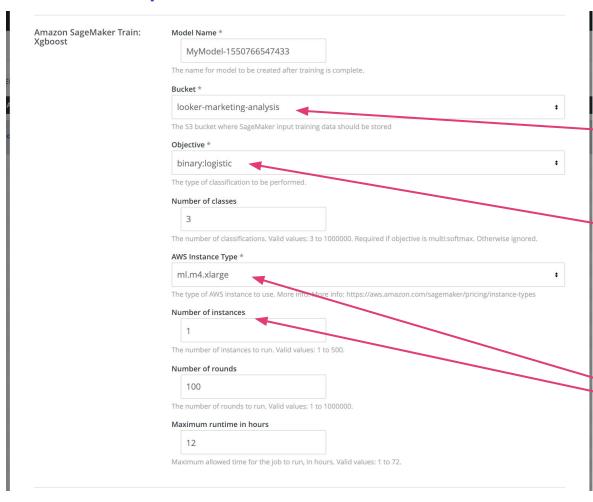
Use **Send** to send once, or schedule it for recurring processes

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5	(		52	4	-999	1		)	0	1		0	0		0	0	

Choose a model training algorithm



#### Define parameters



The model name should be unique and specific, as you will need to call upon it when using your trained model in the future

**Bucket** is the S3 bucket where your model and data will be stored

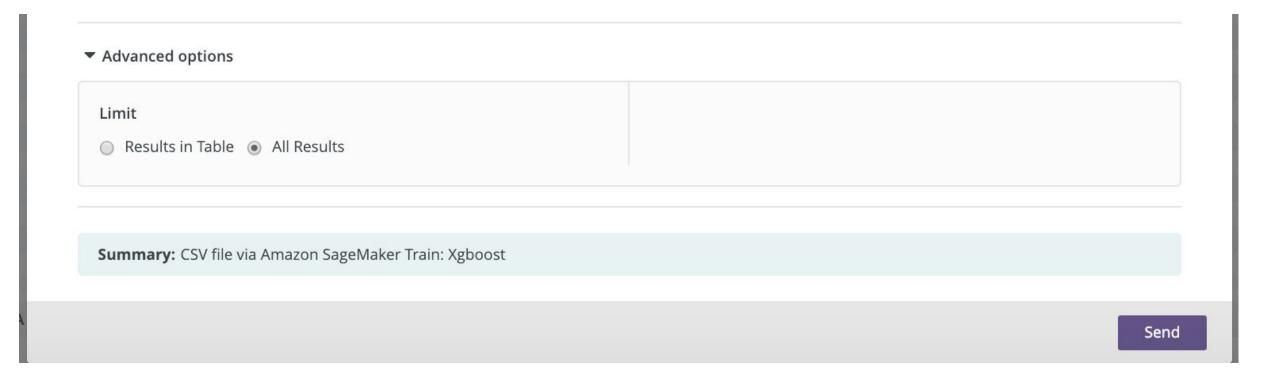
#### **Objective** options:

- binary:logistic = yes/no output (e.g., will a customer enroll or not?)
- reg:linear = predict a number (e.g., what a customer's lifetime value will be)
- multi:softmax = creating groupings

**AWS Instance Type** and **Number of instances** will influence the speed of number crunching



#### Make sure to send All Results





Testing a model and analyzing performance



## How to test your model

- 1. Build the same data set that you used for training your model, but use your testing data (the remaining 30% of the data that was not used for model training)
- 2. Apply your model to the testing data
- 3. Measure how well your model predicts the desired target



## Create a testing dataset

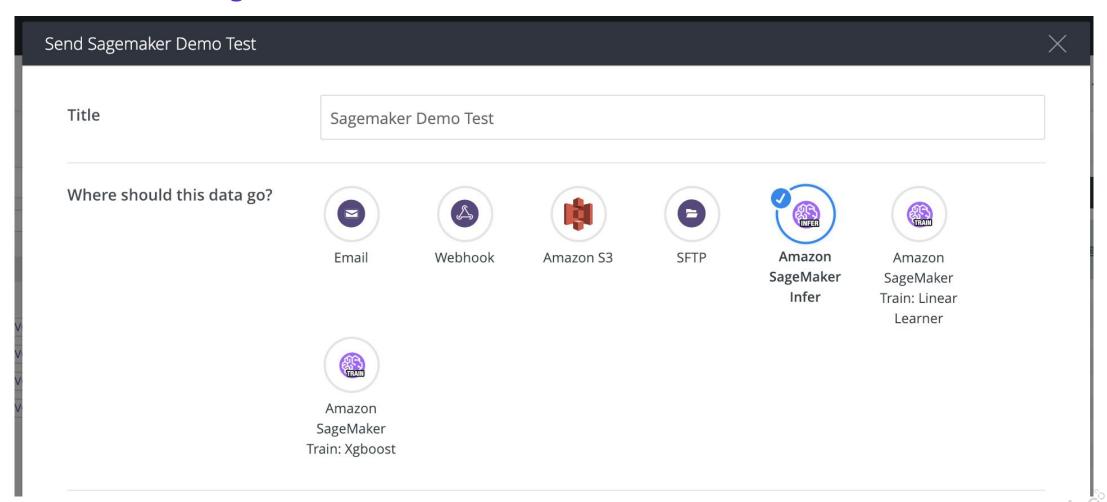
Should be the same as your training dataset, but use the remaining test data

