

# Data on Fire: A Hands-On Intro to Spark in Fabric

*Ohio North Data User Group 2026*



# Jason Romans

Cloud Data & Integration Developer

## The DAX Shepherd



X @sql\_jar

in jason-r-sql-jar

 <https://thedaxshepherd.com/>



📍 Nashville, TN, USA

🛠️ Began Career as a SQL Server DBA

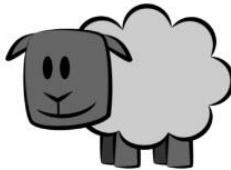
➡️ Transitioned to Microsoft BI Stack

📦 Data Engineering to Data Modeling

✍️ Infrequent Blogger

🧭 Fan of Dimensional Models & Doctor Who

# www.thedaxshepherd.com



## The DAX Shepherd

Musings on the Microsoft BI Stack



[Home](#) [About Me](#) [Simple Talk](#) [Presentations](#) [A Speaker's Journey](#)

## Presentations

### Sessionize

This is my [Sessionize Profile](#) that has the conferences I have spoken at along with future events. It has a couple of my most popular sessions.

### Presentation Slides

This is my [GitHub Repository](#) with the presentation slides for each event.

### Recorded Sessions

Simple Talks Podcast | Episode 4 – Coffee chat with Jason Romans

### About Jason Romans



I love working with the Microsoft BI Stack. I am passionate about learning.

### A Speaker's Journey

# Shoulders of Giants



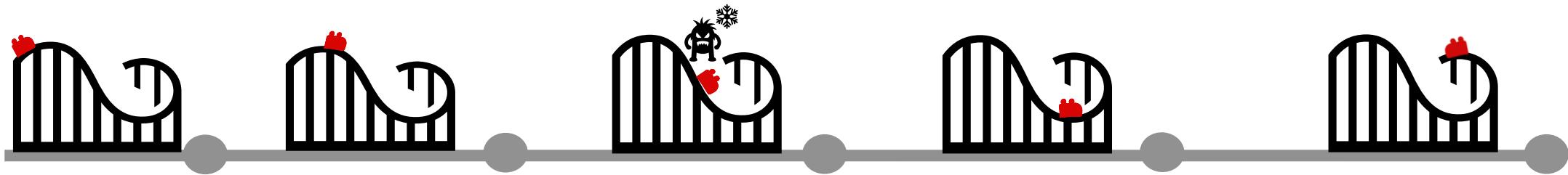
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# Our Journey

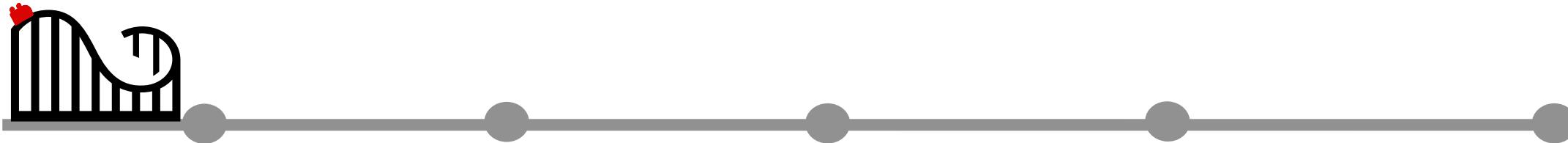
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- 1. Intro**
- 2. Python**
- 3. PySpark**
- 4. Uses**
- 5. Conclusion**

# Our Journey

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**1. Intro**

2. Python

3. PySpark

4. Uses

5. Conclusion

# What lit the fire for Apache Spark

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The Netflix Prize

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Began Oct 2006

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Goal - improve Netflix's Cinematch algorithm by at least 10%

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Prize was 1 million dollars

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Took until 2009

# Couldn't the Elephant\* Help?

\* Hadoop's Mascot is an Elephant

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Hadoop was not optimal for Machine Learning – multiple passes over disk

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Need for new tooling

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Shift to in-memory versus disk

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Like Analysis Services Multi-Dimensional to Tabular

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Contest must have led to work on Spark

# Flashbacks of submitting homework digitally

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Front runner BellKor's Pragmatic Chaos

