IBM watsonx.ai

Technical Hands-on Lab
New models and
Synthetic data

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Contents

1. Introducing watsonx.ai

Watsonx.ai is a core component of watsonx, IBM's enterprise-ready AI and data platform designed to multiply the impact of AI across an enterprise.

The watsonx platform has three powerful components:

- watsonx.ai studio for new foundation models, generative AI and Machine Learning (traditional AI)
- watsonx.data fit-for-purpose data store that provides the flexibility of a data lake with the performance of a data warehouse
- watsonx.governance toolkit, which enables AI workflows that are built with responsibility, transparency, and explainability.

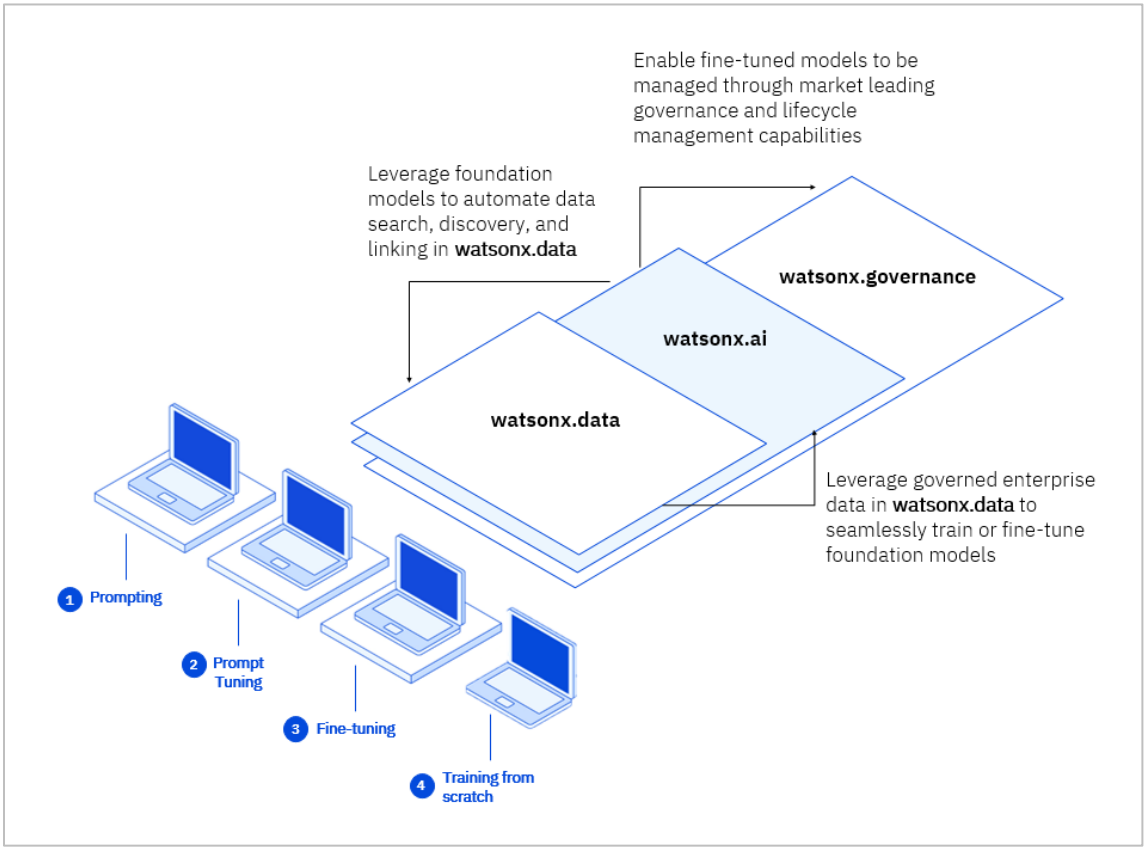


Figure 1: IBM watsonx platform

The watsonx.ai component (the focus of this lab) makes it possible for enterprises to train, validate, tune, and deploy AI models – both traditional AI and generative AI. With watsonx.ai, enterprises can leverage their existing traditional AI investments as well as exploit the innovations and the potential of generative AI using foundation models to bring advanced

automation and AI-infused applications to reduce cost, improve efficiency, scale, and accelerate the impact of AI across their organizations.

2. About this Lab

This IBM watsonx.ai Technical Hands-on Lab Part II is a supplement to the IBM watsonx.ai Technical Hands-on Lab Part 1. It is assumed that you have completed this first Hands-on lab. Detailed instructions and screen flow available there are not repeated here.

In this lab, you will be introduced to the following watsonx.ai capabilities:

- New foundation models available since the publication of the original watsonx.ai Technical Sales Lab Guide Part 1.
- Generating synthetic data for use with traditional AI or foundation models testing/tuning. This lab details two ways to generate synthetic data:
    - **Generate**: Generate different data sets either from scratch
    - **Mimic**: Generate new data based on a small existing data set

You can use the same procedure from Part 1 of the lab to set up an environment to work with the labs here.

2.1 Disclaimer

IBM watsonx.ai is developed and released in an agile manner. In addition to constantly adding new capabilities, the web interface is likely to change over time. Therefore, the screenshots used in this lab may not always look exactly like what you see. You can expect to encounter some of the following:

- Additional foundation models in the library list
- Additional foundation models available for prompt tuning
- Changes in the user interface (location of buttons, text for various fields)
- Additional tabs/buttons

These should not affect how the labs work, but have patience and be prepared to explore a little bit until this lab gets updated.

There are three changes, however, that can affect the results. For example:

- Foundation models can be very sensitive to input. If you enter slightly different text than what the exercise is using (even if it is just one single word or a modified set of labeled data), the outcome can be very different.

- There is ongoing tuning of the models. If the models themselves are updated, then some of the results may vary.

Please post any questions on the #data-ai-demo-feedback Slack channel (IBMers only). IBM partners can request help at the Partner Plus Support website.

3. Getting Help

Lab guide help: If you require assistance in interpreting any of the steps in this lab, please post your questions to the #data-ai-demo-feedback Slack channel (IBMers only). Business Partners can request help at the Partner Plus Support website.

Troubleshooting: See the TechZone Set Up Troubleshooting Guide for a list of the common issues and solutions/workarounds when using TechZone.

IBM watsonx.ai: Assistance with the watsonx.ai product itself is available in the #watsonx-ai-feedback (IBMers) and #watsonx-ai-enablement Slack channels (IBMers only). Additionally, please refer to the watsonx.ai documentation as needed.

4. Prerequisites & Getting Started

You will need an IBM Cloud account to gain access to the TechZone account that hosts the various Watson and watsonx services used in this lab.

4.1 Obtain an IBM Cloud Account

If you have an IBM Cloud account, you can skip this step. If you do not have an IBM Cloud account, Click this link to create one. After registration, you will be sent an email to activate your account. This can take a few hours to process. Once you receive the confirmation email, follow the instructions provided in the email to activate your account.

You can use **IBM TechZone** to perform the exercises in this lab. The detailed setup instructions are available in this document (Section 4 of the L3 Lab Part 1). You must complete the steps before you can proceed with any of the exercises in this lab.

It is assumed that you have completed Part 1 of the L3 lab (or are familiar with the concepts and contents).

5. Foundation models update

IBM continues to roll out new foundation models in watsonx.ai. You should go to Supported foundation models available with watsonx.ai to find the latest list. As of January 2024, the list is as follows:

IBM models:

- granite-13b-chat-v1
- granite-13b-chat-v2
- granite-13b-instruct-v1
- granite-13b-instruct-v2

Models provided by Hugging Face:

- flan-t5-xl-3b
- flan-t5-xxl-11b
- flan-ul2-20b
- gpt-neox-20b
- llama-2-13b-chat
- llama-2-70b-chat
- mpt-7b-instruct2
- mt0-xxl-13b
- starcoder-15.5b

The 6 highlighted models were introduced since the initial release of Part 1 of the Technical Hands-on guide.

The llama-2-13b-chat model is a smaller version of llama-2-70b-chat. Likewise, the flan-t5-xl-3b model is a smaller version of flan-t5-xxl-11b, and at 3 billion (3b) is currently the smallest model on the watsonx.ai supported model list. You can try these out and observe some advantages of smaller models. These include:

- More cost efficient
- Likely less verbose and creative – but completion still heavily depend on the input prompt and any inference parameter tuning

5.1 IBM Granite models

IBM is rolling out its proprietary models. These are built on highly curated data sets that have been vigorously filtered to remove:

- Hate, Abuse, and Profanity content
- Copyright and licensed materials
- Duplications
- Any other undesirable, blacklisted material, and blocked URLs

IBM offers Indemnification for its models (expand and read the Intellectual Property Protection for AI Models section in Foundation models in Watsonx.ai). Clients can use the Granite (and future IBM models like Obsidian which is coming in 2024) with confidence.

Here are the descriptions of the two Granite variants:

- granite–13b-instruct-v1

  Instruct models are tuned to work well with input instructions, typically entered as part of the prompt. This variant is a Supervised Fine-Tuned (SFT) version of the base model to improve its instruction-following. It was tuned using a mix of FLAN and a mixture of other datasets (Dolly, HHRLHF, and IBM internal datasets, etc.). This model is intended as a starting point to help bootstrap further downstream alignment or task-specific tuning.

- granite-13b-chat-v1

  This variant is a purpose-aligned version of the granite.13b.instruct variant specifically for chats. It was aligned using Contrastive Fine Tuning (CFT) to improve its harmlessness and the quality of its generation responses. This model should be used when looking to prompt-engineer out of the box, particularly when longer responses are desired. It also may be helpful as a starting point for further downstream fine-tuning.

In Dec 2023, IBM added version 2 variants of the 2 Granite models: granite-13b-chat-v2 and granite-13b-instruct-v2.

The focus of this part of the lab is not on prompt engineering. You can retry some of the prompt engineering exercises from Part 1 and use the Granite model instead. In this lab's Prompt Tuning section, you will try out the flan-t5-xl-3b model (the Granite model will be available for prompt tuning later in 2024).

The version 1 Granite models were trained on 1 trillion tokens, whereas the version 2 models were trained on 2.5 trillion tokens. The version 2 models are much more efficient and they perform better than the version 1 models. In Proof of Experience (PoX), sellers should get familiar with the v2 models (or the latest version of the model) and use them.

5.1.1 Advantages of IBM models

There are many reasons why clients should consider IBM's foundation models; some of which include:

- IBM models are built on highly curated, filtered, and refined data. IBM removes the following contents before using the data to build IBM's Large Language Models (LLMs)

    - Hate, Abuse, and Profanity content
    - Copyright and licensed materials
    - Duplications
    - Any other undesirable, blacklisted material, and blocked URLs

    As a result, clients can use IBM models with confidence and trust.

- In addition, since the data used to build the model is completely known, IBM models provide complete transparency and explainability. This is typically not available for other models.

- Because of the vigorous cleaning and filtering, IBM models may be smaller by comparison, but they are targeted for business applications. Clients incur lower costs but still reap similar benefits when compared with larger Large Language Models (LLMs) such as GPT, and with data explainability.

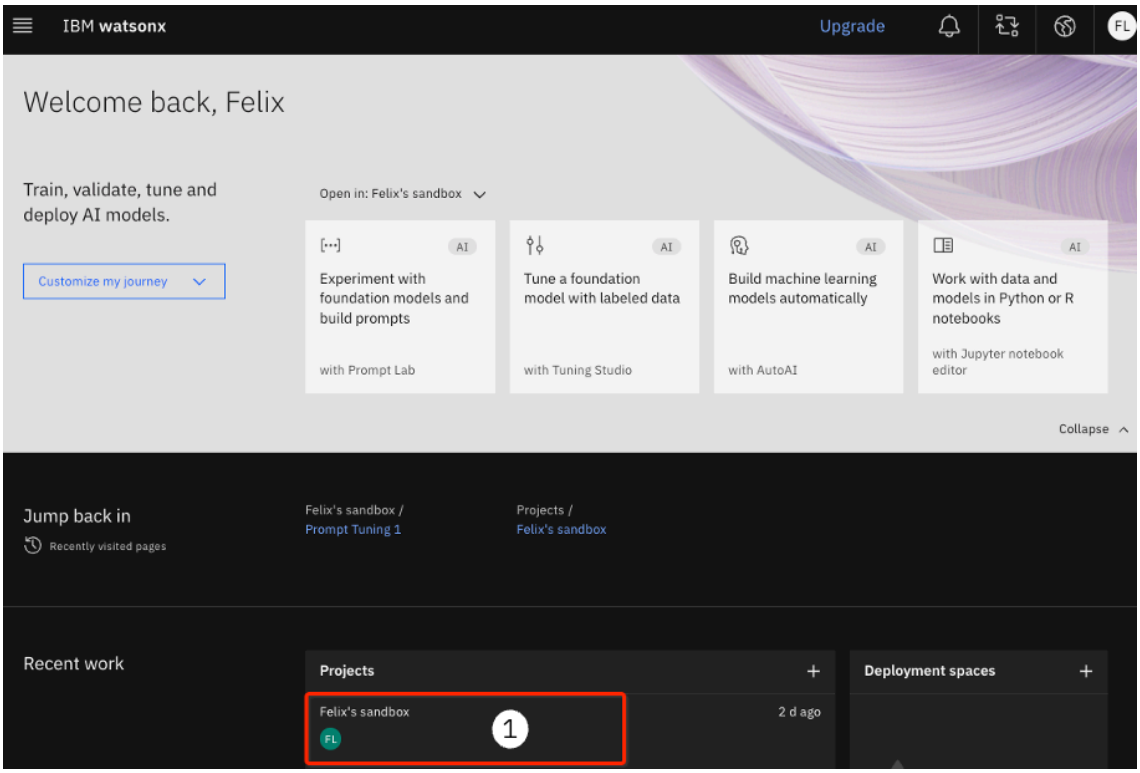
- IBM provides indemnification for using IBM models (see this for more details).

6. Synthetic data generation

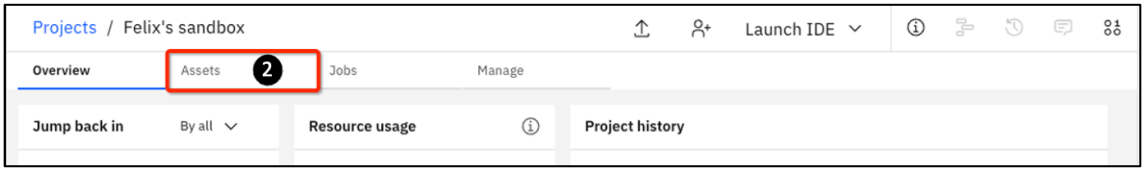
Synthetic data is data that is artificially generated using advanced statistics, as opposed to real data, which is gathered by observing real-world events. Synthetic data can be used with watsonx.ai to augment or replace real data for improving AI models, protecting sensitive data, and mitigating bias. Synthetic data can be generated using foundation models to replicate data with the right statistical attributes. Synthetic data can be used for hackathons, product demos, internal prototyping, exploring market behaviors, or a large number of other use cases that require more data or have privacy concerns.

In this section, you will take a break from investigating foundation models to look at synthetic data generation, another important feature of watsonx.ai.

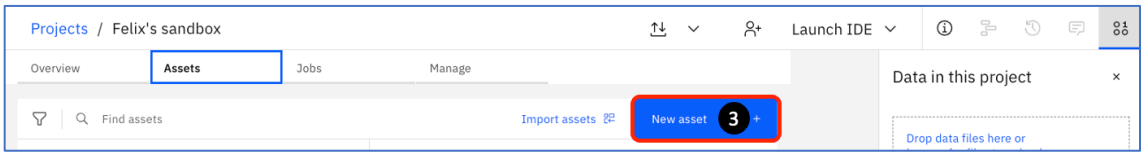
1. Open the watsonx.ai Prompt Lab and click your project. This is most likely called **<your username> sandbox**.



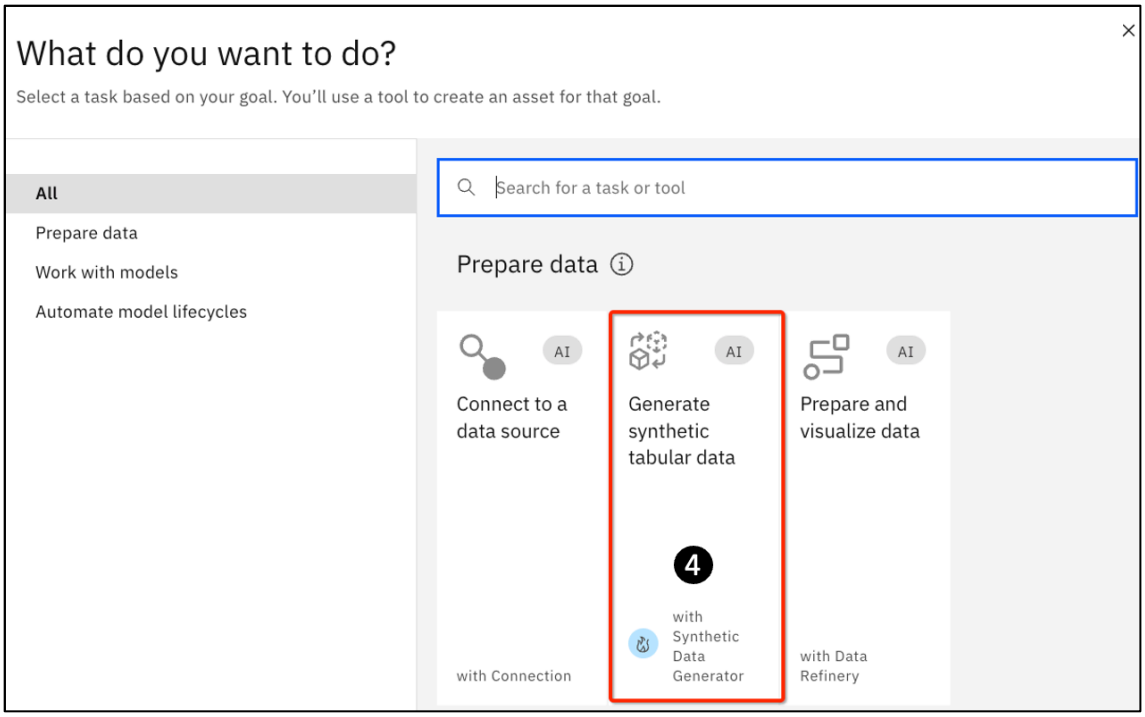
2. Select the **Asset** tab.