	sting	Model Testing Campaign Touches	Model Testing  Days Since Last  Contact	Model Testing Has Housing Loan	Model Testing No Housing Loan	Model Testing Unknown Housing Loan	Model Testing Has Personal Loan	Model Testing No Personal Loan	Unknown Personal	Model Testing Credit Default Status Unknown	Model Testing Is In Credit Default	Model Testing Is Not In Credit Default
1	39	1	-999	0	0	1	0	0	1	1	0	0
2	41	2	-999	0	0	1	0	0	1	0	0	1
3	34	2	-999	0	1	0	0	1	0	1	0	0
4	33	23	-999	1	0	0	0	1	0	0	0	1
5	36	5	-999	0	1	0	0	1	0	1	0	0
6	58	2	4	0	1	0	1	0	0	0	0	1
7	55	4	-999	0	1	0	0	1	0	0	0	1
8	41	3	-999	0	1	0	0	1	0	0	0	1
9	56	5	-999	0	1	0	0	1	0	1	0	0
0	48	2	1	0	1	0	1	0	0	0	0	1
1	45	5	-999	1	0	0	0	1	0	0	0	1
2	30	26	-999	1	0	0	0	1	0	0	0	1
3	30	7	-999	1	0	0	0	1	0	0	0	1
4	57	1	-999	0	1	0	1	0	0	0	0	1
5	54	4	-999	1	0	0	0	1	0	0	0	1
6	39	3	-999	0	1	0	0	1	0	0	0	1
7	54	1	4	1	0	0	0	1	0	0	0	1