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Merger of teams from AT&T Labs and  
Commendo Research

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July 26, 2009 two teams met minimum  
requirements

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The Ensemble (Spark team) had a  
better improvement in score

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Lost by submitting 20 minutes later

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# What is Powered by Spark

- Apache Spark
- HDInsight
- Azure Synapse Analytics
- Databricks
- Microsoft Fabric

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**Now let us  
install  
Spark**

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# Installing Spark

## Step 1 of 42

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```
$ pip install pyspark
No-module named pip:
ModuleNotFoundError
Error importing setuptools module:
    Install' command is unavailable until setuptools is
Ensure pip, setuptools, and wheel are up to date
    For "upgrade spark pip.ptgspec "ll ergk!
Upgrade pyspark --no-cache-dir setuptools wheel
Value for scheme.headers does not match
    to avoid this problem; &f errcode, with exame>
Retrying (Retry(total=4, connect=-4323 after Exceptilo
    annotate; error: (versygtut), line 230, init _eforl
File '/usr/lib/python3.8/supprocs.py', line 231, in me
    trod self.s.connect(sockaddr canne) timeout
File '/usr/lib/python3.8/soket.py', line 26,i meth
    self.s..connect(sockaddr)
Internal to an attack           involve'nexit
Collecting pyspark _apack-3.2.1-bin-hadoop3.2.cg int
Downloading Apache-spark-3.2.1-i-nstaller
    error Value" for scheme.headers does not matchc; ae' matc
    to avoridel tryin connect be found;> to avoid this problem
Retrying (Retry(total=<connect=,) after Exception annotate
-- again:z https://files.pythonhosted.org(hjaps://packages/5665f.1
    (https:'files.pythonhosted.org(hjaps://packages/5665f.1
    confirming) package failed: There was a p: '_crobiemt t
Exception (oo problem confirming the ssl certificate: HTTPS
ssl-certificate:mTTTSPconnectiunool Connection annicatetot/
(host='>>'https://pypu-1.json&oh=t> HTTPSConnectinPool(mol
Could not install pagages due to an vo space on device
[Errno 28) no insstall paccages due to an an an OSEserer:
```

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**Wait!**  
**Microsoft**  
**Fabric makes**  
**this easy**

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# **Notebooks in Microsoft Fabric**

Can apply to other environments

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# Notebook Gallery

[https://community.fabric.microsoft.com/t5/Notebook-Gallery/bd-p/pbi\\_notebookgallery](https://community.fabric.microsoft.com/t5/Notebook-Gallery/bd-p/pbi_notebookgallery)

There was a notebook contest (it is closed now):

