

# Use no-code ML to solve real-world challenges

**Rifkhan Anoor** 

Solutions Architect Amazon Web Services rifkhata@amazon.com

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# Agenda

- Why no-code ML?
- Using ready-to-use models
- Preparing and analyzing data
- Creating custom models
- Using generative Al
- Demo



# Why no-code machine learning?



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# **Building practical ML applications is hard**

### The bottleneck BUILDING BETTER ML APPLICATIONS CAN BE THE BOTTLENECK BECAUSE:

- Line of business teams depend on data science teams to make machine learning (ML) powered decisions
- Data science teams are oversubscribed, while ML needs are only increasing
- High learning curve for technical users to learn how to code
- Friction points in the machine learning journey and prioritizing use cases



### **Business** requirements

# Data preparation and \_\_\_\_\_ Model development, \_\_\_\_\_ Model deployment feature engineering \_\_\_\_\_ training, and tuning \_\_\_\_\_ inference and monitoring





Quickly access and prepare data for Machine Learning



Built-in AutoML to build models and generate accurate predictions

# Amazon SageMaker Canvas



Share ML models and collaborate with data science teams

Build ML models and generate accurate predictions — no code required



Usage-based pricing to avoid licensing fees and reduce TCO



Import ML models from any tool within or outside Amazon SageMaker and generate predictions directly in SageMaker Canvas



### Ways SageMaker low-code/no-code helps

### Accelerate data science teams Do more with your current team by using low-code machine learning tools in order to get to the desired outcomes faster.

#### **Enable business users**

Give business users and analysts the ability to do ML without any code, scaling the number of people who can create ML powered insights, forecasts, and predictions

#### **Collaborate together**

SageMaker LCNC ML has several points of collaboration making it efficent for Business users to use data scientist models or for data scientists to make changes on the models analysts build and creating one place for all the analytics and machine learning in a team or organization

### Amazon SageMaker Canva

Home

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Data Wrangler

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My Models

ML Ops

台 Ready-to-use

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Shared Models

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Self-service access to a business-frie machine learning

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|--|--|-----------|--|---------------------------|---|--------------|
| on SageMaker Can   | vas                                    |           |  |                           |   |              |
| vice access to a business<br>e learning  |  | Ап        | <b>Anazon SageMaker Canvas</b><br>Creating application |                           |   |              |
| Home   |  |           |  |                           |   |              |
| <b>Get started</b><br>Get started with quick actions to build and use ML and ger | nerative AI models – no code required. |           |  |                           |   |              |
| Clean my data  |  | a         |  | C Object de               | ersonal information detection<br>ection |              |
| Prepare and analyze data   | Build a custom model                   | Compare G | enAI models & query docs                               | Explore                   | ready-to-use-models                     |              |
| Learn to build machine learning models for different real world                  | use cases. Explore Workshops 🖪         |           |  |                           |   |              |
| Recent work  |  |           |  | Canvas news               |   |              |
| S Data flows   |  |           | + Create a data flow                                   | Featured blog             |   |              |

Last updated  $\downarrow$ Name

Detect anomalies in manufacturing data using

Amazon SageMaker Canvas

Feb 15

### **Ready-to-use models**

6 Ready-to-use models Home **Document queries** Sentiment analysis Ea  $\odot$ 6 Extract information from structured documents such as paystubs, bank statements, W-2s, and mortgage Detect sentiment in lines of text, which can be positive, negative, neutral, or mixed. Data Wrangler application forms by asking questions using natural language. Powered by Amazon Textract Powered by Amazon Comprehend () My Models **Entities extraction** Language detection ¢ ۲ Extract entities, which are real-world objects such as people, places, and commercial items, or units such as Determine the dominant language in text such as English, French or German. dates and quantities, from text. ML Ops Powered by Amazon Comprehend Powered by Amazon Comprehend Ready-to-use Personal information detection L<sup>C</sup> **Object detection in images** Detect personal information that could be used to identify an individual, such as addresses, bank account Detect objects, concepts, scenes, and actions in your images.  $\star$ numbers, and phone numbers, from text. Shared Models Powered by Amazon Comprehend Powered by Amazon Rekognition F Gen Al Text detection in images Expense analysis Detect text in your images. Extract information from invoices and receipts, such as date, number, item prices, total amount, and payment terms. Powered by Amazon Rekognition Powered by Amazon Textract Identity document analysis **Document analysis** ?Extract information from passports, driver licenses, and other identity documentation issued by the US Analyze documents and forms for relationships among detected text. Help Government. Powered by Amazon Textract Powered by Amazon Textract [→ Log out