3. Click **New asset**.

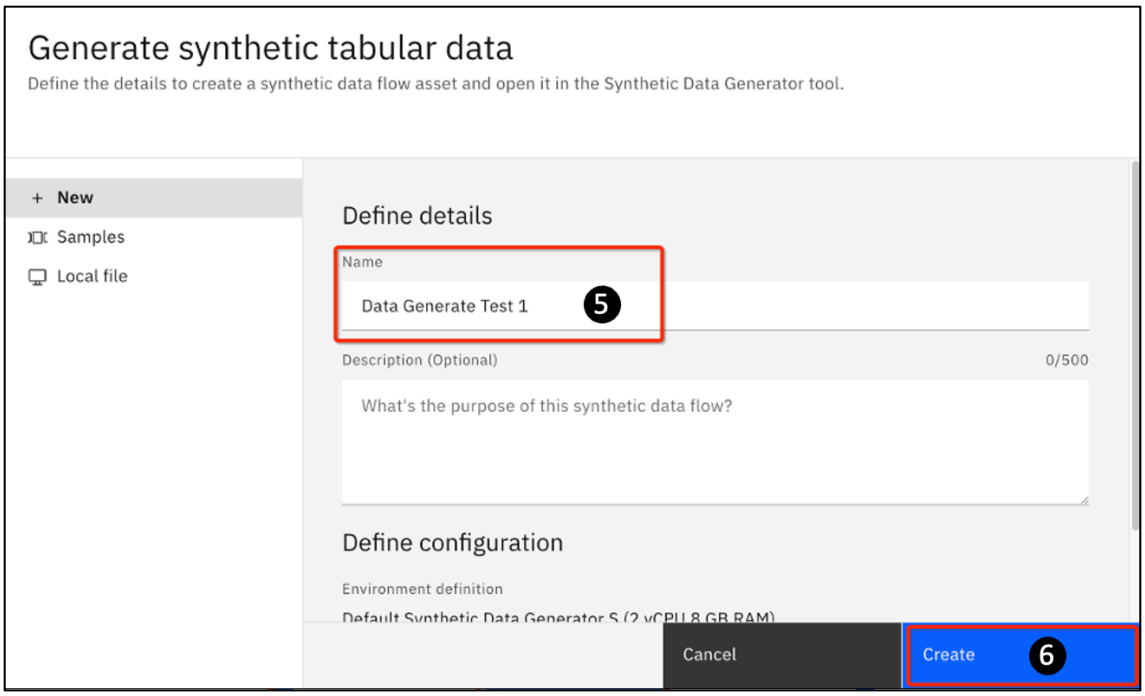


4. Click on the **Generate synthetic tabular data** tile.

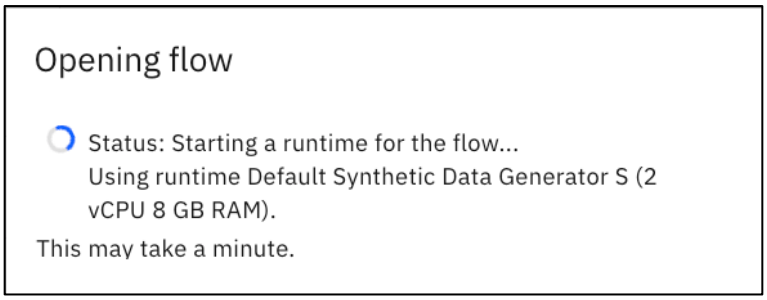


5. On the next panel, provide a name such as **Data Generate Test 1**. You can also optionally provide a description in the **Description field**

6. Click **Create**.



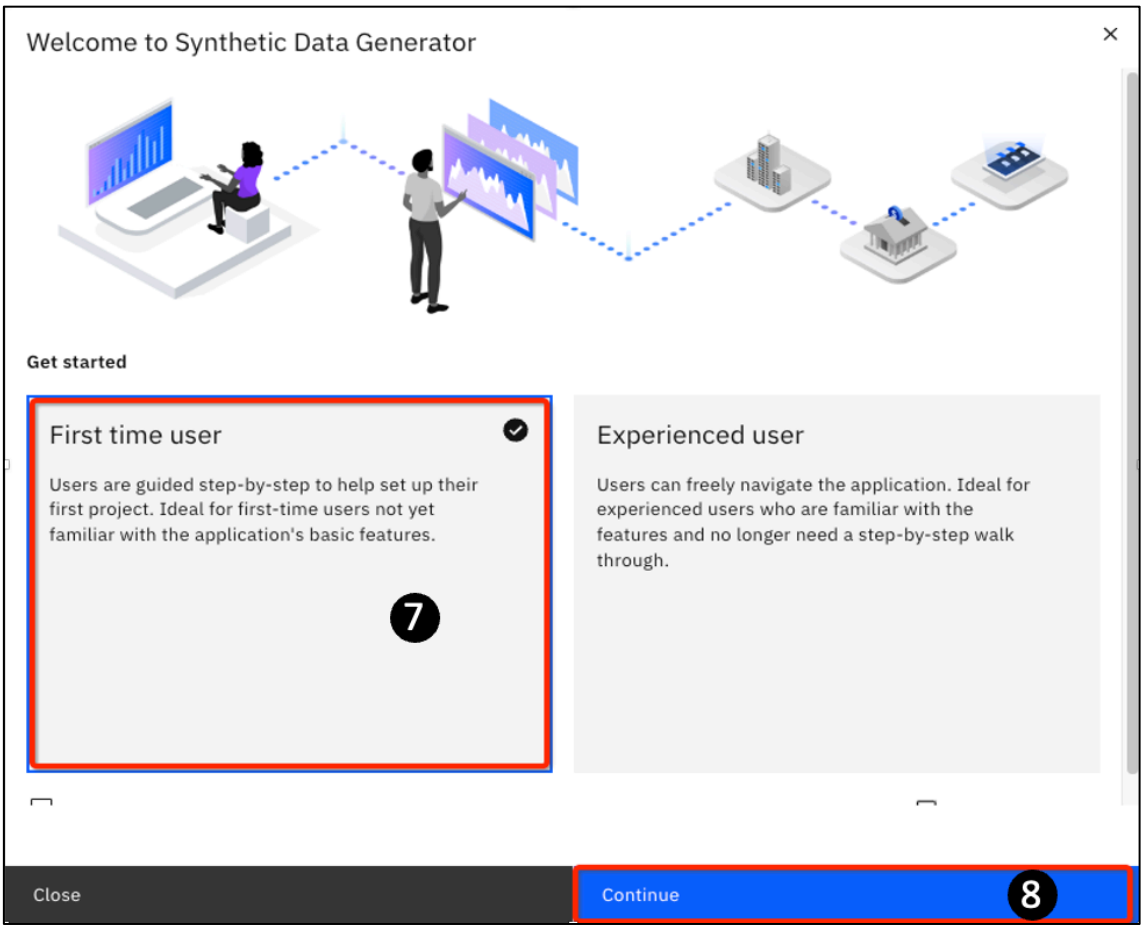
You will see the following message:



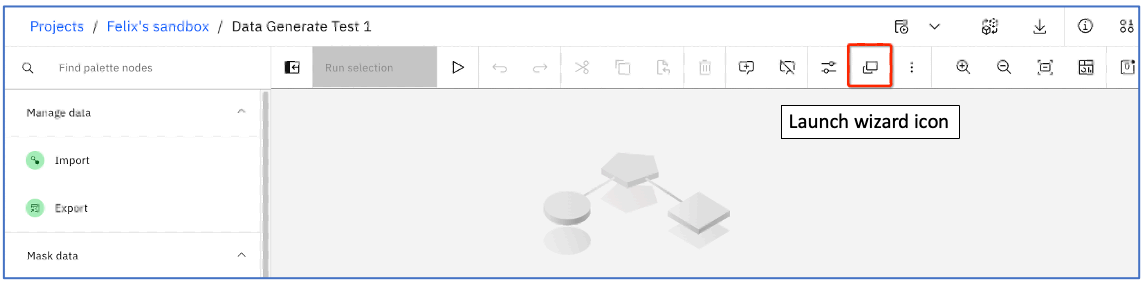
As noted in the message, this process may take a few minutes.

Note: sometimes the process may fail. If so, retry by clicking **Create** again.

7. On the subsequent panel, click on the **First time user** tile.
8. Click **Continue**.



If you click on the **Experienced user** tile and then click **Continue**, you will be taken to the Synthetic data generation canvas tool for data generation. You can always come back to the **Welcome to Synthetic Data Generator** wizard by clicking on the **Launch wizard** icon (you may need to scroll or expand your window to see this icon)



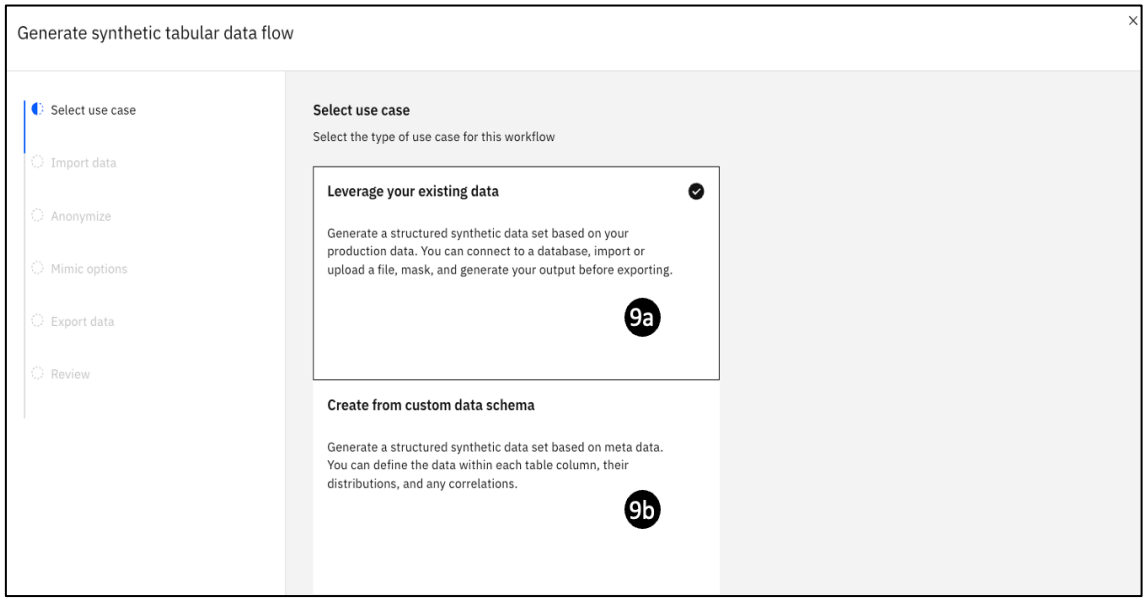
9. If you select the **First-time user** tile, you will see a panel showing 2 tiled options:

    a. **Leverage your existing data** – Use this to leverage existing data sets and generate new synthetic data that resembles (but does not include) your existing data. This is an easy way to generate data that is compatible with a specific schema.

    b. **Create from custom data schema** – Use this to create your own table schema and populate it with synthetic data.

    You will try both methods in this lab.

    Don't select any options yet.

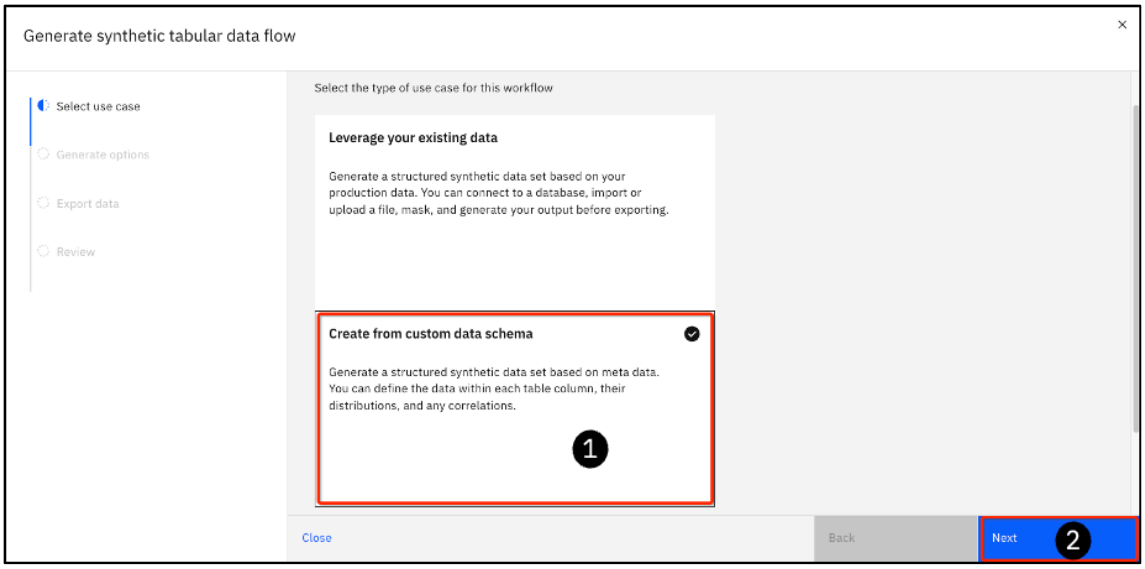


6.1 Create synthetic data by defining customized data schema

In this section, you will create synthetic data from scratch.

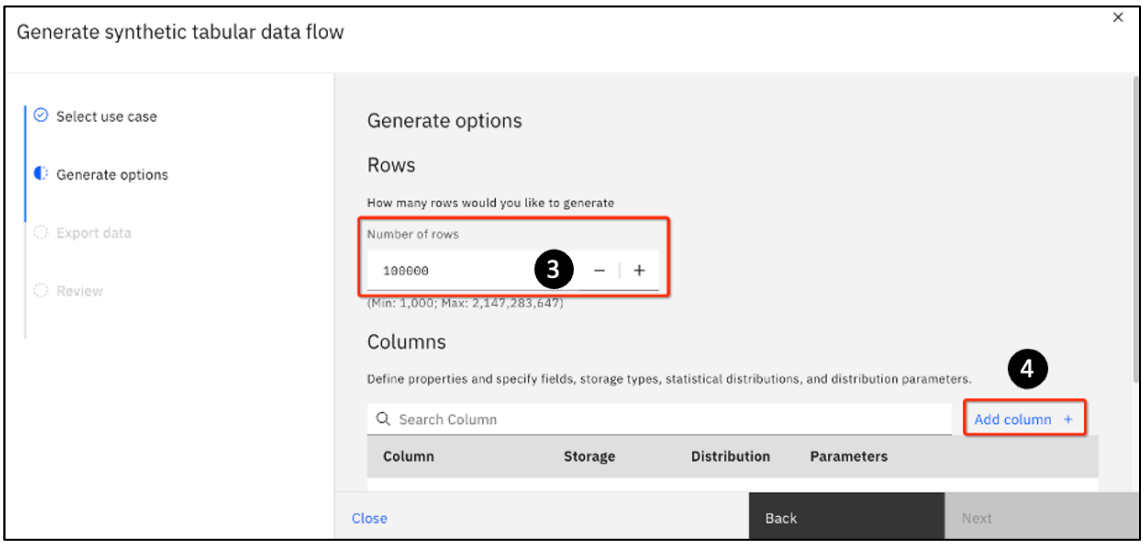
1. From the last step in Section 5, click on the **Create from custom data schema** tile.

2. Click Next.

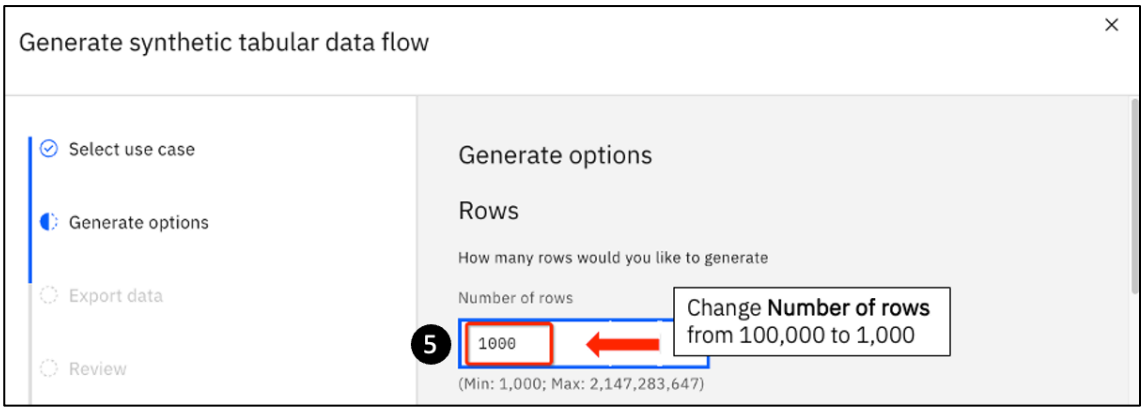


3. The **Generate synthetic tabular data flow** page opens. You can set the number of rows to generate – the default is **100,000** rows.

4. You can also define the columns (the schema) of the table.

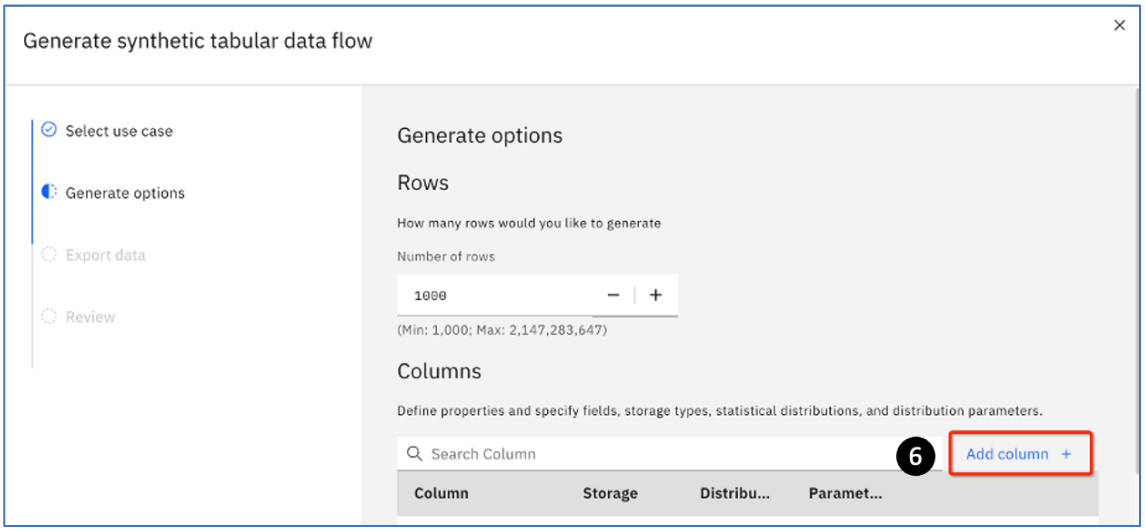


5. By default, watsonx.ai will generate 100,000 rows. For this exercise, change the **Number of rows** field to the minimum number allowed: **1,000**.