<https://powerbi.microsoft.com/en-us/blog/introducing-the-first-ever-fabric-notebooks-competition-for-power-bi/>

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# **Microsoft Fabric Architecture**

- Data is stored in OneLake

# ONELAKE

"THE ONE DRIVE  
FOR YOUR DATA"

VISUALLY  
EXPLAINED

EACH FABRIC ORGANIZATION HAS  
ONE DATA LAKE, ENTIRELY MANAGED FOR YOU  
IT'S UNIFIED ACROSS ALL REGIONS & YOU PAY  
PER GB STORED (NO SCALING NEEDED).



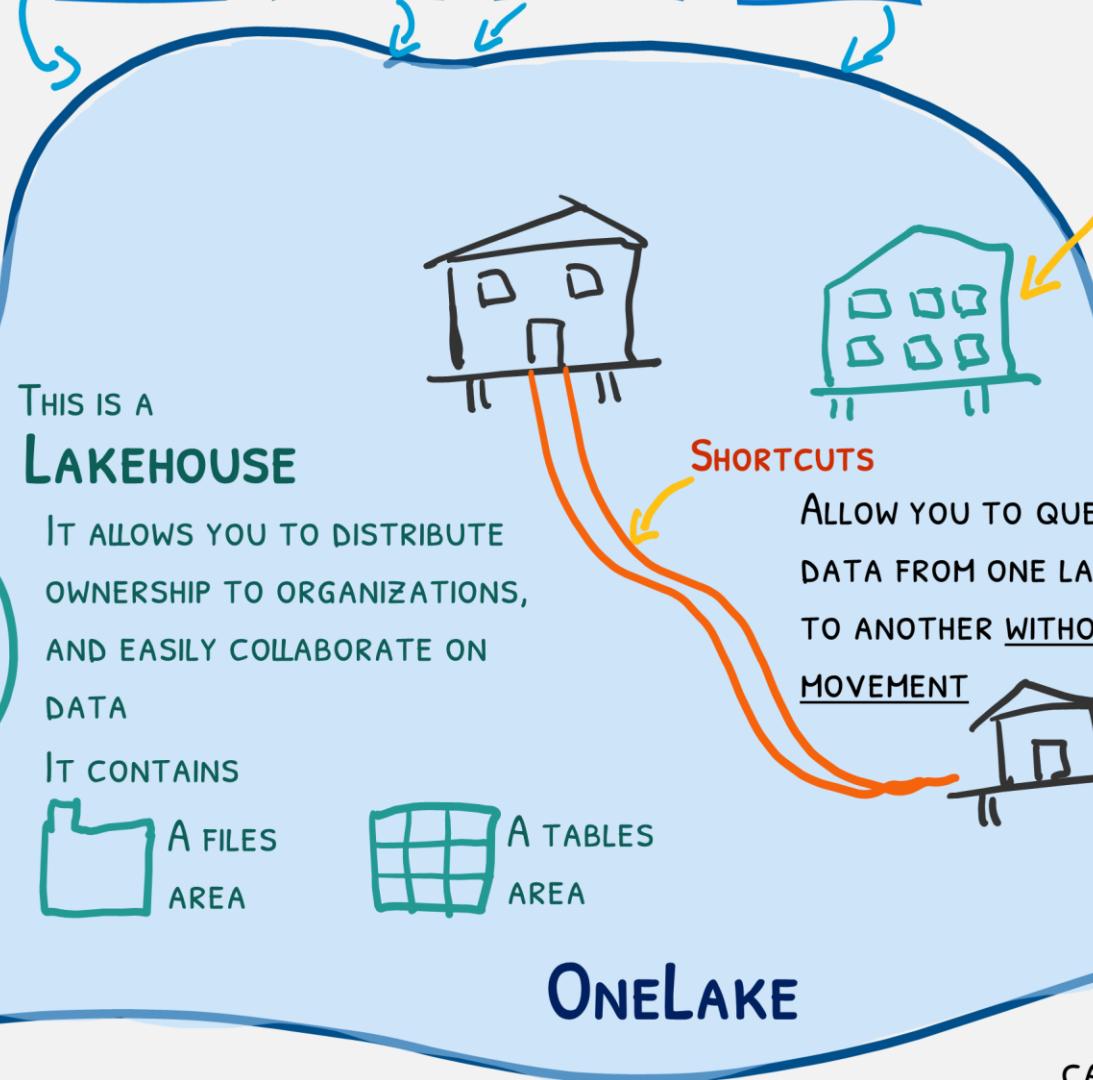
ALL ANALYTICAL ENGINES CAN ACCESS ONELAKE DATA

SQL

SPARK

POWER BI

KQL DB



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# Microsoft Fabric Architecture

- Compute engines sitting on top of files
- Languages and compute
  - i.e. T-SQL with Warehouse

# Compute & Language



PySpark (Python) ▾

Spark

✓ PySpark (Python)

Spark (Scala)

Spark SQL

SparkR (R)

Python

Python

T-SQL Analytics

T-SQL

# Spark (Python, Scala, SQL, R)

PySpark (Python) ▾

Spark

✓ PySpark (Python)

Spark (Scala)

Spark SQL

SparkR (R)

Python

Python

T-SQL Analytics

T-SQL

# Python (Python)

PySpark (Python) ▾

Spark

✓ PySpark (Python)

Spark (Scala)

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SparkR (R)

Python

Python

T-SQL Analytics

T-SQL

# T-SQL Analytics (T-SQL)

PySpark (Python) ▾

Spark

✓ PySpark (Python)

Spark (Scala)

Spark SQL

SparkR (R)

Python

Python

T-SQL Analytics

T-SQL

# Choosing PySpark or Python Compute (quick)

Scenario	Recommended Notebook