# **Object detection of images**



# Expense analysis

| 6             | Ready-to-use models > 🔞 Expense analysis (Ready-to-use model)   |                                 |          |   |          |  |  |
|---------------|---|---------------------------------|----------|---|----------|--|--|
| Home          | Use single prediction to get real-time results on the document you upload. The results are the different summary and line item fields detected from the document.<br>To generate prediction results from multiple document datasets, use batch prediction instead.  |                                 |          | Prediction results Summary fields Line item | 1 fields |  |  |
| Data wiangter | Upload a document to generate predictions. Select sample document   |                                 |          |   |          |  |  |
| My Models     | Upload invoice or receipt Invoice  Receipt  |                                 |          | ITEM  | PRICE    |  |  |
| ML Ops        | Receipt.jpeg Q  | Prediction results              |          |   |          |  |  |
|               | <i>~</i>  | Summary fields Line item fields |          | BROO BROWN ALE                              | \$10.99  |  |  |
| Ready-to-use  | WHOLE   | Search labels                   | =        | BOTTLE DEPOSIT                              | \$0.30   |  |  |
| *             | MARKET  | Confidence (i)                  |          |   |          |  |  |
| Shared Models | Bryant Park BAX   | VENDOR_PHONE<br>917-728-5700    | 100%     | DRSCL STRAWBERRIES                          | \$3.49   |  |  |
| Gen Al        | BROD BRUNN ALE         \$10, 99           BOTTLE (NEPOSIT         \$0, 30           DRSCL STRANSERRIES         \$3, 49           OVF DG LE BRAS         \$2, 28           365 HHL HLK         \$4,09           NEDER LEINERS         \$4,09   | <b>ZIP_CODE</b><br>10036        | 100%     | OVF OG LG EGGS                              | \$2.89   |  |  |
|               | AGGM HOME T CONTRACT         42.23           205 DG ROMAINE RAG         \$2.69           265 SALTED CORP CHIPS         \$2.79           POYOS HATTE RAGTT         \$3.50           365 PHBTR BALLS OG         \$3.99           365 JMED DAPACR TOMELS         \$1.69           365 JMED LAPACR TAGLESA         \$2.69 | <b>Total:</b><br>\$55.64        | 100%     | 365 WHL MLK                                 | \$4.09   |  |  |
|               | LACK CRAPPERUIT \$5.99<br>BUTTLE DEFUSIT \$0.60<br>Phi NO GKND BLEF \$5.99<br>MITUTATET<br>KET SALBEST<br>BOX BILGE   | Sold Items:<br>13               | 100%     | NOOSA HONEY YOGHURT                         | \$2.29   |  |  |
| ?<br>Help     | Local         \$55.64           Sold Items:         13           Pain:         155.64           Dar/02/2019         09:16:42  | INVOICE_RECEIPT_DATE            | 100%     | 365 OG ROMAINE BAG                          | \$2.69   |  |  |
| [→            |   | 04/02/2019                      | <b>`</b> | 365 SALTED CORN CHIPS                       | \$2.79   |  |  |
| Log out       | A When you use Expanse analysis you are using Amazon Textrast in the background to generate prediction results. Expanse analysis's Service Terms and prising analysis Learn more 12   |                                 |          |   |          |  |  |

### Identity document analysis



# **Personal information detection**

| Home          | Ready-to-use models > 🙈 Personal information detection (Ready-to-use model)   |  |                     |
|---------------|---|--|---------------------|
| Data Wrangler | Single prediction       Batch prediction         Use single prediction to get real-time results on the text you enter. The results are the entities extracted from the text.         To generate prediction results from multiple tabular datasets, use batch prediction instead.                       | •  | Pricing Information |
| My Models     | Text field Generate prediction results  | Prediction results                           |                     |
| ML Ops        | Canvas currently only supports English language. If non-English text is entered, you will get incorrect prediction results.   | Confidence ()                                | -                   |
| Ready-to-use  | Hi John, this is Carlos from Acme Financials. Your credit card with account number <u>1234-5678-9012-3456</u> has been activated. Starting on the next billing cycle, we will automatically withdraw your payment from your bank account number <u>1234-5678</u> with routing number <u>123456789</u> . | John<br>• NAME                               | 100%                |
| Shared Models |   | Carlos<br>• NAME                             | 100%                |
| Gen Al        |   | 1234-5678-9012-3456<br>• CREDIT_DEBIT_NUMBER | 100%                |
|               |   | 1234-5678<br>• BANK_ACCOUNT_NUMBER           | 100%                |
|               |   | 123456789<br>• BANK_ROUTING                  | 100%                |
| ?             |   |  |                     |