6. Now you will start to define columns. You will define a simple table with an employee's last name, age, and salary range.

   On this panel, click **Add column +**.

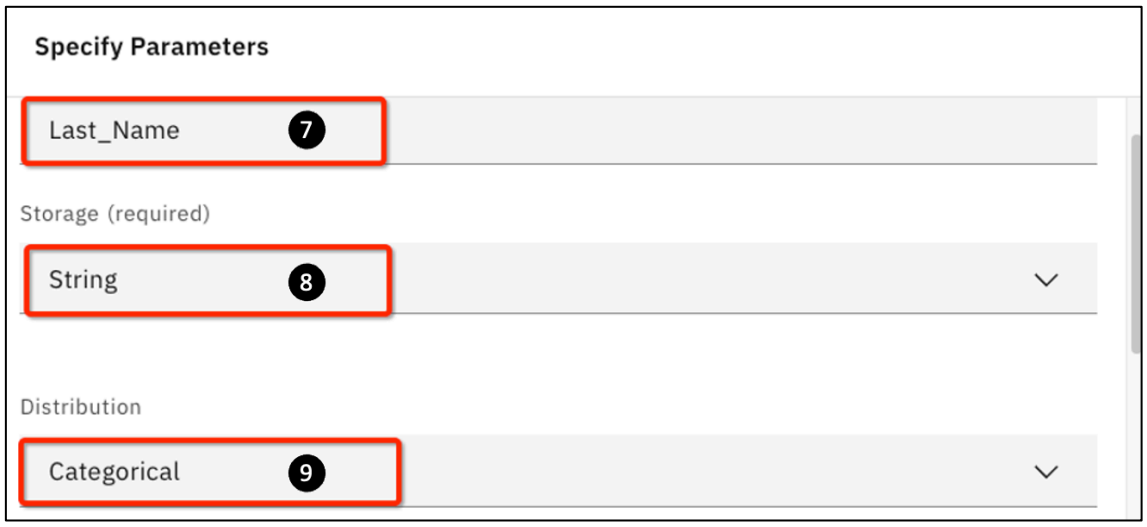


   The following panel appears. Fill in the first 3 fields as follows:

7. **Column**: Enter **Last_Name**

8. **Storage**: Select Enter **String** from the drop-down list

9. **Distribution**: Select **Categorical** from the drop-down list

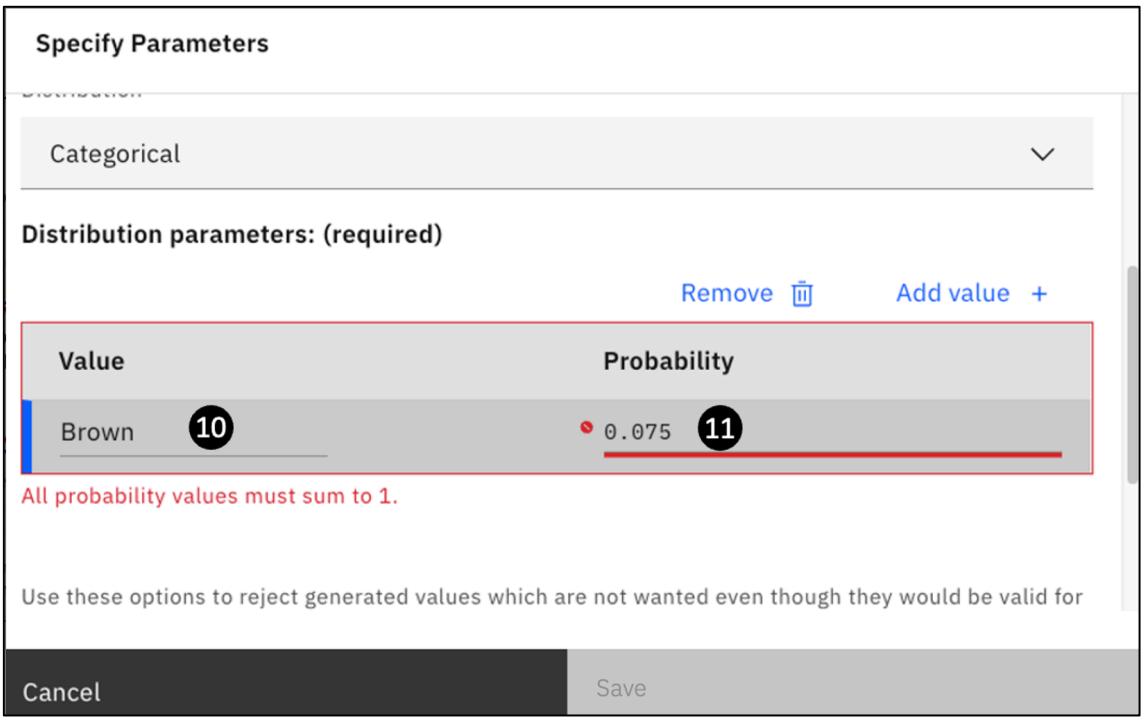


Since you are defining a string column, the **Distribution** is simply a categorical list of last names. In this case, watsonx.ai is asking you to provide a list of possible outcomes (here is a list of last names, in general, it would be whatever valid values that a string variable can take on). You will need to provide a list and the probability value for each item on that list; the sum must be 1.0.

When you scroll further down, you will see fields for **Value** and **Probability**. For the first name of the category, enter the following values:

10. For **Value**: Enter **Brown**

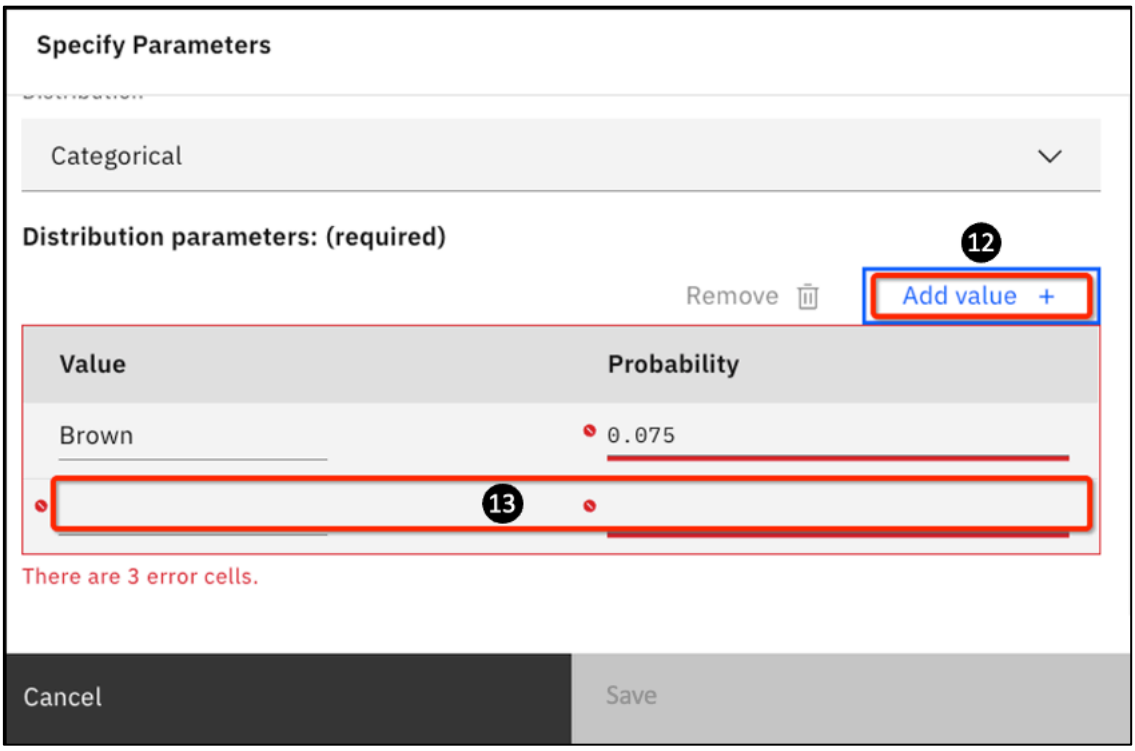
11. For **Probability**: Enter **0.075**



12. Notice that the **Save** button is still grayed out. The reason is stated in red above: All probability values must sum to 1. You will need to keep adding additional values until all the probability adds up to 1.0.

    Click on **Add value +**.

13. A new row will be added, which you will fill in next.

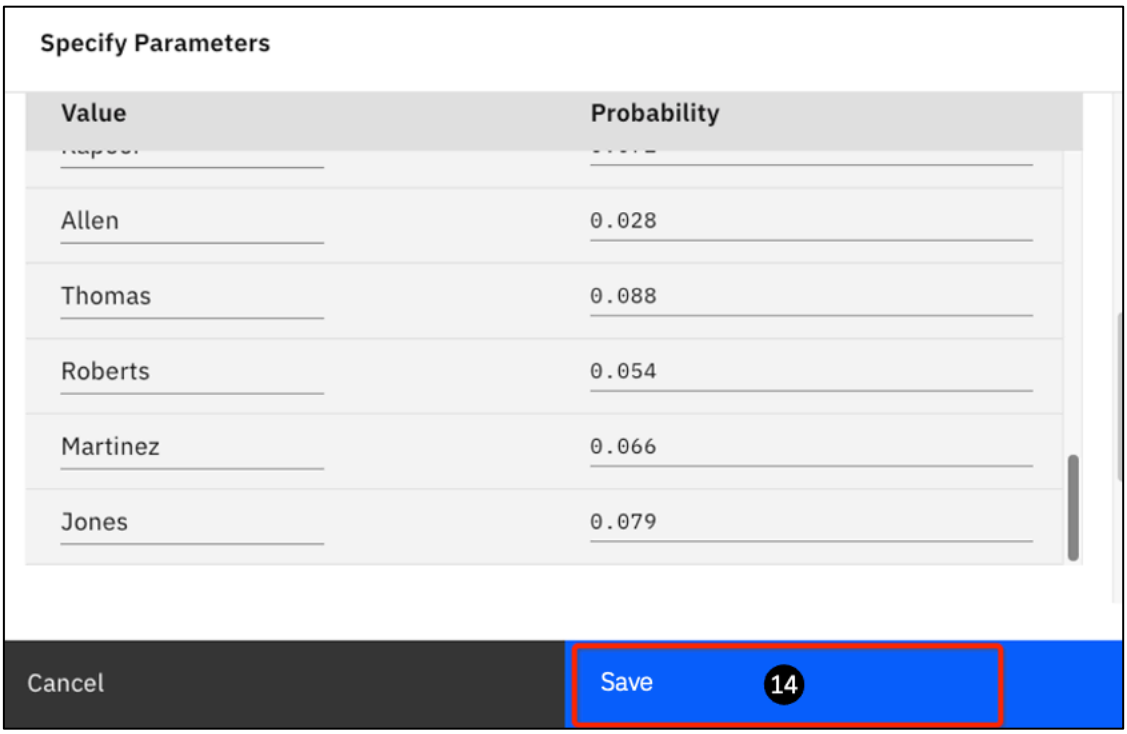


Carefully add all the values in the following table (they add up to a total of 20 last names); remember you already added the **Brown** row.

Value	Probability	Value	Probability
Brown	0.075	Leung	0.096
Gordan	0.054	Wilson	0.019
Newman	0.037	Duncan	0.022
Chen	0.082	Wong	0.085
Lord	0.023	Kapoor	0.072
Muthu	0.027	Allen	0.028
Bird	0.022	Thomas	0.088
Bentley	0.024	Roberts	0.054
James	0.018	Martinez	0.066
Abrams	0.029	Jones	0.079

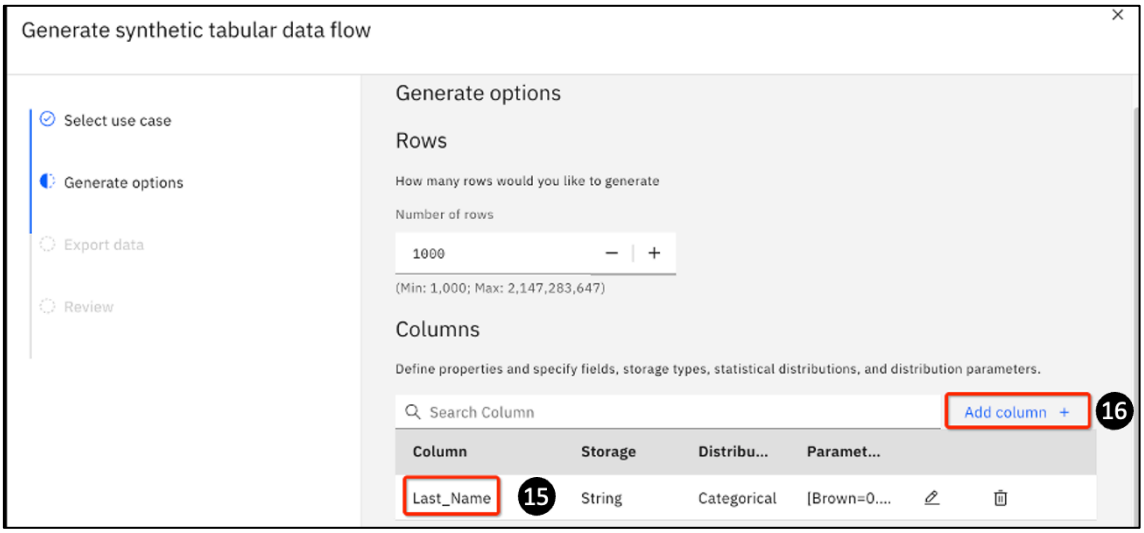
Once you have a list with a probability value adding up to **1.0**, the **Save** button will turn blue; if it doesn't you have an error in the **Probability** numbers ... recheck them.

14. Click **Save** to create the column.



15. You are redirected to the **Generate synthetic tabular data flow** page. Notice that the **Last_Name** column is now added.

16. Click **Add column +** to add another column.



Insert the following data:

17. For **Column**: Enter **Age**

18. For **Storage**: Select **Integer** from the drop-down

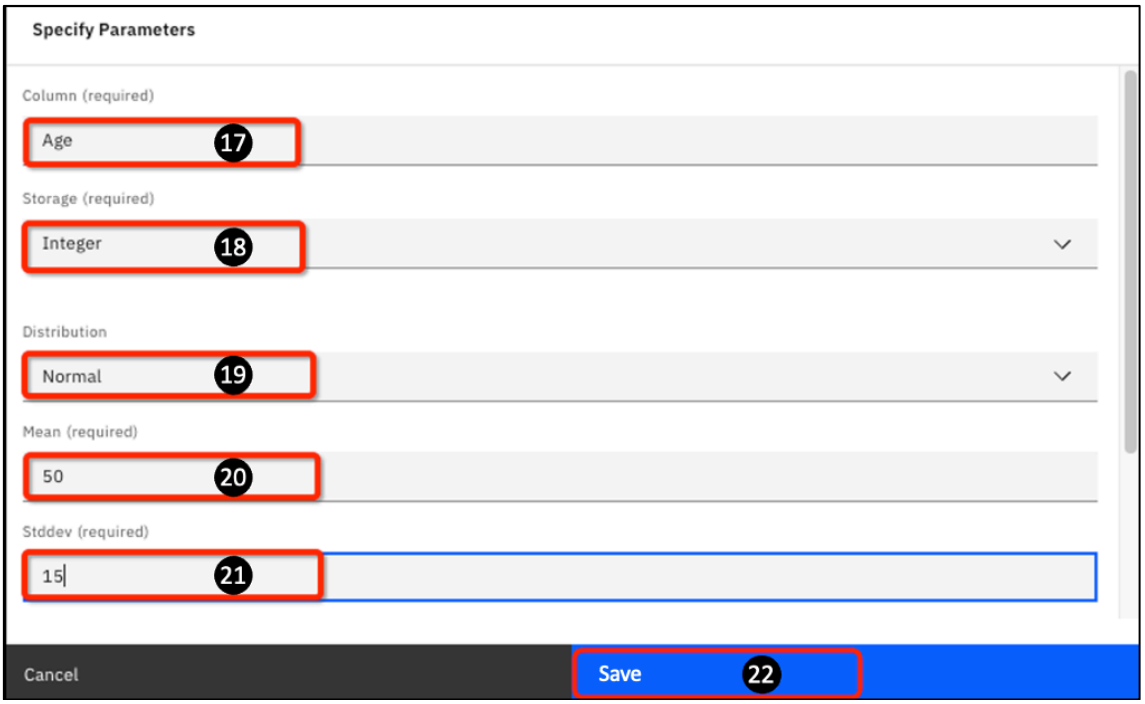
19. For **Distribution**: Select **Normal** from the drop-down

    With an integer column, you can optionally use a **Categorical** distribution (like you did in Step 9). In that case, you will need to provide a list of ages and the probability of each, similar to what you did with **Last_Name**. For this lab, you will use a typical normal distribution for number-based items (this is the default assumed by watsonx.ai)