Includes pre-installed DuckDB and Polars libraries	Python Notebooks
Small to medium data (fits in memory)	Python Notebooks (or PySpark on single-node Spark cluster)
Rapid exploration & prototyping	Python Notebooks (or PySpark on single-node Spark cluster)
Large datasets (10GB+) exceeding memory	PySpark Notebooks
Complex data workflows or ETL pipelines	PySpark Notebooks
High-concurrency or parallel execution	PySpark Notebooks
Needs Spark-native APIs (MLlib, SQL, Streaming)	PySpark Notebooks

<https://learn.microsoft.com/en-us/fabric/data-engineering/fabric-notebook-selection-guide>

# Choosing PySpark or Python Compute

Scenario	Python Notebooks (2-core VM)	PySpark Notebooks (Spark Compute)
Startup Time	The built-in starter pool initializes in approximately 5 seconds, while the on-demand pool takes around 3 minutes.	Start-up ranges from ~5 seconds (starter pool) to several minutes (on-demand Spark clusters).
Quick Transformations & API Calls	Ideal for small to medium sized datasets (up to 1GB)	Optimized for large datasets using vectorized execution.
Moderate Workloads	Not optimized for data sizes nearing memory saturation	Efficient at scaling via distributed compute.
Handling of Large Datasets	Limited by single-node memory. May struggle with scaling.	Distributed processing ensures scalable handling of multi-GB to TB workloads.
High-Concurrency Execution	Manual FIFO-style parallelism per notebook	System-managed concurrency with support for parallel execution.