# Sentiment analysis

| Home          | Ready-to-use models > 🕲 Sentiment analysis (Ready-to-use model)   |                    | + Create a custom model |
|---------------|---|--------------------|-------------------------|
| Data Wrangler | Single prediction         Batch prediction           Use single prediction to get real-time results on the text you enter. The results can be positive, neutral, negative, or mixed.         To generate prediction results from multiple rows of text, use batch prediction instead. |                    | S Pricing Information   |
| My Models     | Text field Generate prediction results  | Prediction results |                         |
| ML Ops        | Canvas currently only supports English language. If non-English text is entered, you will get incorrect prediction results.   | Search labels      | =                       |
| Ready-to-use  | I enjoyed visiting Mexico. It was very comfortable but also expensive. The amenities were ok but the service was better than I expected. <u>Chichen Itza</u> and Museo Nacional de <u>Antropologia</u> are my top favorites.  | Positive           | 98%                     |
| *             |   | Mixed              | 2%                      |
|               |   | Negative           | 0%                      |
| Gen Al        |   | Neutral            | 0%                      |
| 0             |   |                    |                         |
| Help          |   |                    |                         |

dws

# **Text detection in images**

| Home          | Ready-to-use models > 📑 Text detection in images (Ready-to-use model)  |             |                    |      |
|---------------|--|-------------|--------------------|------|
|               | To generate prediction results from multiple image datasets, use batch prediction instead.                     |             |                    |      |
| Data Wrangler | Upload an image to generate predictions.   |             |                    |      |
|               | Upload image   |             |                    |      |
| My Models     | TextDetection.jpg  | ୍ <b>ର୍</b> | Prediction results |      |
| (* <u>*</u> ) |  |             | Search labels      | =    |
| ML Ops        | the second s |             | Confidence 🛈       |      |
| Ready-to-use  |  |             | ● IT'S             | 100% |
| *             | IT'S   |             | • but keep         | 100% |
| _             |  |             | • MONDAY           | 99%  |
| Gen Al        | MONDAY   |             |                    |      |
|               |  |             | • Smiling          | 86%  |
|               | but keep   |             |                    |      |
|               |  |             |                    |      |
|               |  |             |                    |      |
|               |  |             |                    |      |
| 0             |  |             |                    |      |
| Help          |  |             |                    |      |

# **Document analysis**

| Home            | Ready-to-use models >  Document queries Ready-to-use model   |   |  |  |  |  |  |
|-----------------|--|---|--|--|--|--|--|
| Data Wrangler   | Single prediction         Batch prediction           Use single prediction to get real-time results on the document you  | spload. The results are the values detected from the document.  | Pricing Information                                |  |  |  |  |
| ()<br>My Models | Upload a document to generate predictions.   |   |  |  |  |  |  |
| ML Ops          | SampleDocuments.pdf  | Q   Q   Enter a query to search in the document   | +  |  |  |  |  |
| Ready-to-use    | Image: State of the state |   | Confidence 97%<br>Confidence 77%<br>Confidence 70% |  |  |  |  |
| (?)<br>Help     | Page 3   | AVECOMENT LINE STOLET<br>Page to the<br>Page to |  |  |  |  |  |

**Data preparation** 

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# **Creating data flow**





### Selecting data sets

| ×            |                               |                            |                         |   |          |
|--------------|-------------------------------|----------------------------|-------------------------|---|----------|
| Data Source: | 🚯 Local upload                | •                          |                         |   |          |
| Upload fil   | Q Search data source          |                            | Filter by: All (55) 👻   | <ul> <li>Frequently used * ×</li> </ul> |          |
|              | Cocal upload                  | 📫<br>Amazon S3             | Snowflake -             | Redshift -                              |          |
|              | athena athena                 | setebricks<br>Databricks ▼ | Salesforce Data Cloud 🗸 | S<br>MySQL -                            |          |
| _            | <b>q</b>                      | <i>≥</i> 50℃ Server        | 4                       |   |          |
|              | Learn more about data sources |                            |                         |   | ile here |
|              |                               |                            |                         | or                                      |          |
|              |                               |                            |                         | ▲ Select files from your com            | puter    |