20. Notice that watsonx.ai automatically filled in a mean value of **50**.

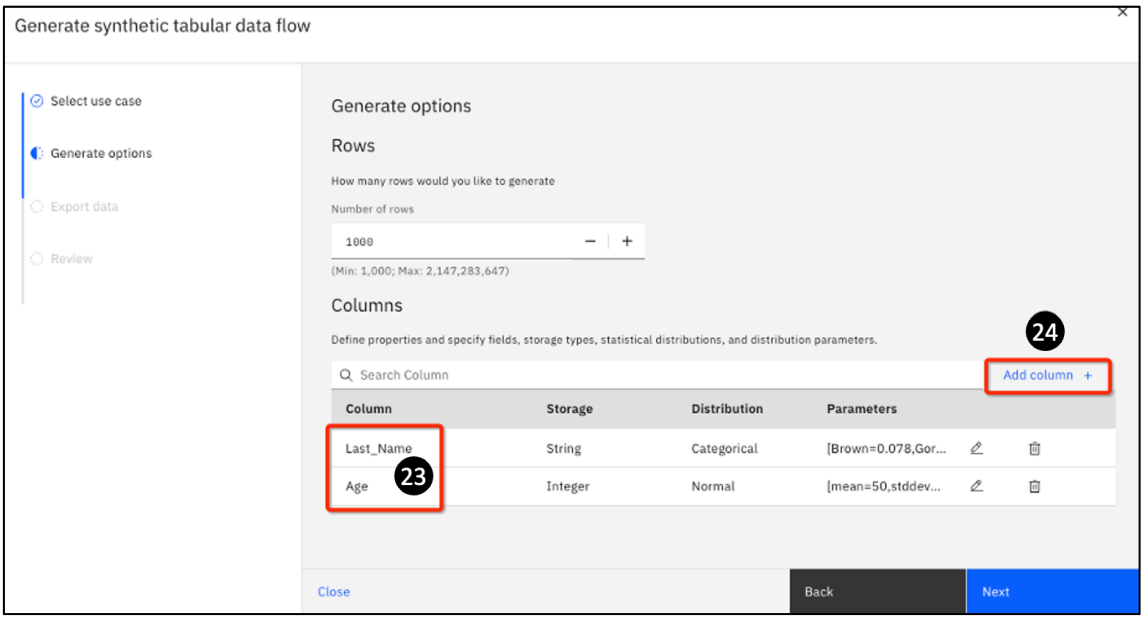
21. Watsonx.ai also puts in a default **Stddev** (standard deviation) value of **10**.
    As you are working with a global company, you might want to have a larger spread of data. Keep the mean value for this lab, but change the **Stddev** to **15** instead of **10.**

22. Click **Save.**



23. The **Generate Synthetic tabular data flow** reopens. The **Last_Name** and **Age** columns are now added.

24. Click **Add column +** to add a third and final column.



25. For the last column, use the following values. For **Column**: Enter **Salary**.

26. For **Storage**: Select **Real** from the drop-down

27. For **Distribution**: Select **Normal** from the drop-down

28. For **Mean**: Enter **140000**

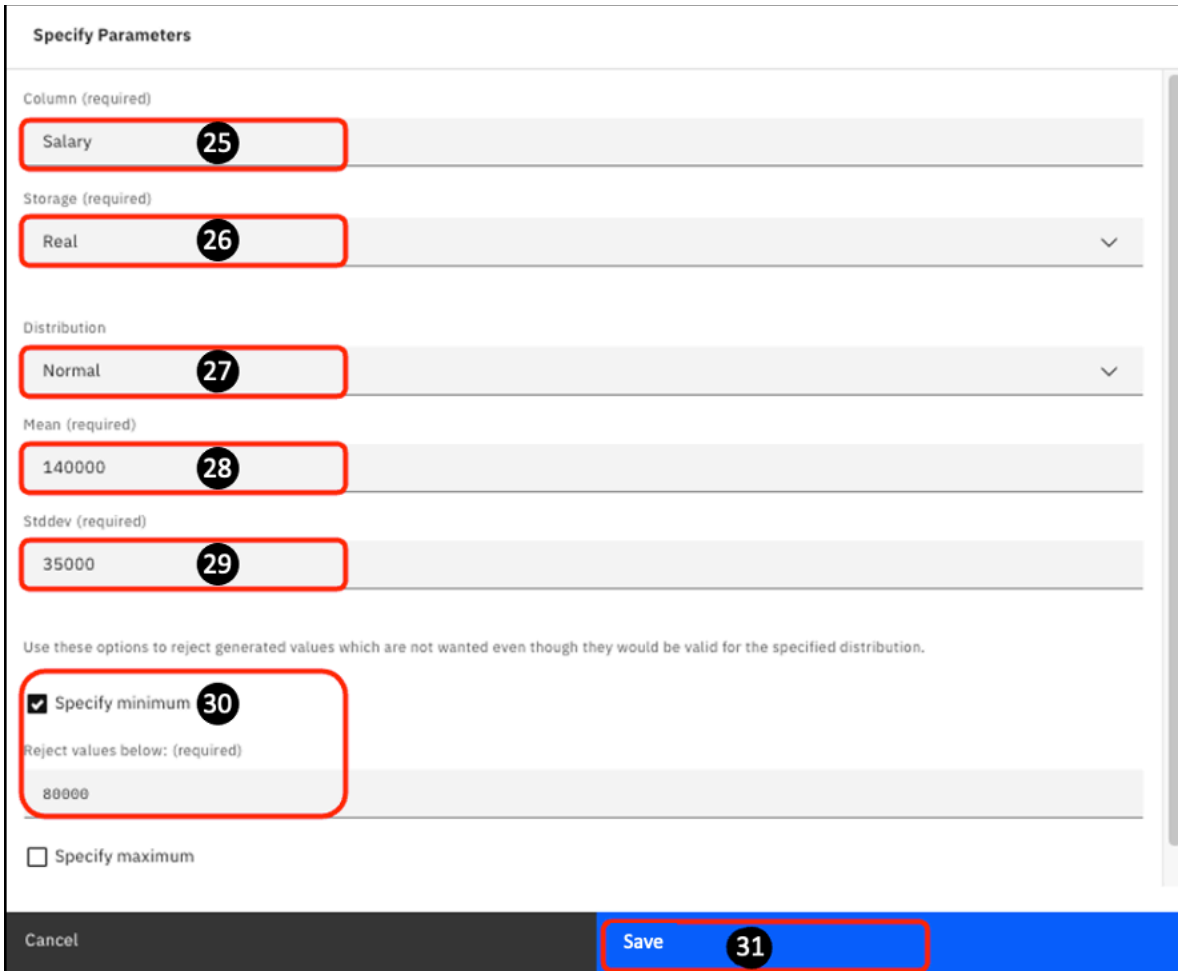
29. For **Stddev**: Enter **35000**

30. Select the **Specify minimum** check box. Enter **80000** for the **Reject values below:** field.

    In this example, you want to ensure that you generate a range where the salary cannot be lower than $80,000. You may want to do this to eliminate a salary that is valid but not desirable.

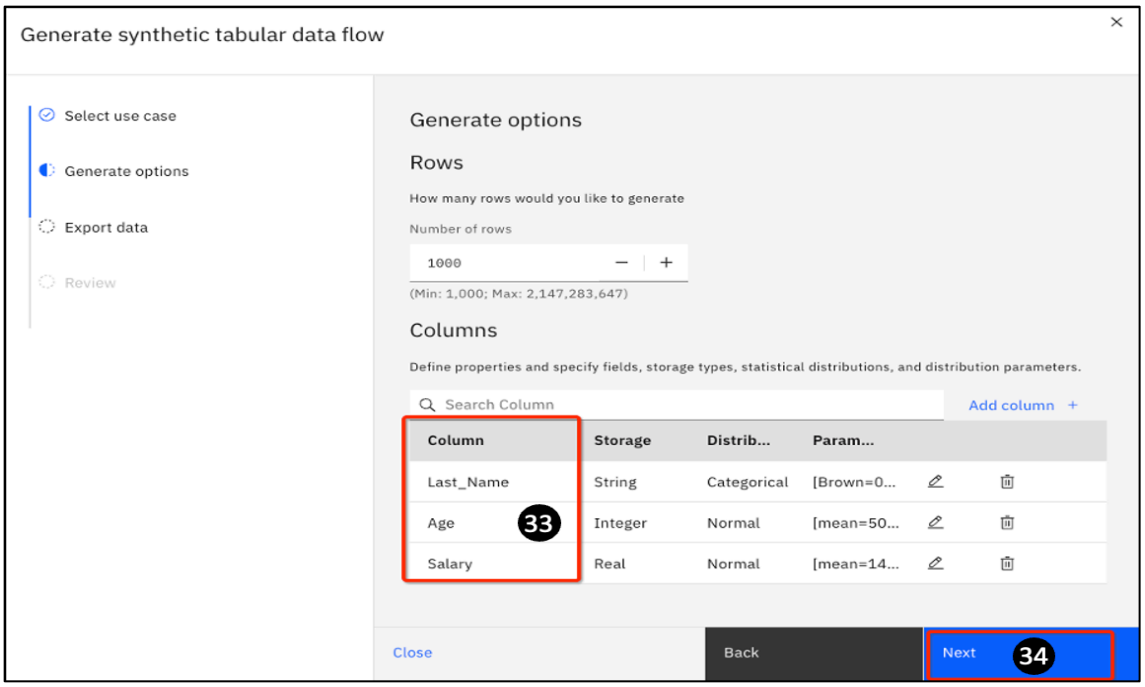
    You may also define a **maximum**. In this lab it is not set.

31. Click **Save**.



33. You are returned to the **Generate synthetic tabular data flow** page. You now see all 3 columns you defined have been added.

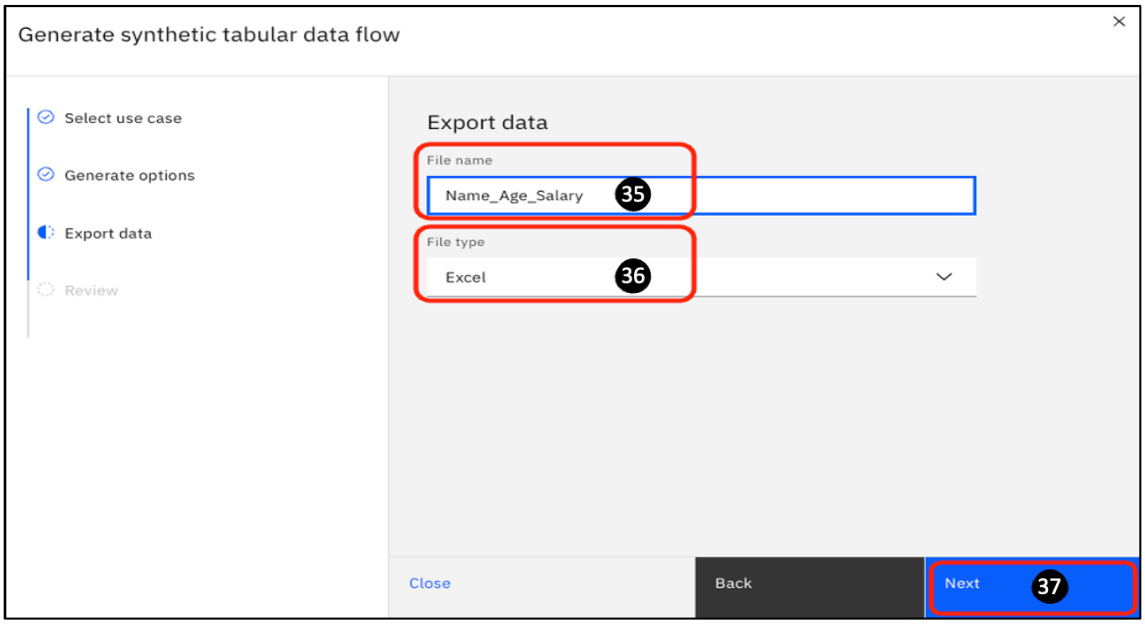
34. Click **Next** to generate the data.



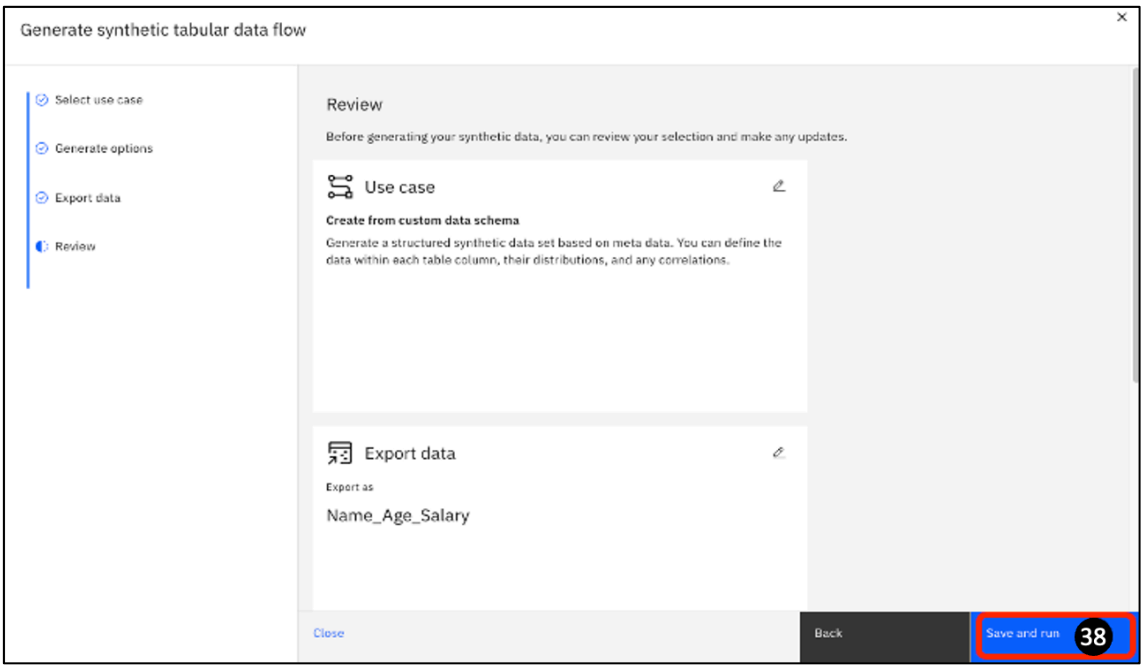
35. On the next panel, you can specify the output **File name**. Change it to **Name_Age_Salary**

36. Click on the **File Type** drop-down and select **Excel**.

37. Click **Next**.



38. On the next page, review the information. If it is correct, click **Save and run**.



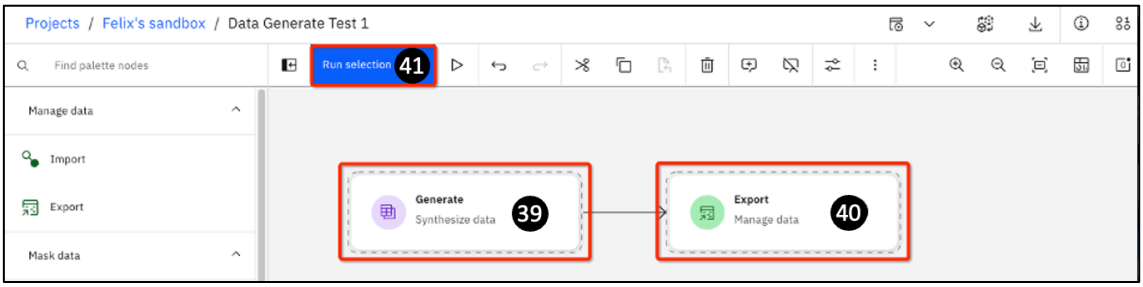
The next page shows a graphical representation of the synthetic data generation tasks. There are 3 main areas:

39. **Generate** – this is where you define how you want to generate your data.

40. **Export** – this is where you define how you want to export your output; in this lab (Step 36) you selected the output to be an Excel file with the name **Name_Age_Salary.xls**.

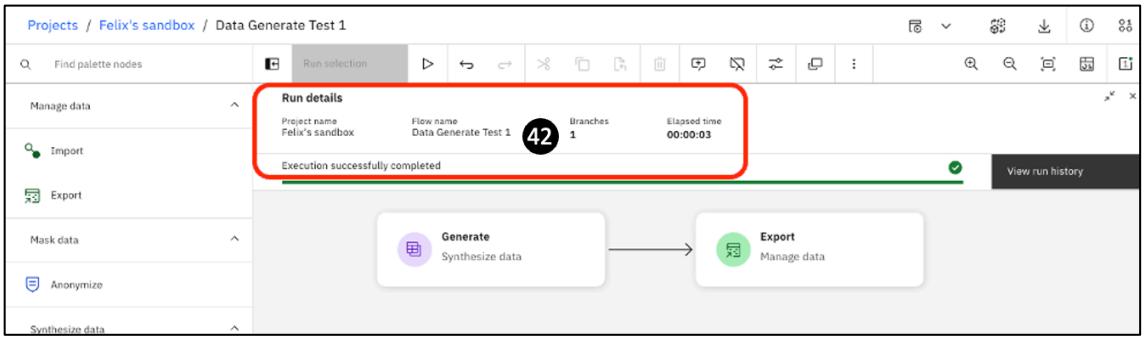
    When you click on **Generate** and **Export**, you will see that dotted lines will now surround both actions.

41. **Run selection** – you can separately highlight the **Generate** and **Export** icons to run the code individually (you will need to first run **Generate** pipeline before you can run **Export**). In most cases, simply select both of the icons to first **Generate** and then **Export** the generated data in one single pass.

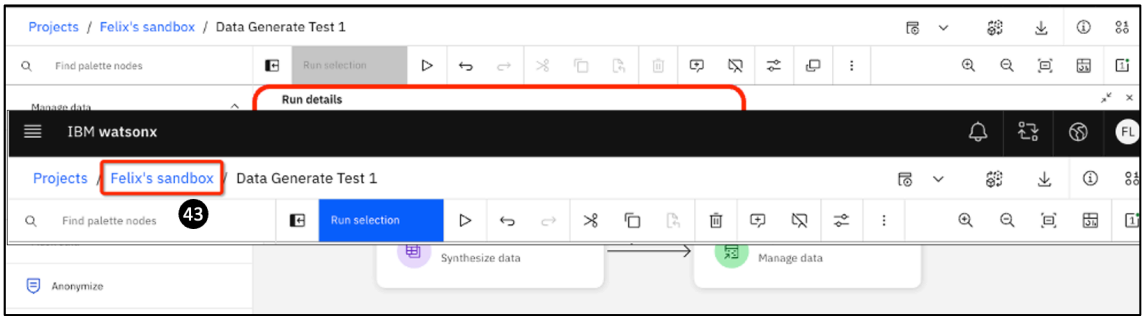


42. The pipeline will take some seconds to run (it can vary depending on the availability of resources – anywhere from several seconds to tens of seconds, so be patient if it takes a little longer).

    You will see a quick summary with the **Run details**.