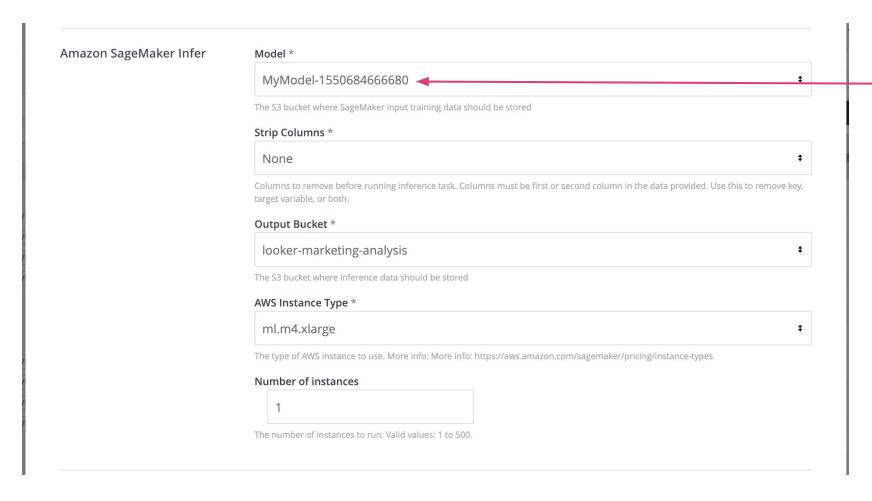
## Send the test data to SageMaker

Use Amazon SageMaker Infer



## Send the test data to SageMaker

#### Apply the model you trained

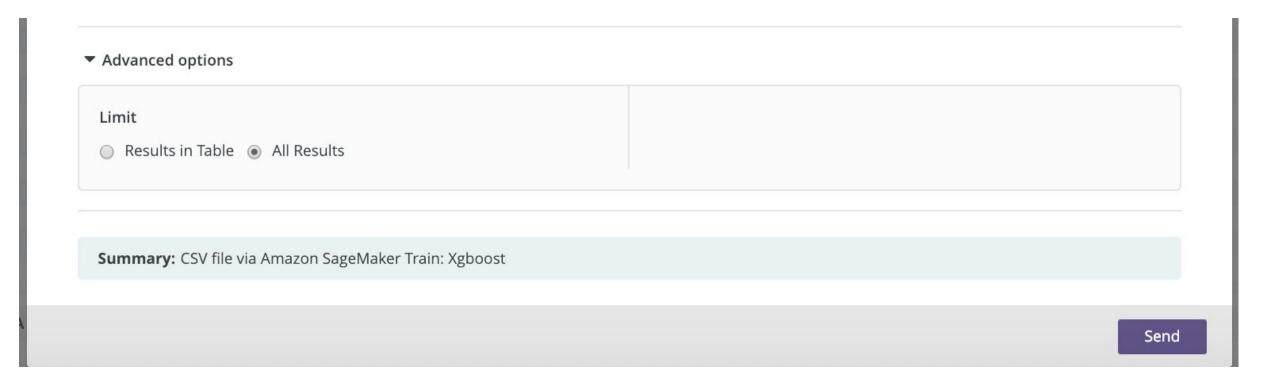


Make sure to use the name of the model that you created when training your model!



## Send the test data to SageMaker

Make sure to send All Results





## **Prediction data set**

	Prediction Analysis Client ID	Prediction Analysis <b>Did Subscribe</b>	Prediction Analysis <b>Predicted Value</b>	Prediction Analysis <b>Prediction</b>
1	91e13bc1-5481-428d-8e97-45327c4a8398	0		34.81%
2	0a9da534-c207-4273-9037-f19aabf2a144	0		27.09%
3	71788ed6-d521-4cf9-8b0c-c15d7b9c8b8e	0		0 43.73%
4	9693b4d0-fbcf-4d0b-8d37-0f3dfdb4a264	0		8.11%
5	9e31f4c0-a5fd-485c-b35a-a010cf3295aa	1		12.70%
6	be8d5091-3c44-4df2-84cb-f854e186d850	0		21.74%
7	4a608cb7-0e2b-4899-a06c-9a4268326d2c	0		5.40%
8	944d6d77-acf6-43dd-8a47-4a103c79f8ca	0		9.46%
9	ccfefca1-8837-4307-90a4-dae1f2bd03b8	0		0 4.65%
10	3758fd1c-fc06-4beb-b61b-8ae8fd4e9d26	0		10.60%
11	1f07fcea-cd31-4f2a-bb6f-a668fd07c2d4	0		9.91%
12	695e4361-07ec-4dda-88ba-726877e11918	0		18.87%
13	c778adee-b543-452c-b7fc-f3bc4d856824	0		3.75%
14	22ebd36e-2950-4acf-a144-7626a681d7f7	0	)	30.36%
15	e65efa5e-a1c5-4ba8-aef0-3b80fc63f336	0		3.27%
16	d8b6e050-a563-4102-bf7e-675a388c9919	0		6.64%
17	f2c0ebcf-33aa-425b-b156-2efaa863ddfe	0		5.35%
18	a41618b2-a20c-45fa-96cb-ba292906223e	0	)	0 6.61%
10	fac Acato acot Assa asto bacocotoonee			2.01114

## Measuring success

#### A few key terms

- True Positives: Clients who enrolled in a term deposit that we predicted correctly
- True Negatives: Clients who did NOT enroll in a term deposit that we predicted correctly
- False Positives: Clients who did NOT enroll in a term deposit that we predicted WOULD enroll in the CD
- False Negatives: Clients who DID enroll in the term deposit that we predicted would NOT enroll in the CD

	Predicted Value >	0	1
Subscribed		Predict ∨	Predict
1	0	3,6	52
2	1	30	58 90



## **Measuring success**

#### Calculating sensitivity and specificity

 Sensitivity: What fraction did we predict would enroll in the term deposit out of all actual enrollments?

90 predicted / 
$$(90 + 368 \text{ actual}) = 90/458 = 0.197$$

• **Specificity:** What fraction did we predict would not enroll in the term deposit out of all clients who did not enroll?

$$3,609 \text{ predicted} / (3,609 + 52 \text{ actual}) = 3,609/3,661 = 0.986$$

	Predicted Value >	0		1	
Subscribed		Predict ∨		Predict	
1	0		3,609		52
2	1		368		90



## Measuring success

Calculating sensitivity and specificity

**▶** FILTERS Cutoff is 0.5 0.1655 0.8980 MAE AUC Predicted vs Actual Confusion Matrix Predictions by Type Prediction Analysis 0 Predicted Value > of Clients 2,000 Prediction Analysis **Did** Prediction Analysis Number Prediction Analysis Number Subscribe of Clients of Clients V 3,609 Number 52 0.6338 FP TN FN TP Sensitivity Specificity **Prediction Type** 



## What do we do with this information?

- 1. Run new client data through the model to identify candidates likely to enroll in a term deposit
- 2. Target these clients for outreach inviting them to subscribe
  - a. Send an email
  - b. Call them directly
- 3. Focus marketing campaigns for bringing in new clients on demographic groups most likely to subscribe to these types of additional programs



# **Questions?** © 2019 Looker. All rights reserved. Confidential.