### Amazon Sagemaker Data Wrangler

| Home            | Data Wrangler: Data flow > 🗟 New data flow 2024-3-31 12:56 PM.flow > canvas-sample-loans-part-2.csv |                           |                         |                         |                           |        | Data quality and insig        | ghts report |
|-----------------|---|---------------------------|-------------------------|-------------------------|---------------------------|--------|-------------------------------|-------------|
|                 | Data Analy  | yses                      |                         |                         |                           |        |                               |             |
| Data Wrangler   | Step 2. Data types  |                           |                         | 🗐 Chat fi               | or data prep 🗄 Show steps | (¢) Cr | Summary<br>Dataset statistics |             |
| ()<br>My Models | id (long)   | employment_length (float) | employer_title (string) | home_ownership (string) | annual_income (float)     |        | Кеу                           | Value       |
| ( <b>b</b> )    | dh.   |                           |                         |                         | . <b>h</b> .t             |        | Number of features            | 5           |
| ML Ops          | <b></b>   |                           |                         |                         |                           |        | Number of rows                | 1000        |
| _               | 7.6593e+5 - 1.0775e+6 123   | 1 - 10 123                | 11 Categories A         | 3 Categories            | 12000 - 2.7600e+5 123     |        | Missing                       | 1.36%       |
|                 | 1077501   | 10                        |                         | rent                    | 24000                     |        | Valid                         | 98.6%       |
| Ready-to-use    | 1077430   | 1                         | ryder                   | rent                    | 30000                     |        | Duplicate rows                | 0%          |
| *               | 1077175   | 10                        |                         | rent                    | 12252                     |        |                               |             |

| ← Create analysis  |          |
|--|----------|
| Analysis type  | Required |
| Histogram  | ~        |
| Custom Visualization                                       |          |
| Data Quality And Insights Report                           |          |
| Data Quality And Insights Report for<br>Amazon Personalize |          |
| Duplicate rows   |          |
| Feature Correlation  |          |
| Histogram  |          |
| Multicolinearity   |          |
| Quick Model  |          |

#### Anomalous samples

Canvas detects anomalous samples using the Isolation forest algorithm after basic preprocessing. The isolation forest associates an anomaly score to each sample (row) of the dataset.

- Low anomaly scores indicate anomalous samples.
- · High scores are associated with non-anomalous samples.
- Samples with negative anomaly score are usually considered anomalous and samples with positive anomaly score are considered non-anomalous.

When you look at a sample that might be anomalous, we recommend that you pay attention to unusual values. For example, you might have anomalous values that result from errors i the most anomalous samples according to the Canvas's implementation of the isolation forest algorithm. We recommend using domain knowledge and business logic when you examine

| Anomaly scores | id      | employment_length | employer_title             | home_ownership | annual_income |
|----------------|---------|-------------------|----------------------------|----------------|---------------|
| 0.134          | 1064924 | 6.0               | united states air force    | rent           | 48000.0       |
| 0.134          | 1068180 | 7.0               | united states air force    | rent           | 49500.0       |
| 0.134          | 972383  | 10.0              | new buck corporation       | mortgage       | 50700.0       |
| 0.14           | 1067026 | 10.0              | us air force               | rent           | 66000.0       |
| 0.14           | 977277  | 2.0               | the woodlands ficial group | mortgage       | 175000.0      |
| 0.143          | 1058946 | 10.0              | newark public schools      | mortgage       | 103000.0      |

### Chat for data prep

#### Welcome to chat for data prep!

From here, you can explore, visualize, and transform your data using natural language. To get started, we have some guided prompts for you.

| Plot histogram of the column id                   | Q What is the maximum value of the column annual_income | Q What is the mean value of the column annual_income |
|---|---|--|
|   |   |  |
|   |   |  |
|   |   |  |
| Plot a chart for annual income in \$10000 buckets |   |  |



The code first converts the annual\_income column to \$10,000 buckets by floor dividing the values by 10,000. It then creates a bar chart using altair, with the bucketed annual\_income column on the x-axis and the count of records in each bucket on the y-axis. This generates a histogram showing the distribution of annual\_income in \$10k buckets.





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# Let's build a ML model to predict college student dropout



### Creating a new model

#### Create new model

#### Model name

#### - Model name

#### My new model 024-3-31 1:21 PM

Use only letters, numbers, and underscores up to 32 characters.

#### Problem type

Select the problem type you want the model to solve.



#### Predictive analysis

Build models using tabular datasets to predict single or multiple categories as well as regression and time-series forecast problems.

| 0 | Image analysis |  |  | ( |
|---|----------------|--|--|---|

Build models using image datasets to predict single or multiple categories for image classification problems.

#### Text analysis

Build models using tabular datasets to predict single or multiple categories for text classification problems.

#### Fine-tune foundation model

Customize a foundation model on your data to improve its performance for a specific task or domain.