Resource Customization & Scaling	Fixed compute (2-core VM); does not auto scale. Users can manually scale out using %%config within the notebook.	Flexible resource allocation; supports autoscaling and custom Spark configurations.

<https://learn.microsoft.com/en-us/fabric/data-engineering/fabric-notebook-selection-guide>

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# Type of Compute for Notebooks

- Spark Based
  - Cluster
- Single Node Python
  - 2 vCores, 16G RAM
- T-SQL Analytics
  - Warehouse

# Python Notebook

- Has libraries installed for dealing with “small-big” data
  - Less than 10 Gigabytes
  - Fits in memory
- Example Libraries installed
  - Polars
  - DuckDB

# Languages for Spark

Different choices of languages

Built with Scala

- PySpark (Python)
- Spark (Scala)
- Spark SQL
- SparkR (R)



Spark

✓ PySpark (Python)

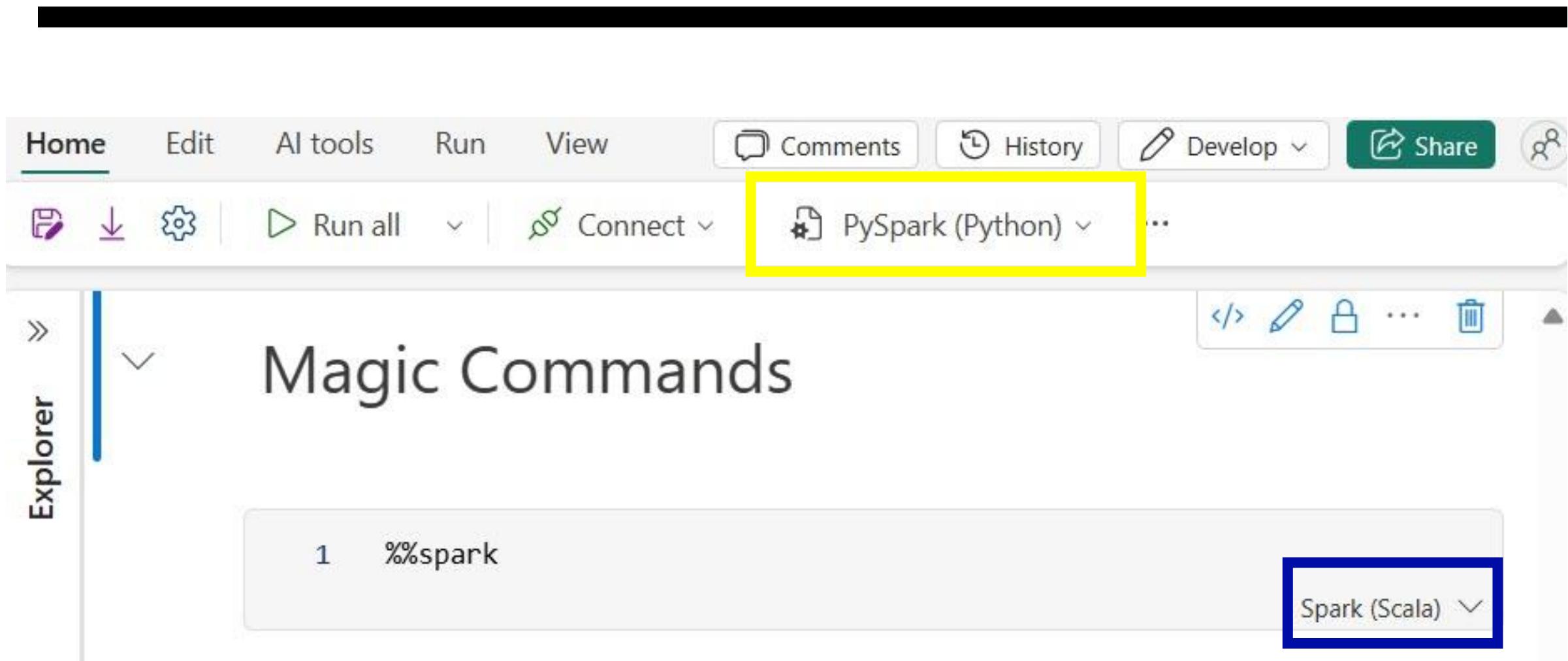
Spark (Scala)

Spark SQL

SparkR (R)

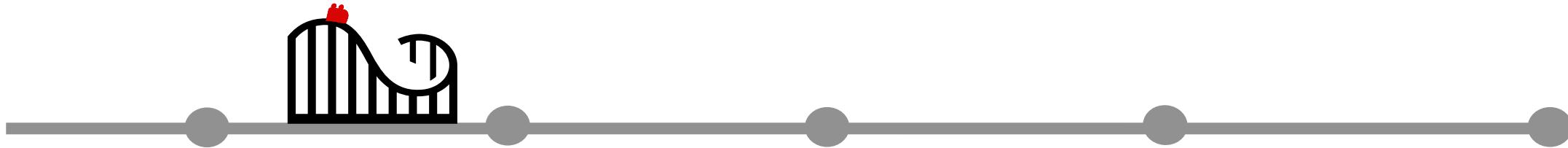
# Magic Commands – set language by cell

Magic command	Language	Description
%%pyspark	Python	Execute a Python query against Apache Spark Context.
%%spark	Scala	Execute a Scala query against Apache Spark Context.
%%sql	SparkSQL	Execute a SparkSQL query against Apache Spark Context.
%%html	Html	Execute n HTML query against Apache Spark Context.
%%sparkr	R	Execute a R query against Apache Spark Context.