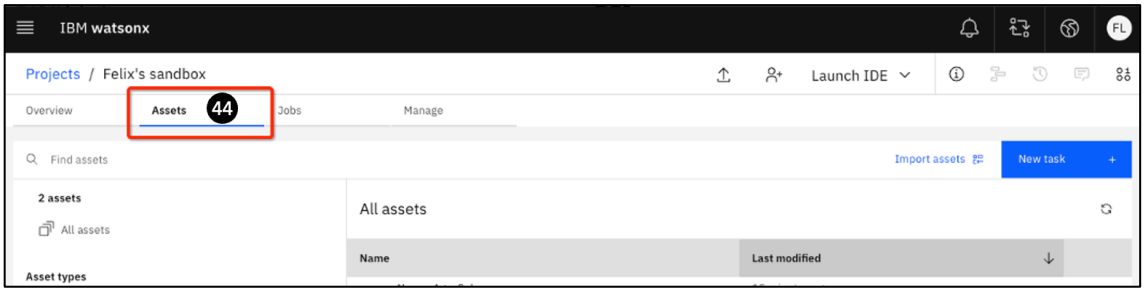


43. Go to the breadcrumb (top left) and click on your project (looks like **<your_name>'s sandbox**).



    Watsonx.ai should open up in your project's **Assets** tab.

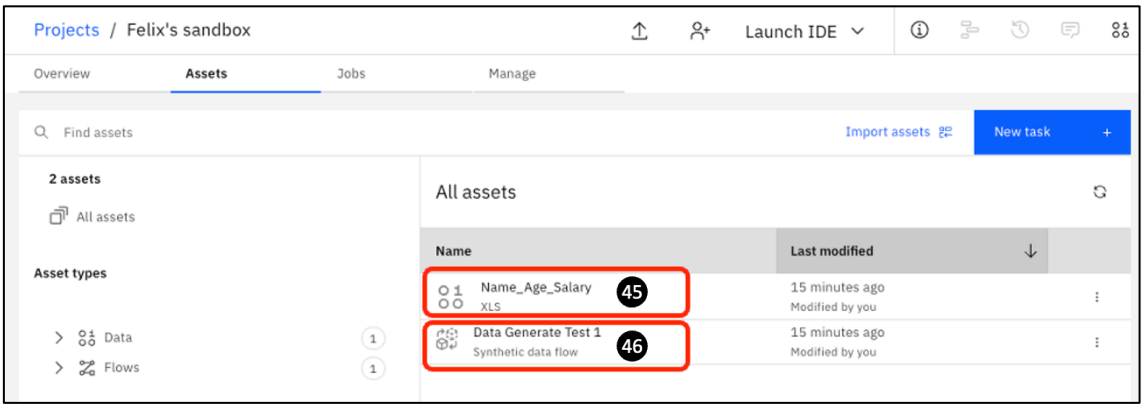
44. If not, select the **Assets** tab.



    You will see the following (you may have other assets):

45. **Name_Age_Salary.xls ...** the name of the XLS file.

46. **Data Generate Test 1** ... the name of the Synthetic data flow specified in Section 6 Step 5 of this lab.



6.1.1 Using watsonx.ai to examine and update your synthetic data

One of the key points in generating synthetic data is how closely the data resembles real-life data. It is important to keep in mind that to the AI model, there is no inherent meaning in **Last_Name**, **Age**, and **Salary**. These are simply tokens used. This means that it can sometimes generate data that is "valid" but perhaps makes little sense (or quite unlikely in real life).

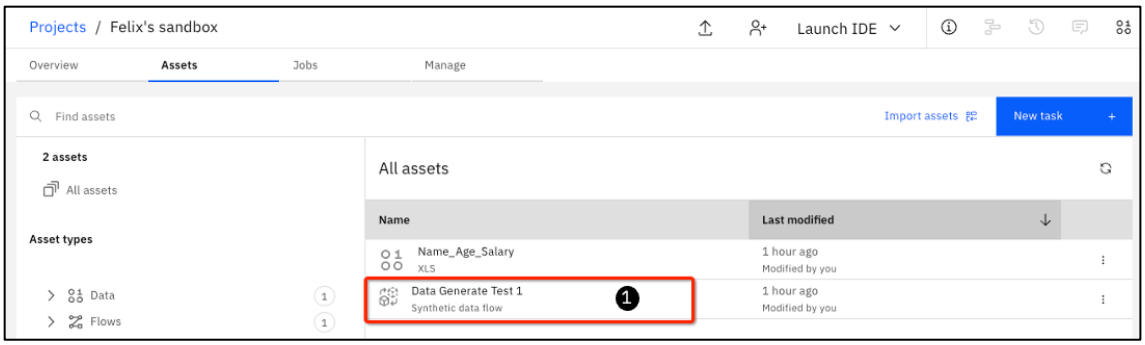
In the last section, you generated a **Name_Age_Salary.xls** file with **1000** rows of synthetic data. This data was generated randomly, so your data may not have the same entries as highlighted below; although if you look carefully, the same type of issues are probably present.

Here are some generated data that clearly exhibit various issues.

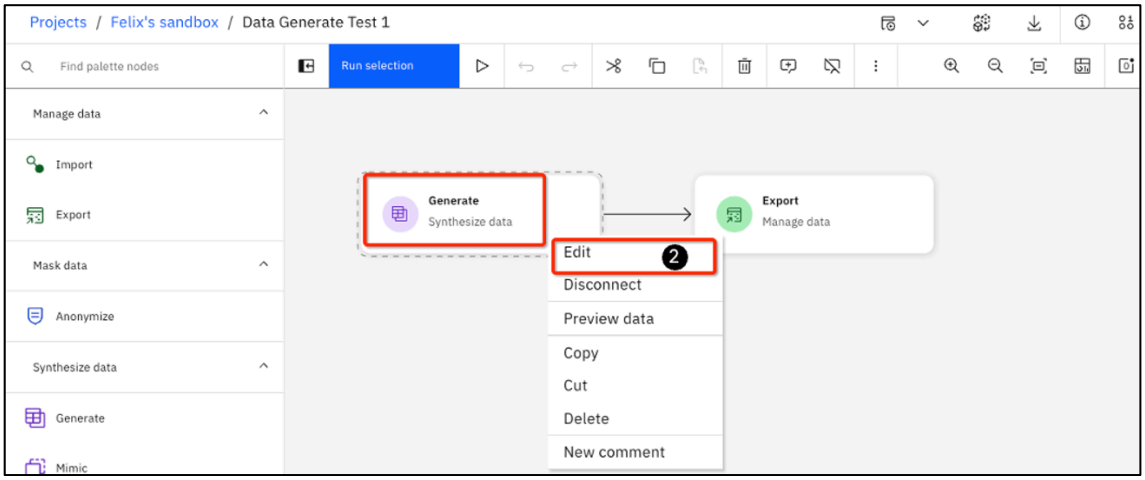
- There are 2 names with age 0, 8 names with age < 10, and 30 names < 20. Certainly, you would want to remedy this.
- At the other extreme, there are 28 names of age > 75, with 3 of them older than 90. You probably want to also remedy this.
- One more subtle issue is that many older employees are making a lot less than younger employees. This is possible but the distribution simply looks unreal.

In this section, you will look at how to use watsonx.ai to generate better data.

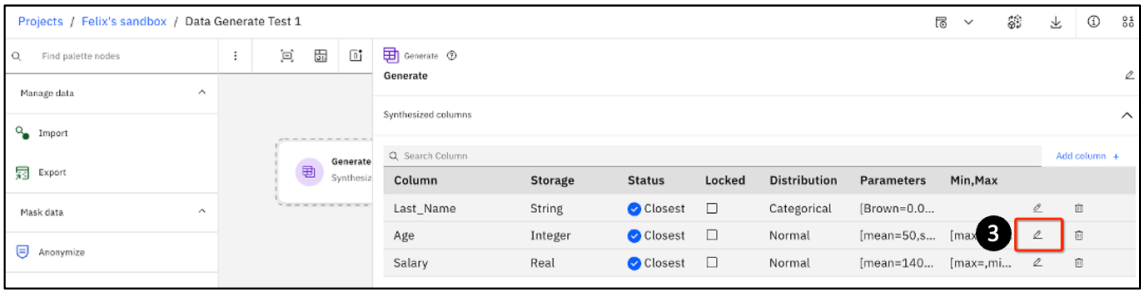
11. Ensure you are in the **Assets** tab of your project and click the **Data Generate Test 1** asset.



12. The Flow page opens. Hover over **Generate** to display 3 vertical dots, then click on them and select **Edit**.



13. Click on the **pencil** ( ) icon for the **Age** row.



14. The **Specify parameters** page opens. Scroll down to find the **Specify minimum**, and **Specify maximum** checkboxes.

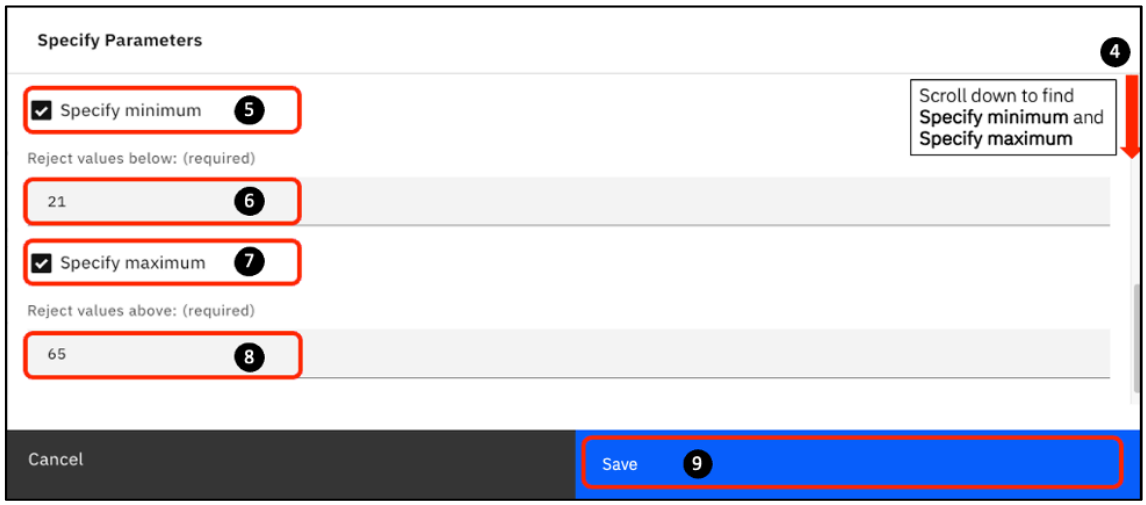
15. Select the **Specify minimum** checkbox.

16. For **Reject values below**: Enter **21**.

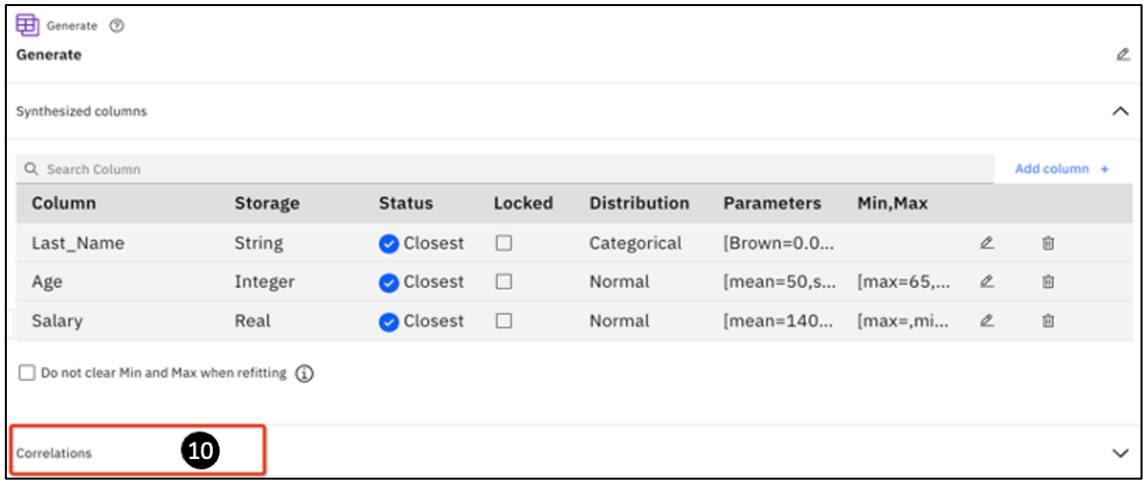
17. Select the **Specify maximum** checkbox

18. For **Reject values above**: Enter **65**.

19. Click **Save**.

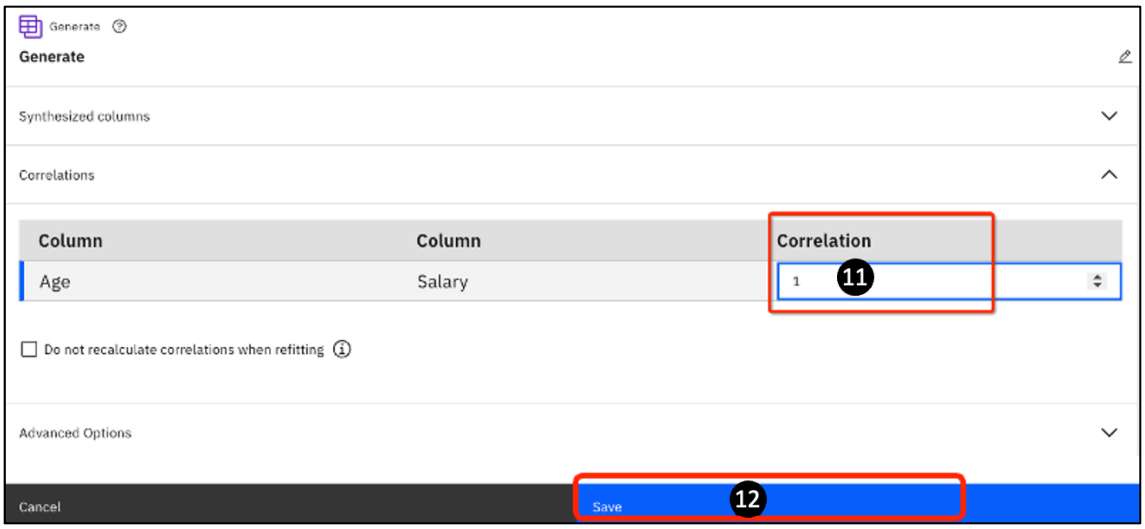


10. The **Generate** page opens. Click on **Correlation**.



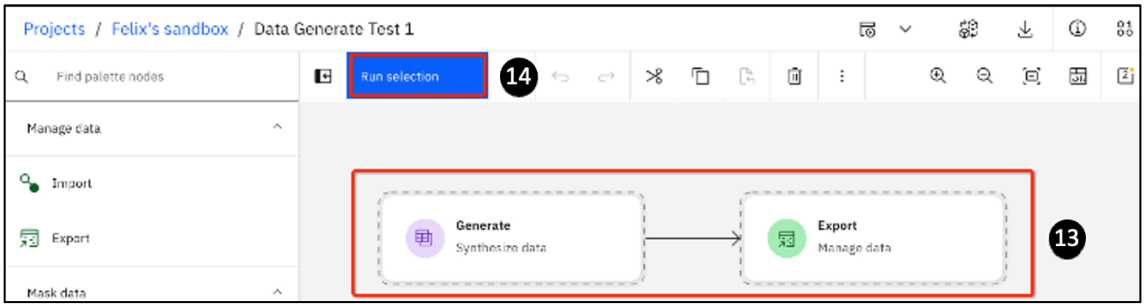
11. Watsonx.ai automatically finds the columns that can correlate: Age and Salary (there is no correlation between a String and a number). Notice that initially the value of **Correlation** is set to **0** – meaning that there is no correlation. Change the value to **1**.

12. Click **Save**.

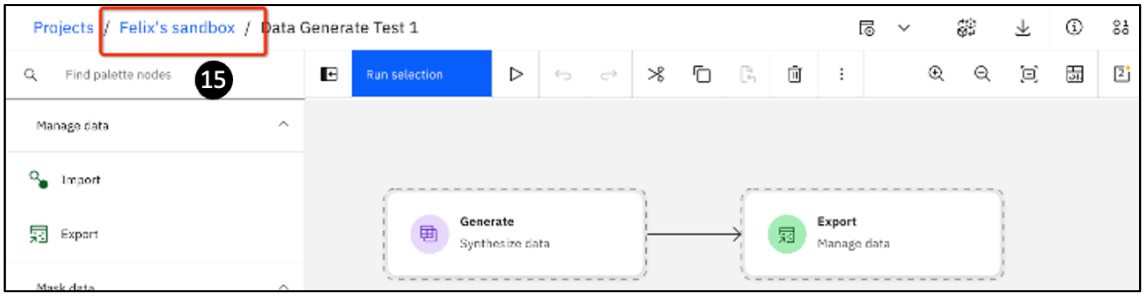


13. The **Data Generate Test 1** page opens. Click both **Generate** and **Export**.

14. Click **Run selection**.

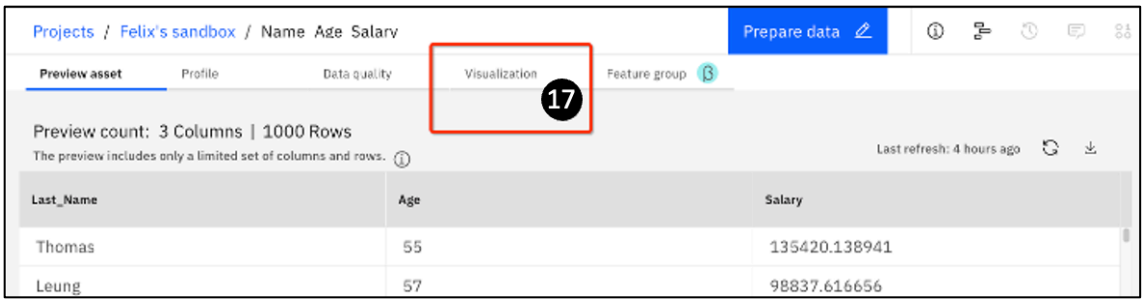


15. Click on your project's name on the breadcrumb: **<your username>'s sandbox**.



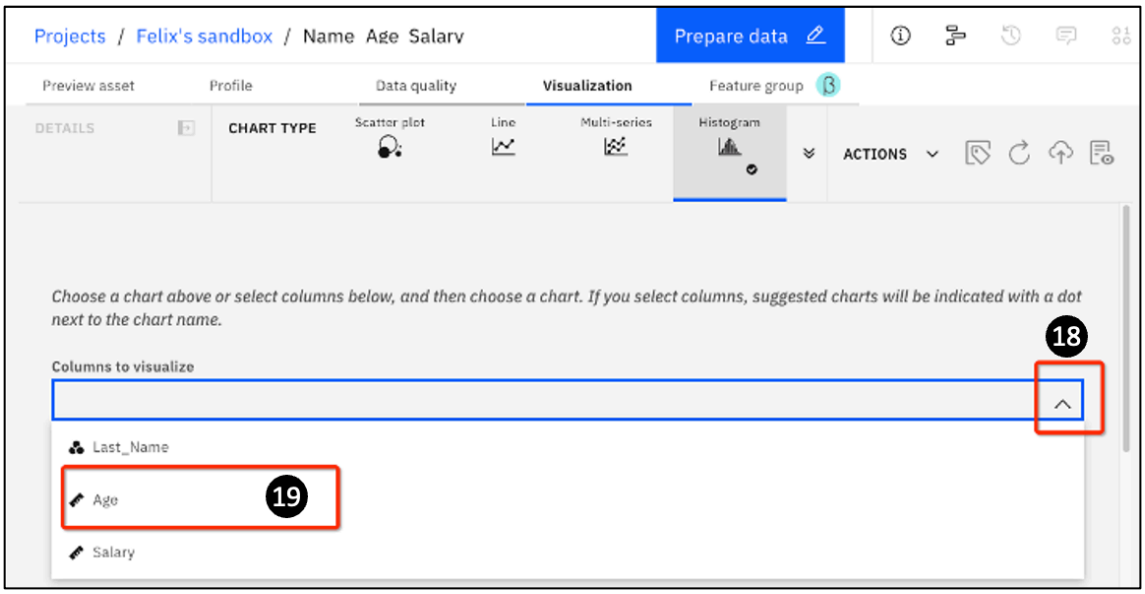
16. Your project should open in the **Assets** tab. If not, select the **Assets** tab. You should see the newly exported **Name_Age_Salary.xls** file. Click on this file to open it. When you examine the file, the previous issues with employees being too young (< 16) and too old (> 65) are gone.