 $\times$ 

### **Training data set**

| Ho   | me  | Insert   | Draw              | Page Layout          | Formulas           | Data              | Revie         | w Viev           | vŷ         | Tell me         |              |                   |                |            |                 |             |                       |                         |                        |  |                              | Ľ          | r s |                    |        |
|--|---|----------|-------------------|----------------------|--------------------|-------------------|---------------|------------------|------------|-----------------|--------------|-------------------|----------------|------------|-----------------|-------------|-----------------------|-------------------------|------------------------|--|------------------------------|------------|-----|--------------------|--------|
| P  | aste  | X<br>È ~ | Calibri (I<br>B I | Body)                | 2 • A A            | <b>∧</b> ~ =<br>≡ |               | <del>8</del> 7 ▼ | 89<br>E    | Wrap Text       | ♥<br>enter ♥ | General<br>\$ • % | <b>9</b> 5.0   | ×<br>00.00 | Condition       | nal Forma   | at Cell<br>ble Styles | E Inser<br>Dele<br>Form | nt∨<br>te∨ [<br>mat∨ 4 | ∑ × A<br>Z V<br>V Sort a<br>Sort a<br>Filter | ¥ Find &<br>Find &<br>Select | Add-ins    | 6   |                    |        |
| 8  | Possil  | ole Data | Loss Sor          | ne features might t  | oe lost if you s   | ave this v        | workbook i    | n the comr       | ma-delir   | mited (.csv)    | format. To   | o preserve        | these featu    | ires, s    | ave it in an E  | xcel file f | format.               |                         |                        |  |                              | S          | ave |                    |        |
| A1 $\Rightarrow$ X $\checkmark$ $f_{\rm X}$ Marital_status |   |          |                   |                      |                    |                   |               |                  |            |                 |              |                   |                |            |                 |             |                       |                         |                        |  |                              |            |     |                    |        |
|  |   | R        | S                 | T U                  | V                  | W                 | X             |                  | Y          | Z               | AA           | AB                | AC             |            | AD              | AE          | AF                    | AG                      | AH                     | AI   | AJ                           | AK         |     |                    |        |
| 1  | es Gend   | er S     | cholarship_       | Age_at_enro Internat | tional Curricular_ | ur Curricul       | ar_ur Curricu | lar_ur Currie    | cular_ur C | Curricular_ur C | Curricular_u | r Curricular_     | ur Curricular_ | ur Curr    | icular_ur Curri | cular_ur Cu | urricular_ur Cu       | urricular_ur Un         | employme               | Inflation_rat                                | GDP                          | Target     |     |                    |        |
| 2  | 1   | 1        | 0                 | 20                   | 0                  | 0                 | 0             | 0                | 0          | 0               | 0            |                   | 0              | 0          | 0               | 0           | 0                     | 0                       | 10.8                   | 1.4  | 1.74                         | 4 Dropout  |     |                    |        |
| 3  | 0   | 1        | 0                 | 19                   | 0                  | 0                 | 6             | 6                | 6          | 14              | 0            | )                 | 0              | 6          | 6               | 6 1         | 3.6666667             | 0                       | 13.9                   | -0.3   | 0.79                         | 9 Graduate |     |                    |        |
| 4  | 0   | 1        | 0                 | 19                   | 0                  | 0                 | 6             | 0                | 0          | 0               | 0            | )                 | 0              | 6          | 0               | 0           | 0                     | 0                       | 10.8                   | 1.4  | 1.74                         | 4 Dropout  | -   |                    |        |
| 5  | 1   | 0        | 0                 | 20                   | 0                  | 0                 | 6             | 8                | 6          | 13.4285714      | 0            | )                 | 0              | 6          | 10              | 5           | 12.4                  | 0                       | 9.4                    | -0.8   | -3.12                        | 2 Graduate | -   |                    |        |
| 6  | 1   | 0        | 0                 | 45                   | 0                  | 0                 | 6             | 9                | 5          | 12.33333333     | 0            |                   | 0              | 6          | 5               | 6           | 13                    | 0                       | 13.9                   | -0.3   | 0.75                         | 9 Graduate |     |                    |        |
| /<br>9   | 1   | 0        | 1                 | 18                   | 0                  | 0                 | 7             | 010              | 7          | 11.85/1429      | 0            |                   | 0              | 2          | 1/              | 2           | 14 345                | 0                       | 15.5                   | 2.8  | -0.92                        | 5 Graduate |     |                    |        |
| 9  | 0   | 1        | 0                 | 22                   | 0                  | 0                 | 5             | 5                | 0          | 0               | 0            | 1                 | 0              | 5          | 5               | 0           | 0                     | 0                       | 15.5                   | 2.8  | -4.06                        | 6 Dropout  |     |                    |        |
| 10   | 1   | 0        | 1                 | 21                   | 1                  | 0                 | 6             | 8                | 6          | 13.875          | 0            | )                 | 0              | 6          | 7               | 6 1         | 4.1428571             | 0                       | 16.2                   | 0.3  | -0.92                        | 2 Graduate |     |                    |        |
| 11   | 0   | 0        | 0                 | 18                   | 0                  | 0                 | 6             |                  |            |                 |              |                   |                |            |                 |             |                       |                         |                        |  |                              |            |     |                    |        |
| 12   | 1   | 0        | 0                 | 18                   | 0                  | 0                 | 6             |                  | L          | My m            | odels        | > New             | model 2        | 024        | -4-1 9.20       | AM >        | Version               | h 1                     |                        |  |                              |            |     |                    |        |
| 13   | 1   | 0        | 1                 | 18                   | 0                  | 0                 | 8             |                  |            | isty it         | louets       | / NCW             | mouci 2        | 024        | 4 1 3.20        |             | VCISIOI               | • •                     |                        |  |                              |            |     |                    |        |
|  |   |          |                   |                      |                    |                   |               | Hor              | ne         | Sel             | lect         |                   | Build          |            | Anal            | yze         | I                     | Predict                 |                        | Deploy                                       |                              |            |     |                    |        |
|  |   |          |                   |                      |                    |                   |               | Data Wr          | angler     | Selec           | t datas      | et                |                |            |                 |             |                       |                         |                        |  |                              |            |     |                    |        |
|  | You can import a tabular dataset or choose one that has already been imported. Your dataset must contain at least one input column and a target column. |          |                   |                      |                    |                   |               |                  |            |                 |              |                   |                |            |                 |             |                       |                         |                        |  |                              |            |     |                    |        |
|  |   |          |                   |                      |                    |                   |               |                  |            | Q               | Search da    | atasets in        | Canvas         |            |                 |             |                       |                         |                        |  |                              |            |     |                    |        |
|  |   |          |                   |                      |                    |                   |               | ML               | )<br>Dps   | A               | AU           |                   | Joined         |            |                 |             |                       |                         |                        |  |                              |            |     |                    |        |
|  |   |          |                   |                      |                    |                   |               | 4                | A          |                 | Name         |                   |                |            |                 |             |                       | Colur                   | nns                    | Rows   |                              | Cells      |     | Created            | Status |
|  |   |          |                   |                      |                    |                   |               | Ready-           | to-use     | ۲               | student_o    | dropout           |                |            |                 | V1          | 1                     | 37                      |                        | 4,424  |                              | 163,688    |     | 04/01/2024 9:20 AM | Ready  |