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# Python Language



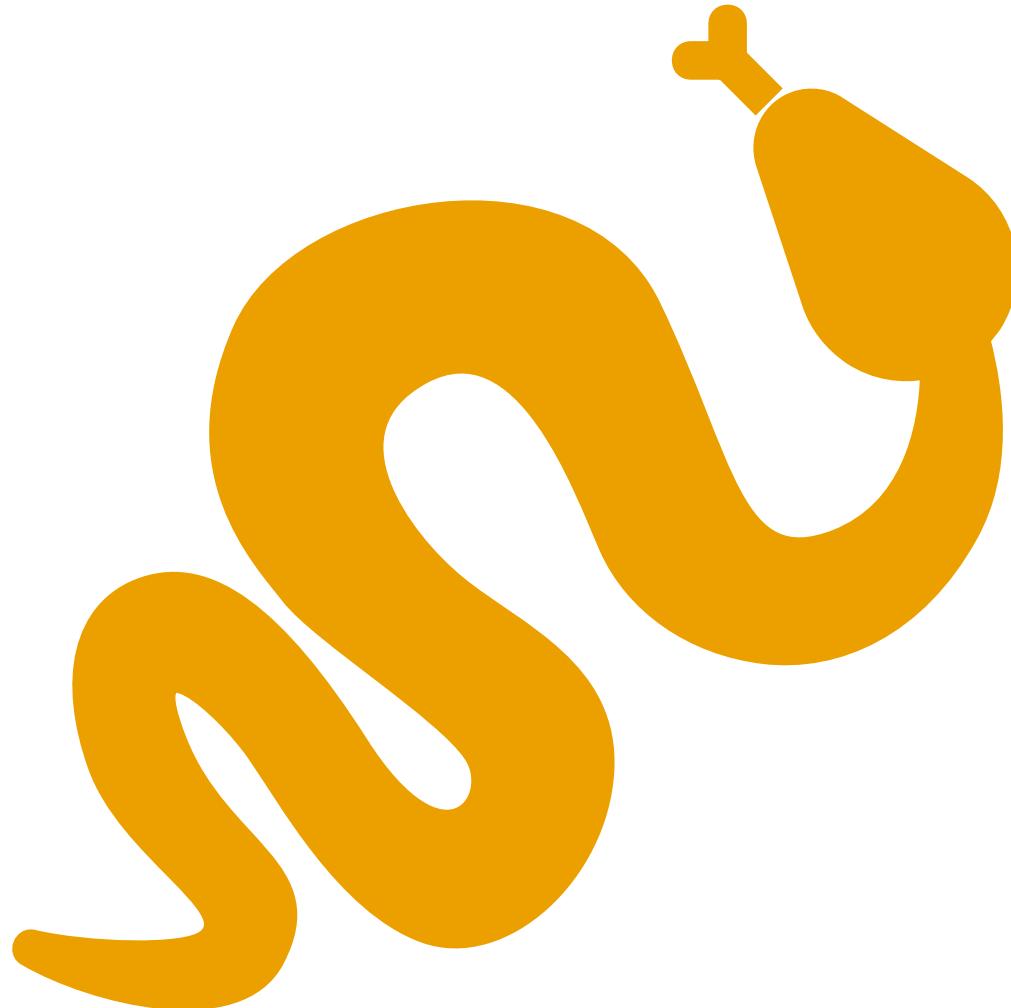
HOW YOU INTERACT  
WITH SPARK



HOW YOU MANIPULATE  
THE DATA

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# Python Demo

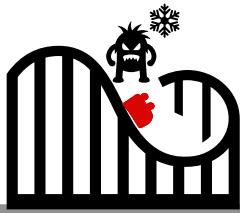


*\*\*You can thank me for not  
having an actual picture of  
a snake here*

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# Our Journey

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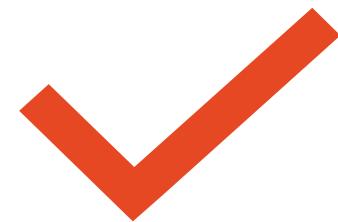


1. Intro
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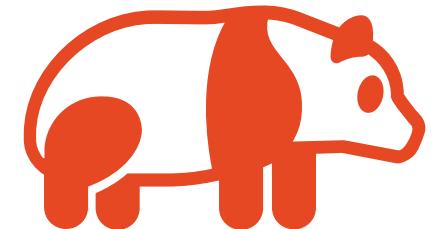
# PySpark



Python API for  
Spark



Most operations on  
a DataFrame



Like Pandas but  
distributed

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# DataFrame

- Resilient Distributed Dataset (RDD)
- Conceptually the same as a table
  - Abstraction
  - Rows
  - Columns

A close-up photograph of a black dog's head and shoulders. The dog is wearing a pair of dark sunglasses with brown frames. It is lying on a blue and green patterned blanket on a grassy surface. In the background, there are some blurred buildings and trees.

Spark is  
Lazy – in a  
good way

# Lazy Evaluation

- Waits until an action is requested
- Actions
  - Counting number of rows in a Spark DataFrame
  - Showing output
  - Writing data to a file or data source
  - Transferring data from a Spark DataFrame to a native object in Python