17. Click **Visualization** on the **Name_Age_Salary** preview page.

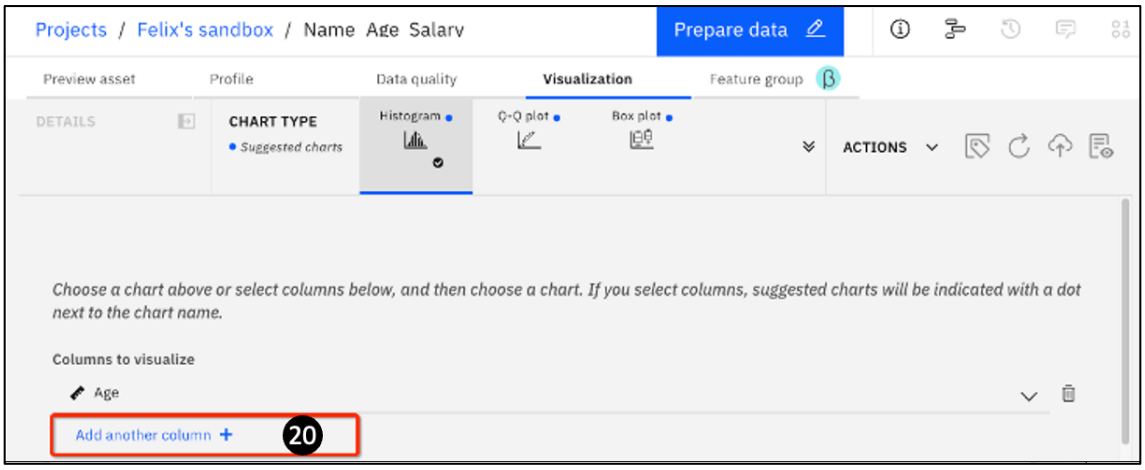


18. On the **Visualization** page, click the **Columns to visualize** drop-down.

19. Select **Age**.

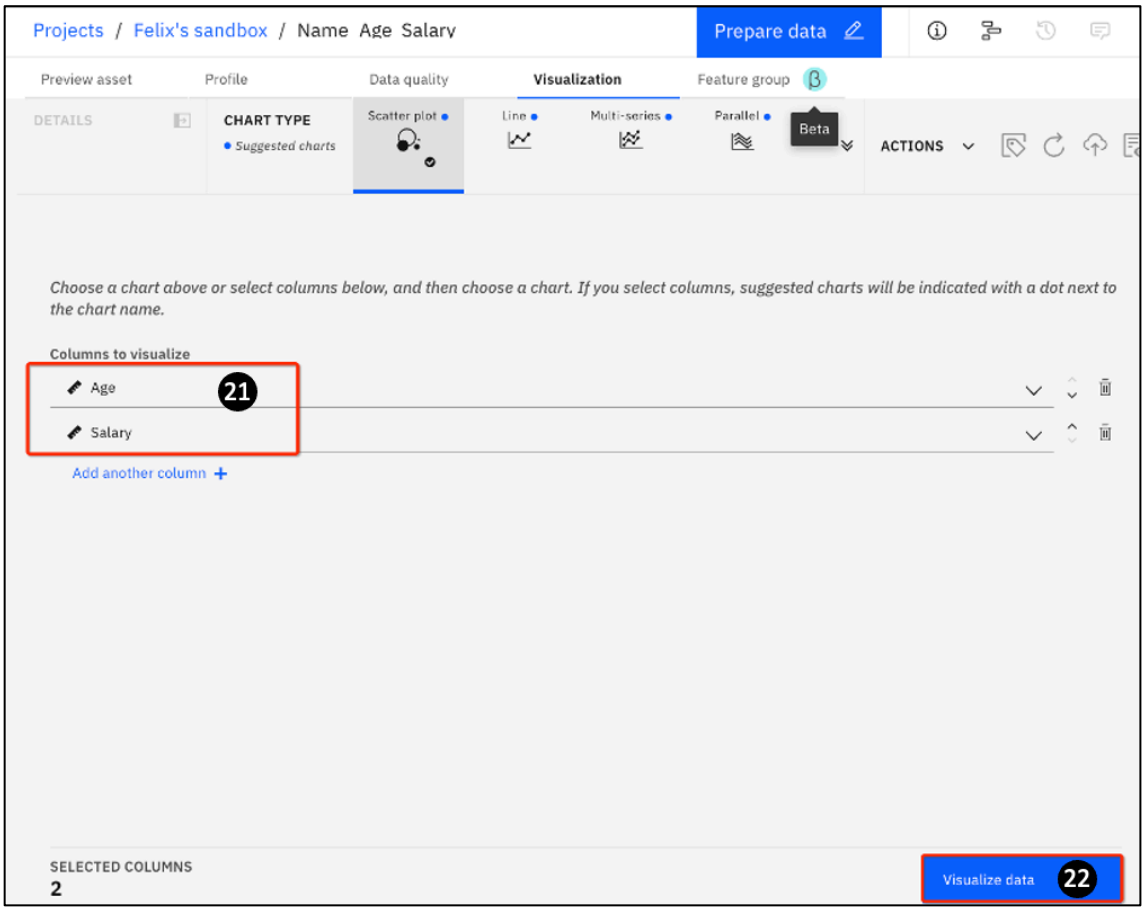


20. Click **Add another column +**, then repeat Step 10 to add a **Salary** column:

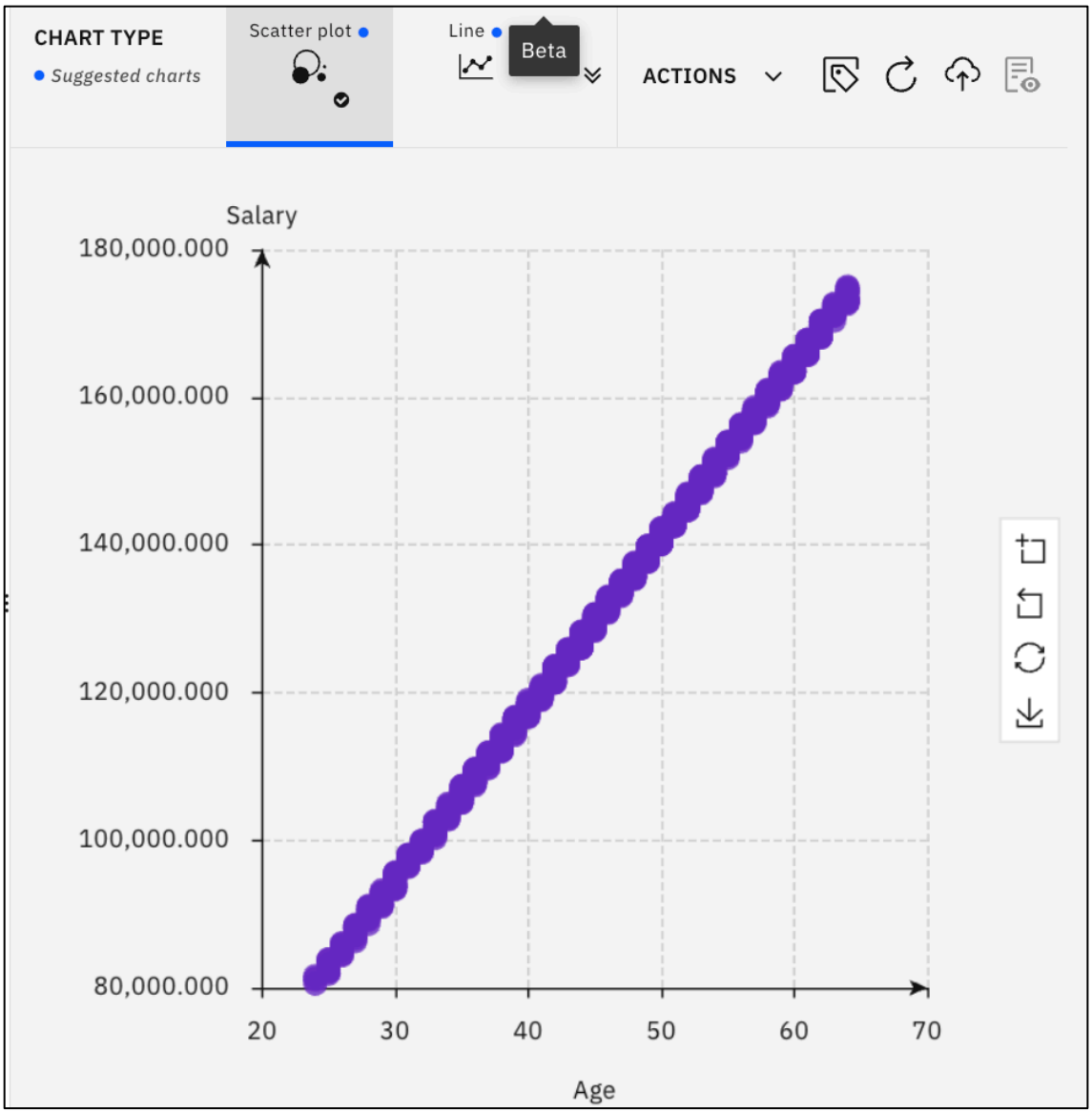


21. You now have both the **Age** and **Salary** columns added.

22. Click **Visualize data**.



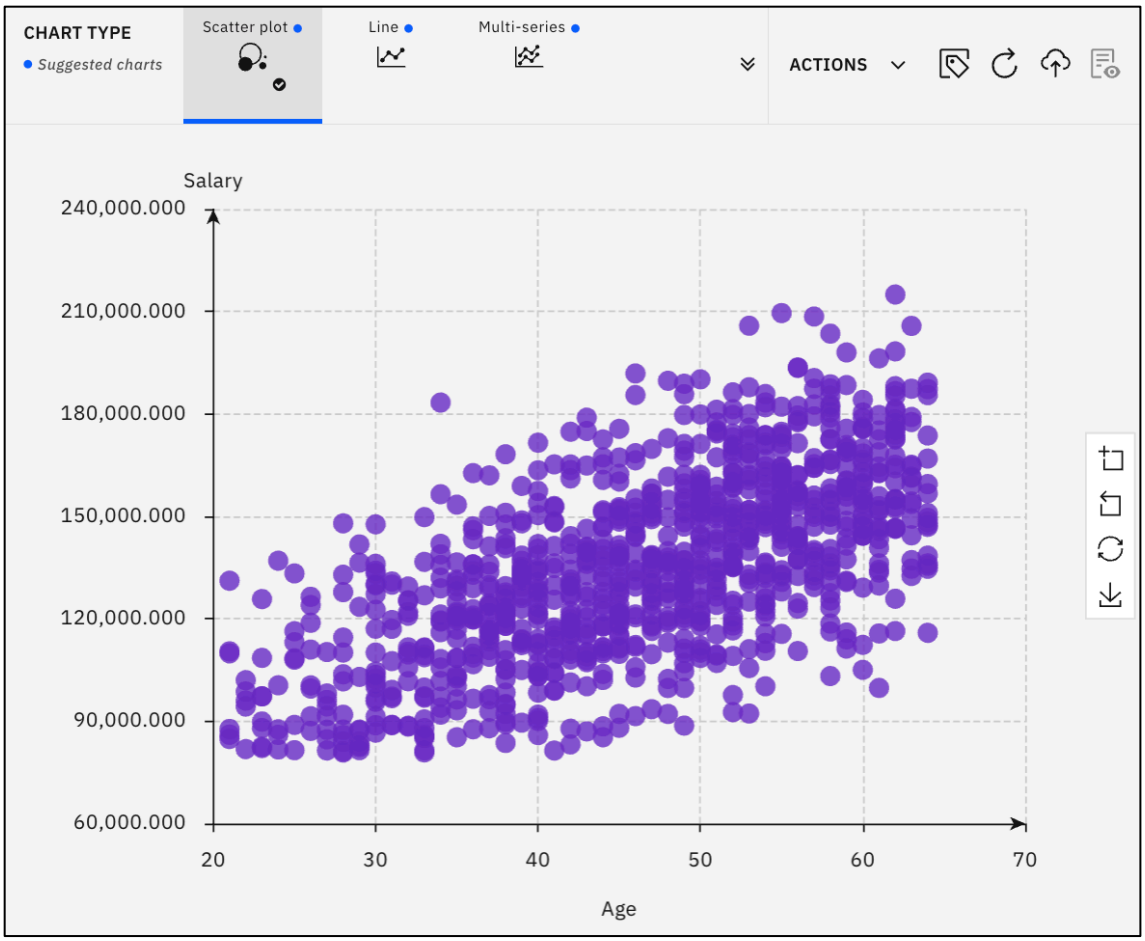
23. You will see something similar to this:



Looking at this though, it does NOT look realistic – because this is a perfect correlation – meaning that the older you get, the higher your salary. While this may be a general trend, experience tells you that it is not realistic. You need something with more variance.

24. You realize that setting the value for **Correlation** to **1** in Step 5 is the problem. To get a more realistic set of data, repeat Steps 5-13. This time setting the value of **Correlation** to **0.8** in Step 5. Run through Steps 6-13 to re-generate and visualize the data again.

    Now, you should see a scatter plot looking similar to this:



You can other values such as **0.7** if you want. However, this set of data looks reasonable to be used.

Section summary

In this section, you generated synthetic data to your specifications. IBM watsonx.ai provides a wide range of capabilities – allowing you to control how the data can be generated, including:

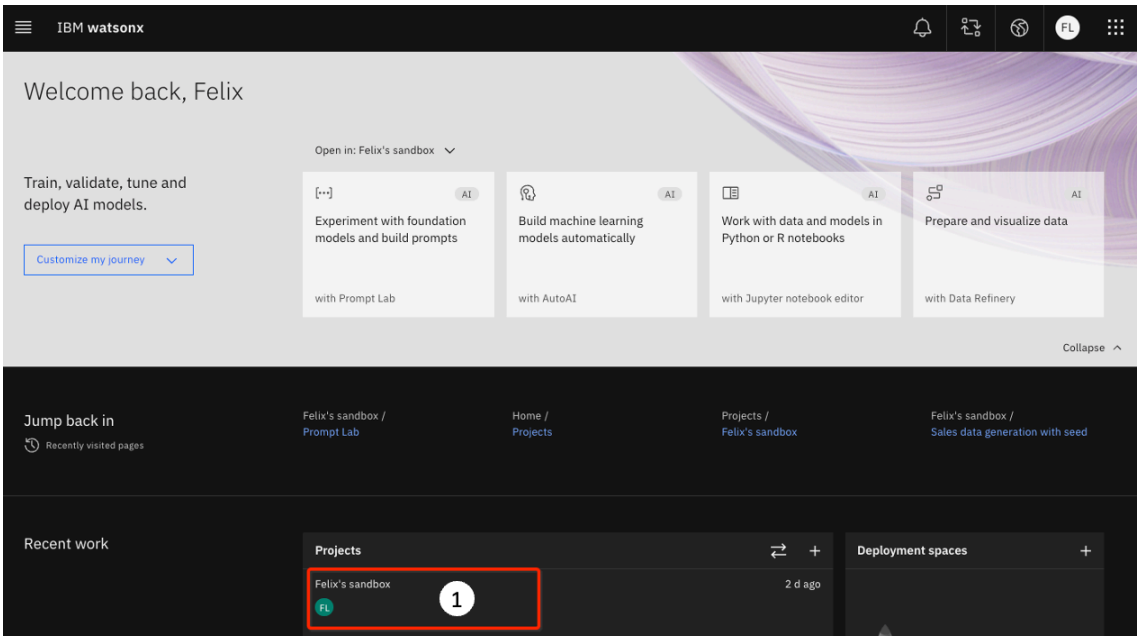
- Columns of different types: string, integer, real, time, date, timestamp
- Different data distributions: normal, binary, binomial, and categorical. See Appendix B for more information. This provides the ability to create data that resembles real-life data.
    - You can do “manual” probability assignments to entries like you did in Section 5.1 Step 2. However, keep in mind that as you may be generating hundreds of thousands of rows this can be time-consuming.
- You can define maximum and minimum boundaries for data distribution to reflect real-world data.
- You can define the correlation between different columns to reflect real-world data.