### Model configurations

#### **Configure model**

| Basic Training method   |         |
|---|---------|
| Model type (i) Configuring the Ensemble or Hyperp   | aramete |
| Advanced - Optional   Auto Recommended  | ld      |
| Objective metric         Canvas selects the algorithms that are mos           The best-performing model candidate is characterized         Canvas selects the algorithms that are mos | t re    |
| Training method and algorithms O Ensemble   |         |
| Data split O Hyperparameter optimization  | 7       |
| Max candidates and runtime  |         |
|   |         |
|   |         |

#### er optimization training method will default to Standard build. Analyze Predict Deploy Configure model & Reset to default settings X Basic **Training method** Model type (i) Configuring the Ensemble or Hyperparameter optimization training method will default to Standard build. Advanced - Optional Auto Recommended $\sim$ Canvas selects the algorithms that are most relevant to your dataset and the best range of hyperparameters to tune model candidates. Objective metric The best-performing model candidate is chosen. Ensemble $\wedge$ Training method and algorithms Canvas chooses an AutoML algorithm based on your data and trains a multi-layer stack ensemble model to make predictions for regression and classification problems. Data split Hyperparameter optimization $\sim$ Max candidates and runtime Algorithms Select the algorithms that you'd like to test for improving the model's prediction accuracy. 8/8 selected XGBoost Linear Models A supervised learning algorithm that attempts to accurately A framework that uses a linear equation to model the predict a target variable by combining an ensemble of relationship between target label and feature vector in estimates from a set of simpler and weaker models. observed data. LightGBM CatBoost A framework that uses tree-based algorithms, gradient A framework that uses tree-based algorithms with gradient boosting, and histogram-based algorithms to optimize speed boosting. Optimized for handling categorical variables. Cancel Save



### Preview model



4

Curricular\_units\_2nd\_sem\_approv



Х

☆ Preview model

- 8



(5)

6 Course

Curricular\_units\_2nd\_sem\_evalua

7 Curricular\_units\_2nd\_sem\_enroll

8 Age\_at\_enrollment

5.418%

3.848%

3.818%

3.581%

3.278%

-0.24.

-2.24

All other classes

### Prediction using the model

| 21     | <b>v</b>   | <u>~ `</u> | Jx         |           |          |            |          |          |       |          |      |         |       |              |         |           |              |          |                 |            |         |         |           |          |         |           |         |                    |        |  |
|--------|------------|------------|------------|-----------|----------|------------|----------|----------|-------|----------|------|---------|-------|--------------|---------|-----------|--------------|----------|-----------------|------------|---------|---------|-----------|----------|---------|-----------|---------|--------------------|--------|--|
|        | V          |            | W          | Х         |          | Y          |          | Z        |       | AA       |      | A       | 3     | AC           |         | AD        | AE           |          | AF              | AG         |         | AH      | AI        |          | AJ      | AK        | AL      | -                  |        |  |
| tional | Curricular | _ur Cu     | rricular_u | Curricula | ar_ur Cu | urricular_ | ur Cu    | urricula | ar_ur | Curricul | ar_u | Curricu | lar_u | Curricular_u | ır Curr | ricular_u | r Curricular | _ur C    | urricular_ur    | Curricular | r_ur Un | employm | Inflation | _rat GDF |         | Target    |         |                    |        |  |
| 0      |            | 0          | 0          |           | 0        |            | 0        |          | 0     |          | 0    |         | 0     | (            | )       | 0         | )            | 0        | 0               |            | 0       | 10.8    |           | 1.4      | 1.74    |           |         |                    |        |  |
| 0      |            | 0          | 6          |           | 6        |            | 6        |          | 14    |          | 0    |         | 0     | 6            | 5       | 6         | 5            | 6 1      | 13.6666667      |            | 0       | 13.9    |           | -0.3     | 0.79    |           |         |                    |        |  |
| 0      |            | 0          | 6          |           | 0        |            | 0        |          | 0     |          | 0    |         | 0     | e            | 5       | 0         | )            | 0        | 0               |            | 0       | 10.8    |           | 1.4      | 1.74    |           |         |                    |        |  |
| 0      |            | 0          | 6          |           | 8        |            | 6 1      | 3.4285   | 714   |          | 0    |         | 0     | 6            | 5       | 10        | )            | 5        | 12.4            |            | 0       | 9.4     |           | -0.8     | -3.12   |           |         |                    |        |  |
| 0      |            | 0          | 6          |           | 9        |            | 5 1      | 2.3333   | 3333  |          | 0    |         | 0     | 6            | 5       | 6         | 5            | 6        | 13              |            | 0       | 13.9    |           | -0.3     | 0.79    |           |         |                    |        |  |
| 0      |            | 0          | 5          |           | 10       |            | 5 1      | 1.8571   | 429   |          | 0    |         | 0     | 5            | 5       | 17        | r            | 5        | 11.5            |            | 5       | 16.2    |           | 0.3      | -0.92   |           |         |                    |        |  |
| 0      |            | 0          | 7          |           | 9        |            | 7        |          | 13.3  |          | 0    |         | 0     | 8            | 3       | 8         | :            | 8        | 14.345          |            | 0       | 15.5    |           | 2.8      | -4.06   |           |         |                    |        |  |
| 0      |            | 0          | 5          |           | 5        |            | 0        |          | 0     |          | 0    |         | 0     | 5            | 5       | 5         |              | 0        | 0               |            | 0       | 15.5    |           | 2.8      | -4.06   |           |         |                    |        |  |
| 1      |            | 0          | 6          |           | 8        |            | <i>c</i> | 10       | 075   |          |      |         |       |              |         |           |              | <u> </u> | 4 4 4 3 0 5 7 4 |            | 0       | 46.0    |           | 0.2      | 0.00    |           |         |                    |        |  |
| 0      |            | 0          | 6          |           | 9        |            |          |          |       |          |      |         |       |              |         |           |              |          |                 |            |         |         |           |          |         |           |         |                    |        |  |
| 0      |            | 0          | 6          |           | 6        | To n       | nak      | e pre    | dict  | ions c   | on a | datas   | et. s | elect it or  | imp     | ort it.   | The dat      | aset     | that you        | ı select   | must    | have th | e sam     | e numt   | er of f | eature co | umns as | the training datas | et. 🕐  |  |
| 0      |            | 0          | 8          |           | 8        |            |          |          |       |          |      |         | / -   |              |         |           |              |          | ,,              |            |         |         |           |          |         |           |         |                    | 0      |  |
| 0      |            | 0          | 6          |           | 6        |            |          |          |       |          |      |         |       |              |         |           |              |          |                 |            |         |         |           |          |         |           |         |                    |        |  |
|        |            |            |            |           |          |            |          |          |       |          |      |         |       |              |         |           |              |          |                 |            |         |         |           |          |         |           |         |                    |        |  |
|        |            |            |            |           |          | Q          | L S      | earch    | h da  | tasets   | s in | Canva   | S     |              |         |           |              |          |                 |            |         |         |           |          |         |           |         |                    |        |  |
|        |            |            |            |           |          |            | -        |          |       |          |      |         |       |              |         |           |              |          |                 |            |         |         |           |          |         |           |         |                    |        |  |
|        |            |            |            |           |          |            |          |          |       |          |      |         |       |              |         |           |              |          |                 |            |         |         |           |          |         |           |         |                    |        |  |
|        |            |            |            |           |          |            |          |          |       |          |      |         |       |              |         |           |              |          |                 |            |         |         |           |          |         |           |         |                    |        |  |
|        |            |            |            |           |          |            |          | Name     | •     |          |      |         |       |              |         |           |              |          |                 | Colum      | 20      | Pr      | MAC       |          | Colle   |           | Create  | d                  | Status |  |
|        |            |            |            |           |          |            |          | Name     | C     |          |      |         |       |              |         |           |              |          |                 | cotuni     | 15      | N.      | ////5     |          | cens    |           | create  | u .                | Status |  |
|        |            |            |            |           |          |            | -        |          | -     |          | -    |         | -     |              | -       |           | _            | -        |                 |            |         |         |           |          |         |           |         |                    |        |  |
|        |            |            |            |           |          |            |          | stude    | ent_d | lropou   | t_pr | edictio | n     |              |         |           | V1           |          |                 | 37         |         | 13      | 5         |          | 481     |           | 04/01   | /2024 10:00 AM     | Ready  |  |
|        |            |            |            |           |          |            |          |          |       |          |      |         |       |              |         |           |              |          |                 |            |         |         |           |          |         |           |         |                    |        |  |