6.2 Create synthetic data by mimicking existing data/schema

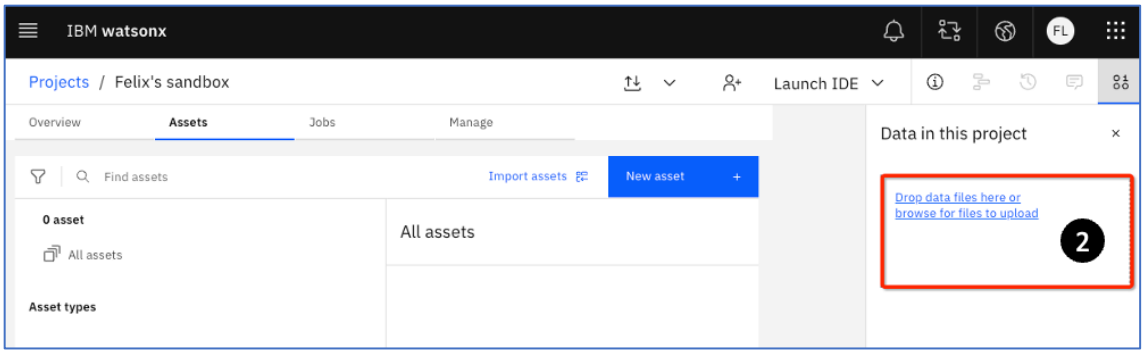
Another way to generate a large body of synthetic data is by leveraging existing data. In this section, you will provide a small sample to watsonx.ai and generate a large set of synthetic data that resembles the characteristics of your input data (in distribution, correlation, etc.).

6.2.1 Adding data asset to your sandbox project

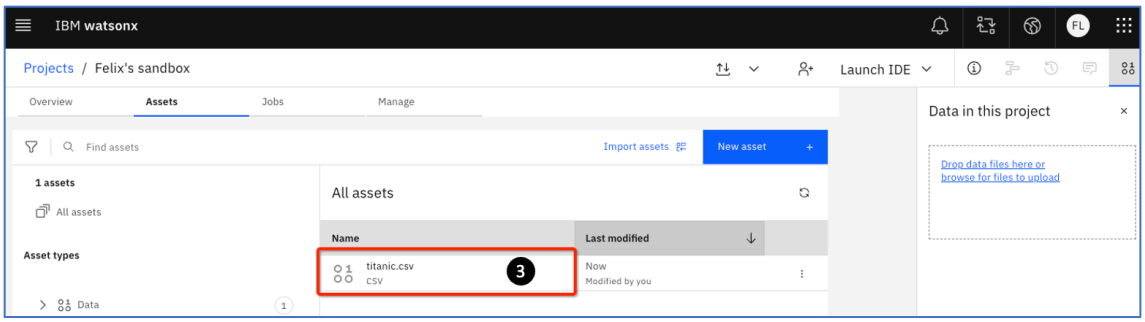
1. Open the watsonx.ai console and click on the sandbox project: **<your name> sandbox**.



2. Download this data asset from this link as a seed file. Store on a local directory. Add the file to your project by clicking on the **Drop data files here or browse for files** link to upload the **titanic.csv** file from a local directory.



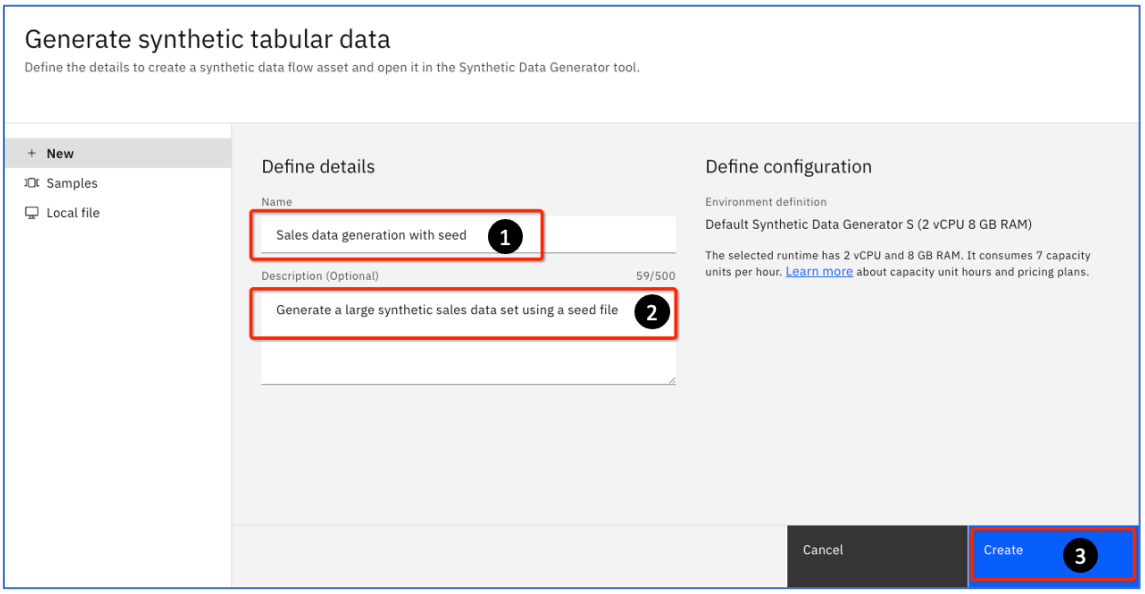
3. The sandbox project page opens. You will see that this file shows up in the **Assets** tab.



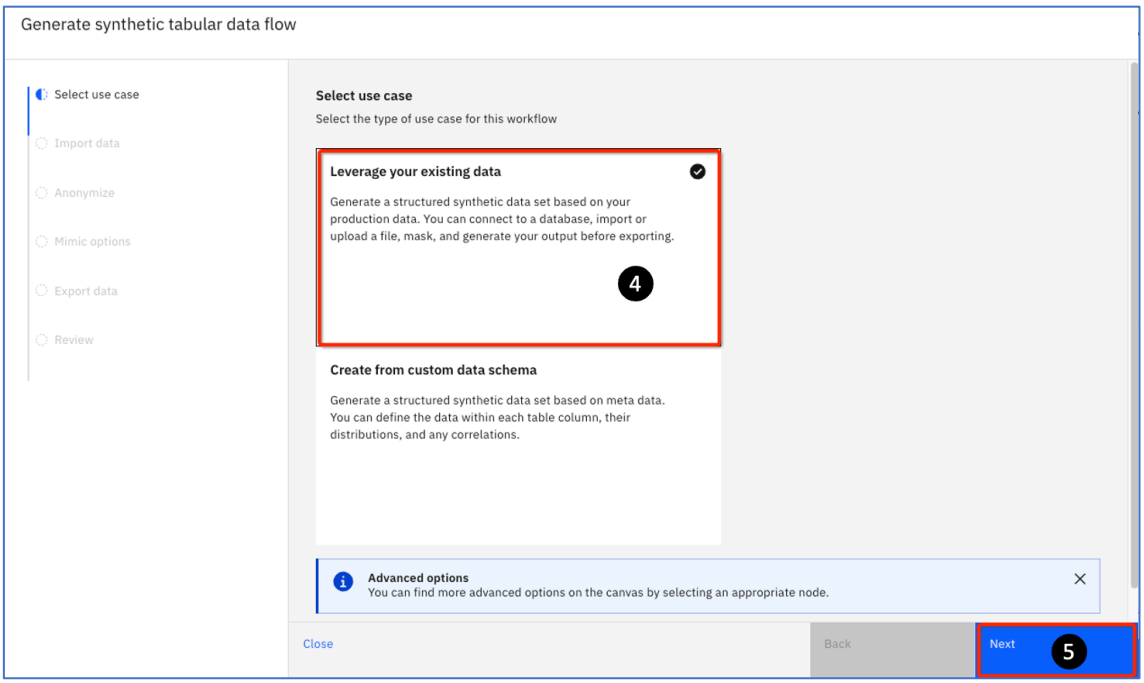
6.2.2 Generating data with a seed file

Repeat Steps 1 – 5 from Section 5.1. For Step 5, use the following values:

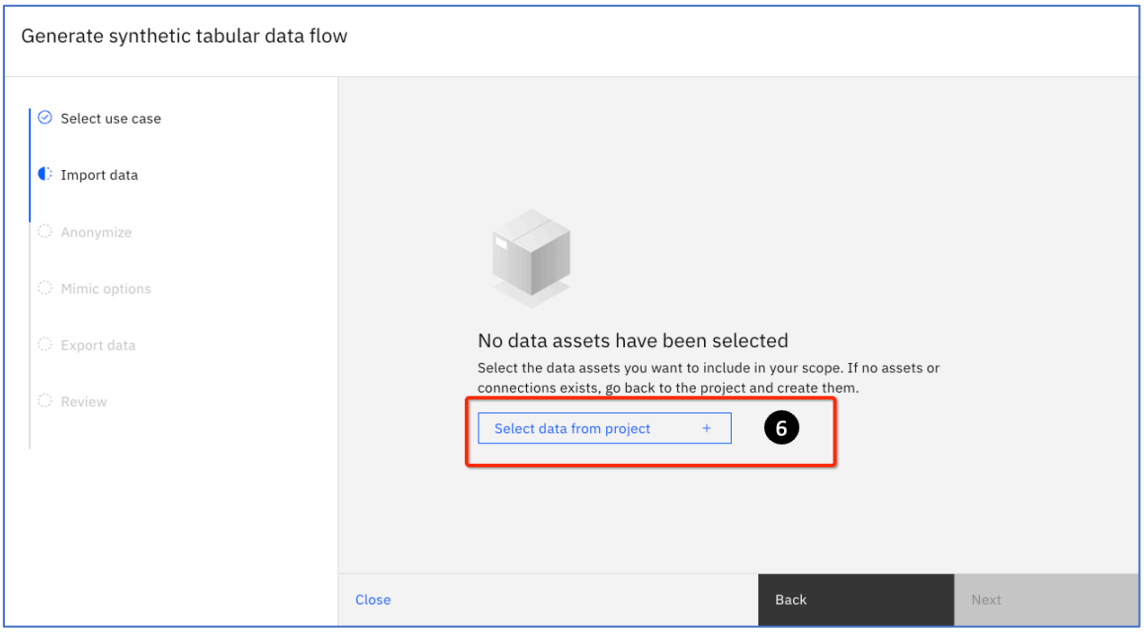
1. For **Name**: Enter **Sales data generation with seed**
2. For **Description**: Enter **Generate a large synthetic sales data set using a seed file**
3. Click **Generate**.



4. Repeat Steps 6 – 9 from Section 5.1. Only this time for Step 9, select the **Leverage your existing data** use case on the **Select use case** tab.
5. Click **Next**.



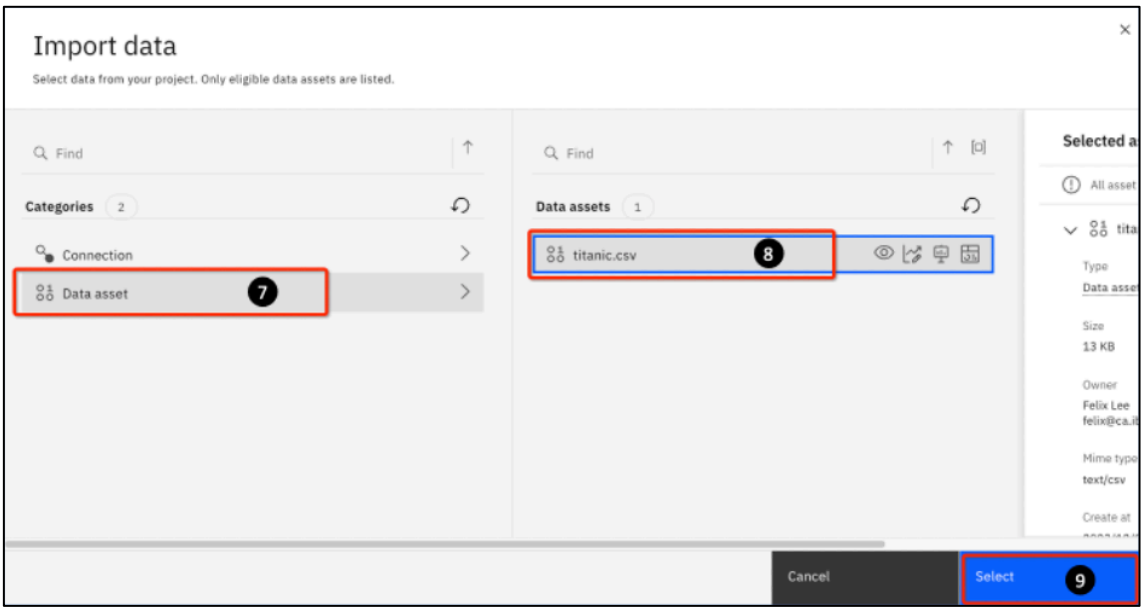
6. The focus is changed to **Import data** task. Click on **Select data from project**.



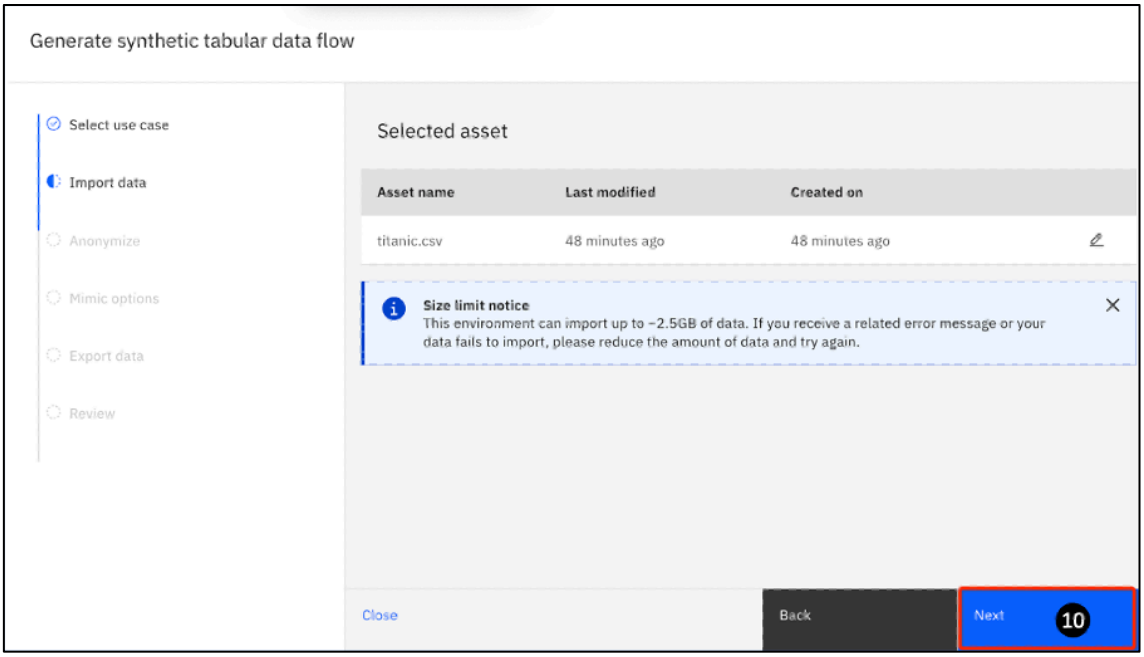
7. Click on **Data asset**. This will slide open a pane on the right.

8. Select the **titanic.csv** file.

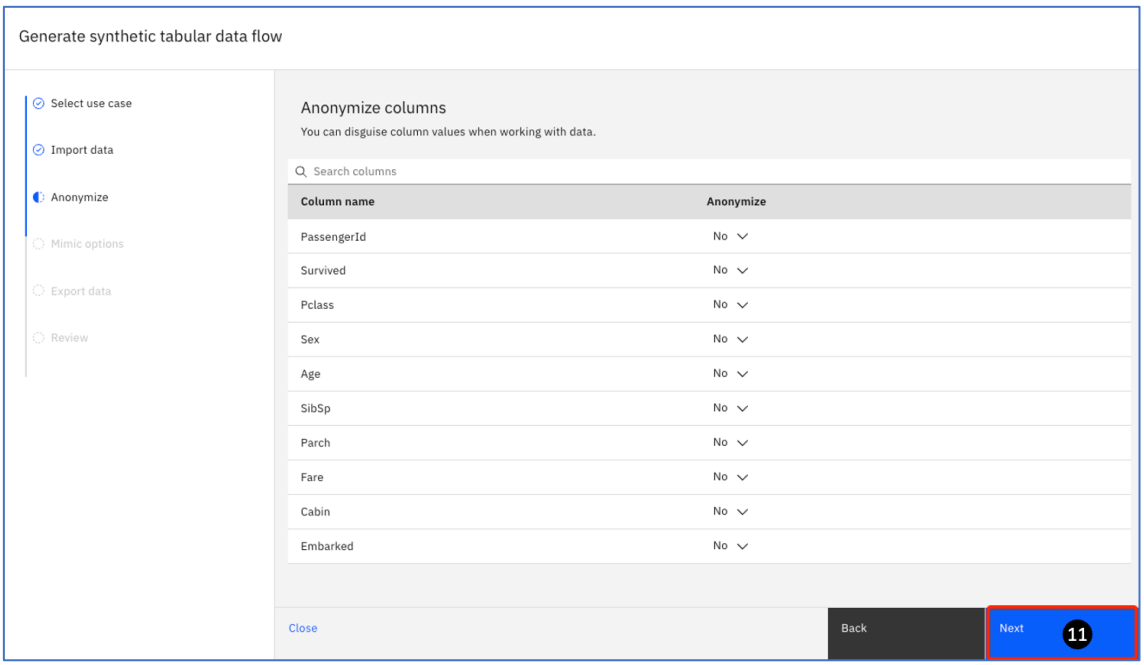
9. Click **Select**.



10. You are returned to the **Generate Synthetic tabular data flow** page. Note that the **titanic.csv** file has now been imported. Click **Next**.



11. Focus now changed to the **Anonymize** task, options are provided to determine if any columns need to be anonymized. For this lab, anonymization is not required. Click **Next**.



12. This tab lets you some **mimic** options. In **mimic**, the synthetic data generated takes on the characteristics of the input data (in terms of data type, distribution, etc.) By default, watsonx.ai will generate 100,000 rows. For this exercise, change **Number of rows** to the minimum number allowed: 1,000.