Student\_dropout

#### batchInfer-New model 2024-4-1 9:20 AM-student\_dropout\_prediction-1711980102

| Prediction (Target) | Probability | Marital_status | Application | Application | Course | Daytime_eve | Previous |
|---------------------|-------------|----------------|-------------|-------------|--------|-------------|----------|
| Dropout             | 77.5%       | 1              | 17          | 5           | 171    | 1           | 1        |
| Graduate            | 95.9%       | 1              | 15          | 1           | 9254   | 1           | 1        |
| Dropout             | 99.5%       | 1              | 1           | 5           | 9070   | 1           | 1        |
| Graduate            | 76.4%       | 1              | 17          | 2           | 9773   | 1           | 1        |
| Graduate            | 96.7%       | 2              | 39          | 1           | 8014   | 0           | 1        |
| Dropout             | 74.1%       | 2              | 39          | 1           | 9991   | 0           | 19       |

10 11

### What is generative AI?

- Generative artificial intelligence is artificial intelligence capable of generating text, images, videos, or other data using generative models, often in response to prompts. Generative AI models learn the patterns and structure of their input training data and then generate new data that has similar characteristics.
- Large language models (LLM) are very large deep learning models that are pre-trained on vast amounts of data



### No code generative Al





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# **Customer stories**

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# What universities are saying

One of the hardest parts about programming with machine learning is configuring the environment to build. Students usually have to choose the compute instances, security polices, and provide a credit card. My students needed Amazon SageMaker to abstract away all of the complexity of setup and provide a free powerful sandbox to experiment. This lets them write code immediately without needing to spend time configuring the ML environment.

### Dan Roth

Distinguished Professor of Computer and Information Science at the University of Pennsylvania



# What universities are saying

Amazon SageMaker will help my students learn the building blocks of machine learning by removing the cloud configuration steps required to get started. Now, in my natural language processing classes, students have more time to enhance their skills.

### Sanjiv Das

Professor of Finance and Data Science at Santa Clara University





### How to get started with Amazon SageMaker Canvas



### aws.amazon.com/sagemaker/canvas





# Thank you!



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