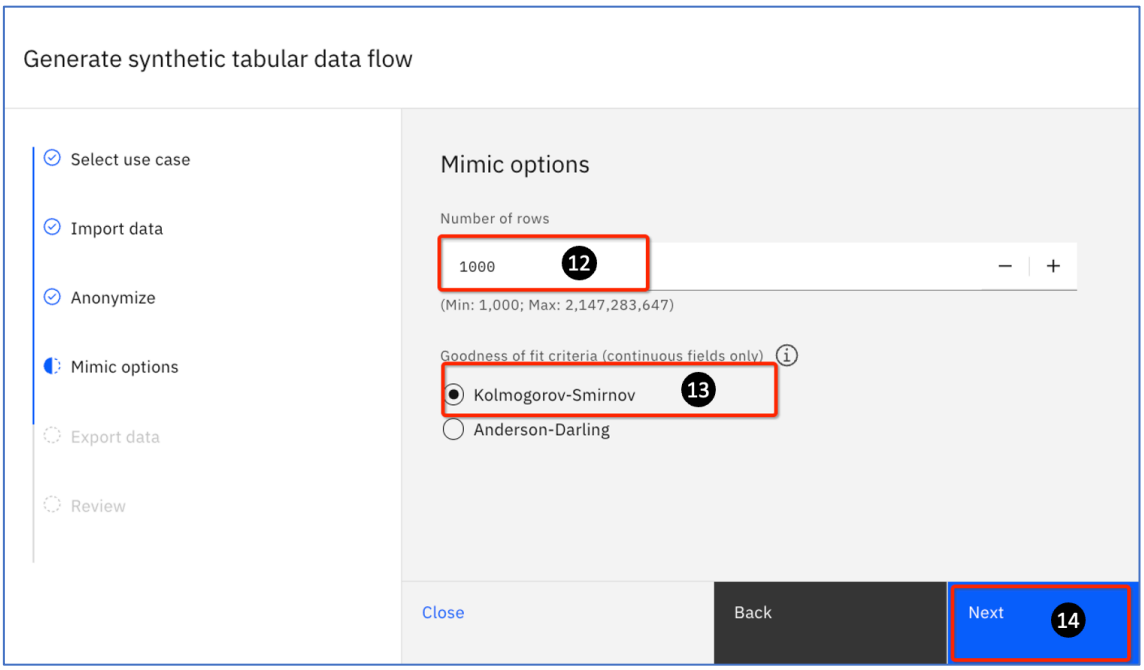
13. For the **Goodness of fit** criteria, use the default **Kolmogorov-Smirnov**.

    Both **Kolmogorov-Smirnov** and **Anderson-Darling** are statistical tests that measure how close are two sets of data (the seed data and the one being generated).

    Kolmogorov-Smirnov is a better test for the more sensitive data around the center of the data distribution, whereas Anderson-Darling is more sensitive to the tails.

    For this exercise, simply take the default.

14. Click **Next**.

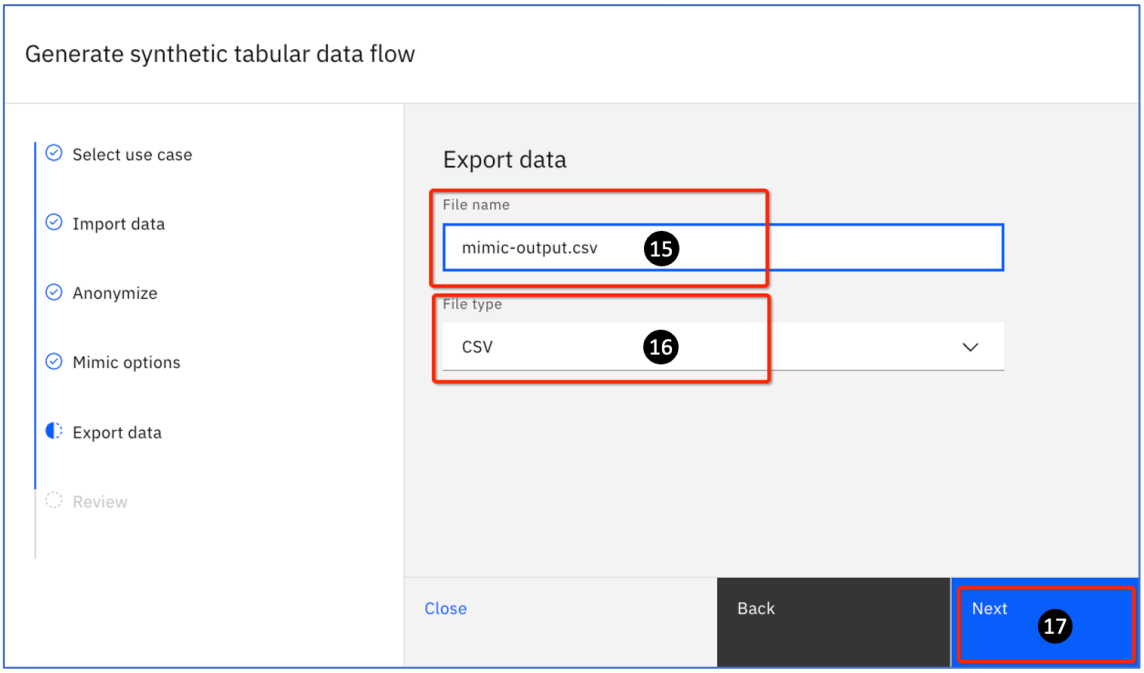


15. For **File Name**: Enter **mimic-output**

16. For **File type**, keep the default value of **CSV**

    Note: There are other formats like - delimited, Excel, JSON, parquet, SAV, XML).

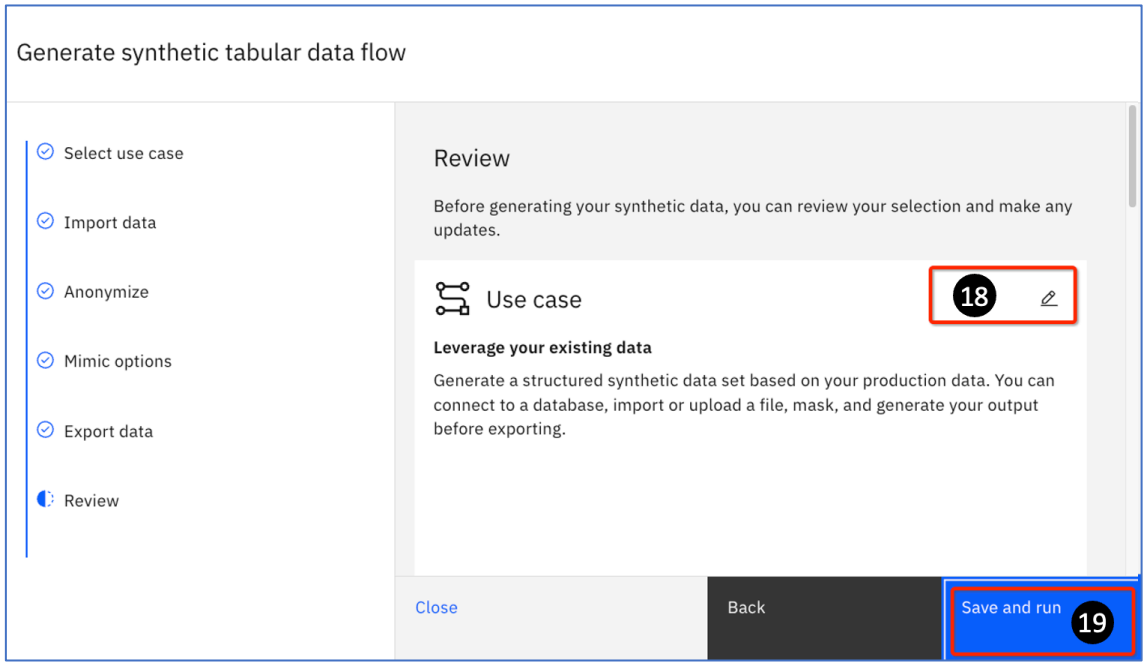
17. Click **Next**.



18. Focus is now on the **Review** task. Click the **Edit** icon ( ) repeatedly to step through Steps 5 through 17. Review the information.

    Use case: Leverage your existing data
    Import data: titanic.csv
        Number of columns:12
        Anonymize: 0
    Mimic options:
        Number of rows: 1000
        Goodness of fit: Kolmogorov-Smirnov
    Export data: Export as: mimic-output.csv

19. After verification click on **Save and run**.

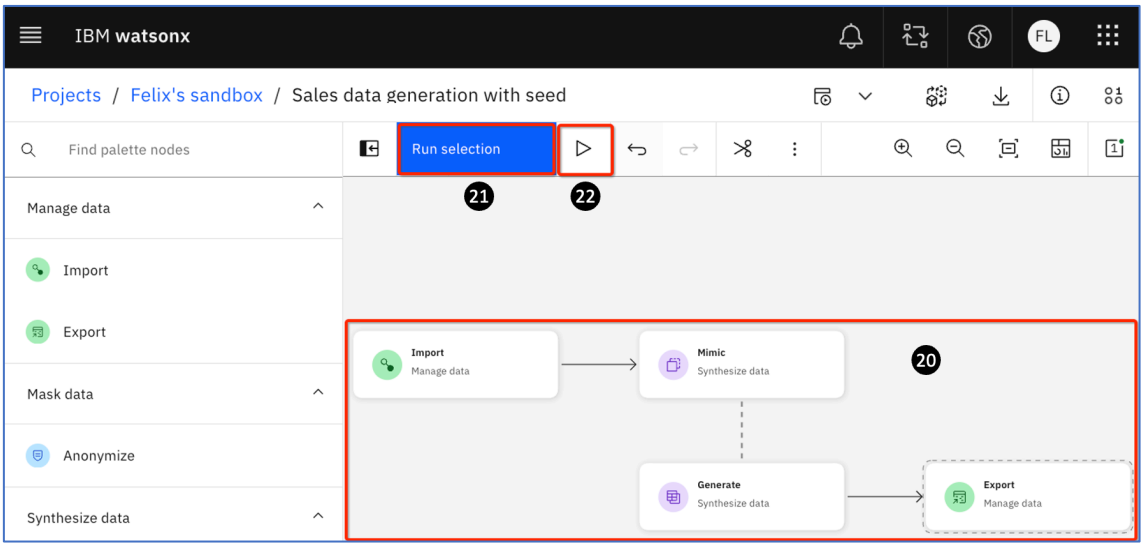


20. The next page shows a graphical representation of the tasks. There are 4 main areas:

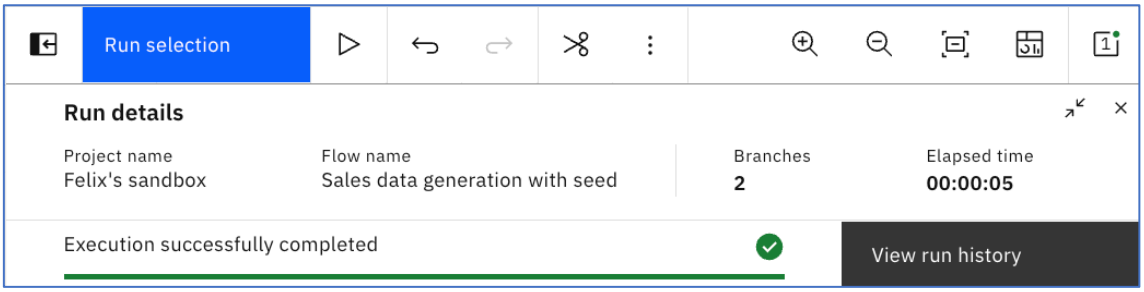
    - **Import** – this is where you define how you want to generate your data.
    - **Mimic** – this is where the data is mimicked.
    - **Generate** – this generates data.
    - **Export** – this is where you define how you want to export your output – in this example, this would be in a CSV file named **output.csv**.

21. **Run selection** – you can choose to run Generate on its own (to do so, click the **Generate** tile before clicking **Run** selection) before running the **Export** pipeline; or you can choose to run both steps in one pass.

22. Click the **Play** icon to run all nodes in the pipeline.



23. The pipeline will take some seconds to run (it can vary depending on the availability of resources – anywhere from several seconds to tens of seconds, so be patient if it takes a little longer). You will see a quick summary as follows:

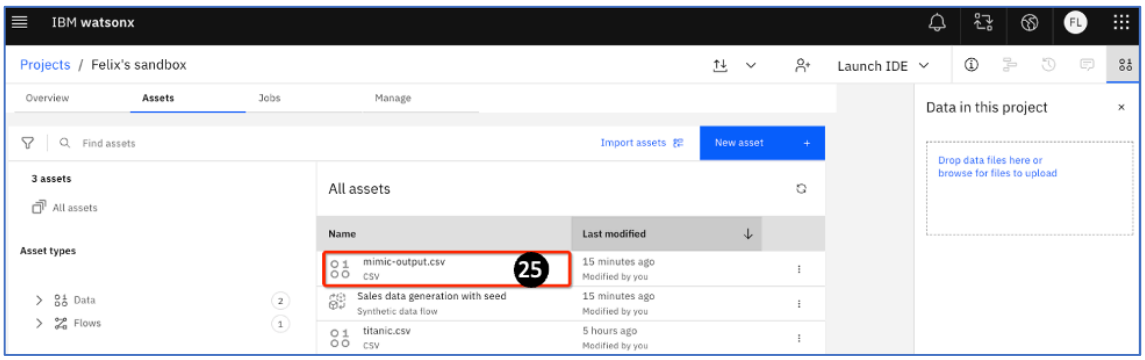


24. Go to the breadcrumb and click your project (likely **<your_name>'s sandbox**).

25. You will see the following (you may have other assets):

- CSV: is the output file **mimic-output.csv**
- Synthetic data flow is the name you used: Sales data generation with seed
- The original file – **titanic.csv**

Click on **mimic-output.csv** to look at the newly generated dataset. This contains 1000 rows of synthetically generated data.

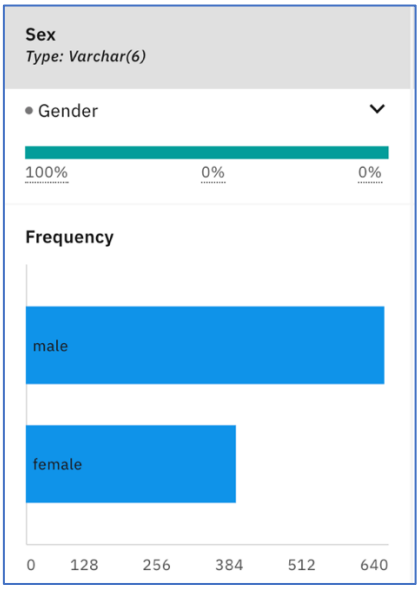


26. The output should look something like this:

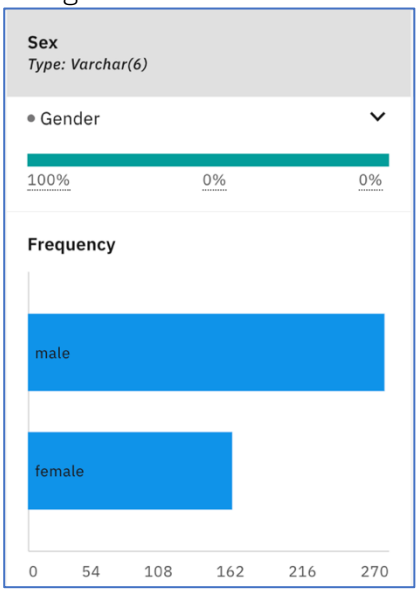
PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare	Sex	Cabin	Embarked
1116	0	1	33.270904	1	1	49.675491	male	A21	S
1076	0	1	42.687557	0	1	60.103383	male		S
1114	0	2	5.77919	1	1	21.437806	female		S
1197	0	0	40.851028	0	0	88.615865	male		S
1265	0	2	29.030022	1	1	29.129059	female		Q
969	0	1	23.4798	1	0	53.02443	female	C54	S
1130	0	2	31.980727	0	0	15.564615	female		S
1195	0	1	28.946602	1	-1	22.435221	female		S

27. Now let's compare the distribution of the original data set and the generated dataset. As you can see, the distributions for gender/sex are similar for both the generated dataset and the original dataset.

Generated dataset

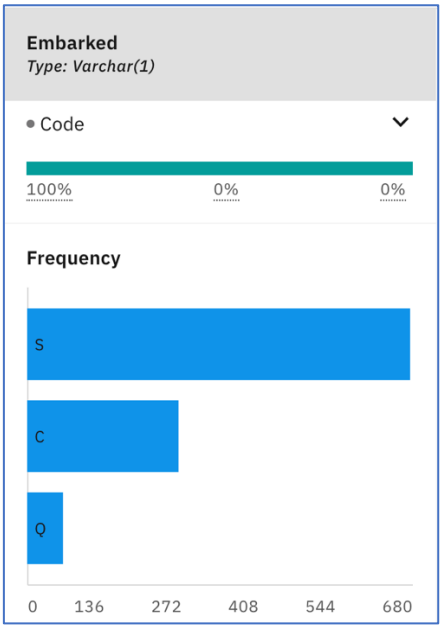


Original dataset

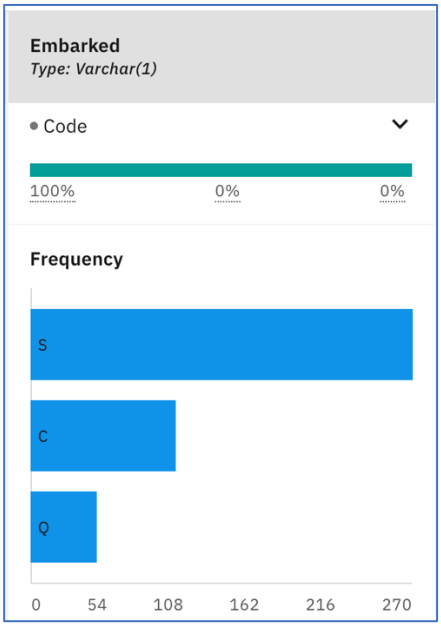


Similarly, the distribution of **Embarked** looks similar.

Generated dataset



Original dataset



Section summary

In this section, you generated synthetic data using an existing dataset. IBM watsonx.ai provides a wide range of capabilities – allowing you to control how the data can be mimicked, including:

- The number of data points that you want to generate.
- Different methods to generate data - Kolmogorov-Smirnov and Anderson-Darling
- You can also choose to anonymize some columns.
- You can profile the datasets and build correlations between different columns to reflect real-world data.

The advantage of generating data using a seed file is that there is no need to manually define the data schema. Its distribution will also closely resemble that of the input data. If the input data is a good representation of the overall dataset, the generated data will also resemble the client's business reality.

Appendix A. Revision History

Date	Changes
-	Original version.