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# Benefits of Lazy Evaluation

- Saves resources
- Plan can be optimized

Pandas (non-spark, historic) is  
eager evaluation

# Fabric in Visual Studio Code



EDIT NOTEBOOKS

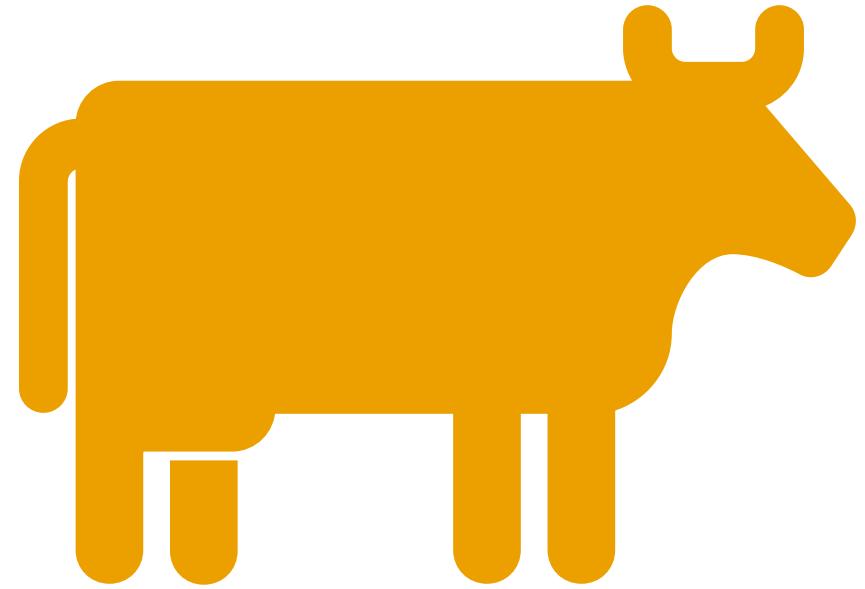


CONNECT TO COMPUTE  
IN MICROSOFT FABRIC

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# Data Wrangler

Like Power Query, but for  
PySpark and Python

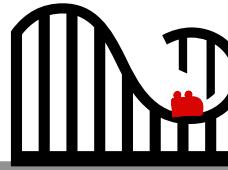


# PySpark Demo



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# Uses



**Big Data Processing** - handling massive datasets



**Machine Learning at Scale** - training ML models on large data



**Real-Time Stream Processing** - processing live data streams



**ETL & Data Pipelines** - building data workflows



**Advanced Analytics** - complex calculations and BI



**Data Exploration & Discovery** - interactive data analysis

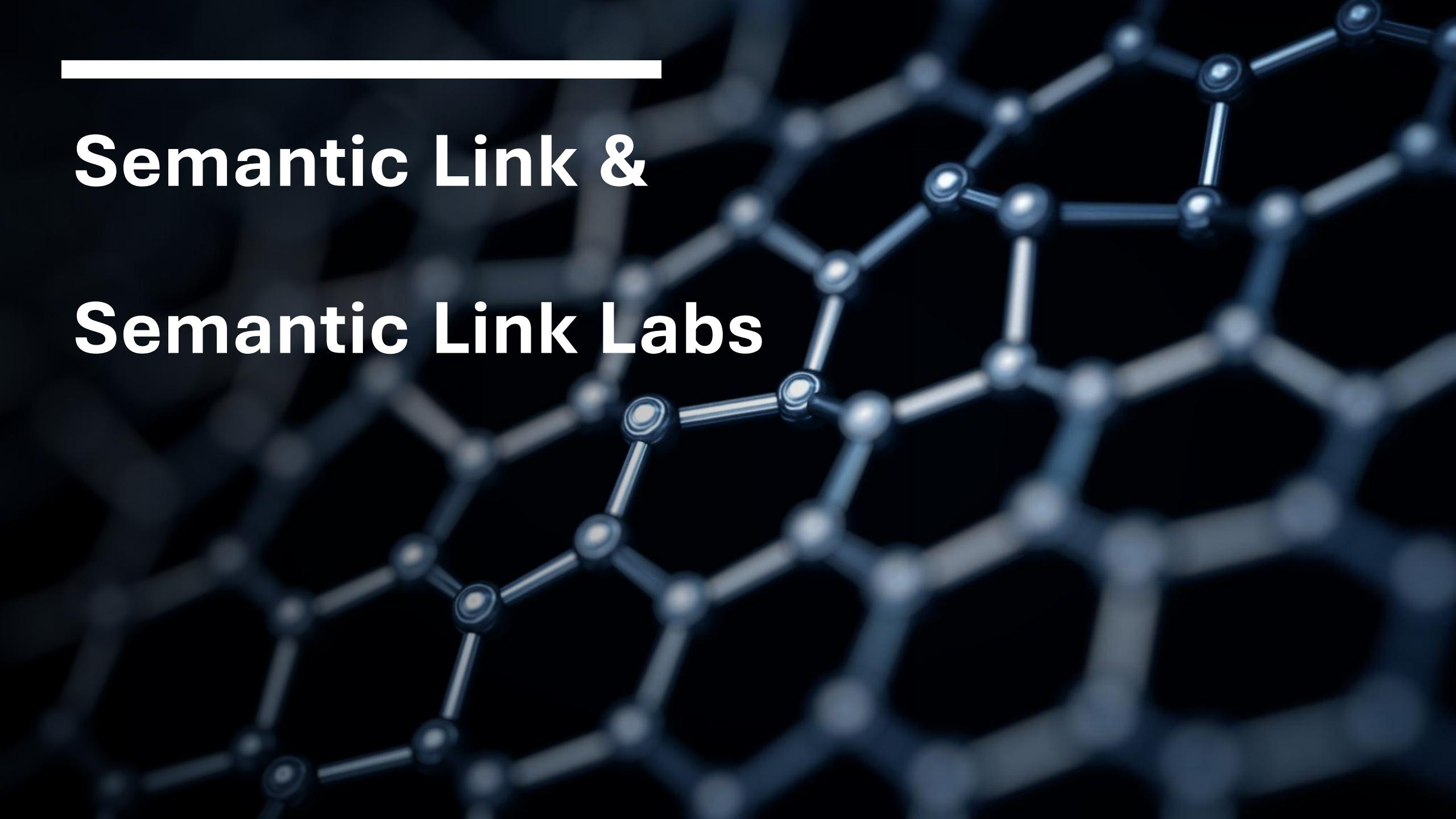
# Executing Notebook using a Pipeline

- Either
  1. Use Environment with Libraries
    - Microsoft recommended way
    - Only for Spark
  2. Python inline installation
    - Enable %pip install for pipeline, add "\_inlineInstallationEnabled" as bool parameter equals True in the notebook activity parameters.

Reference:

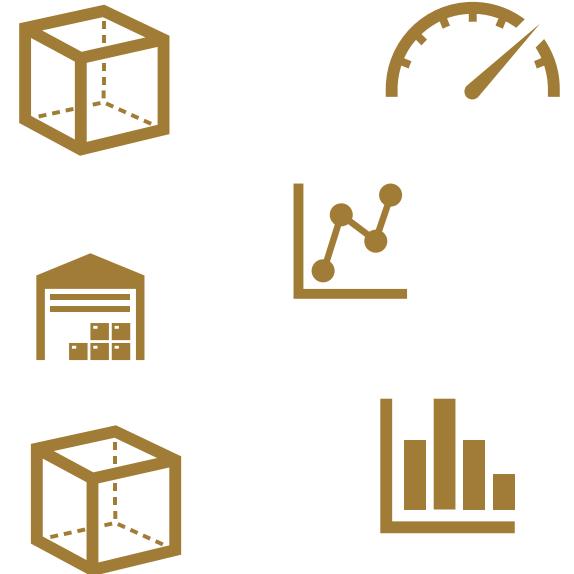
- <https://learn.microsoft.com/en-us/fabric/data-engineering/library-management>

# Semantic Link & Semantic Link Labs



# SEMANTIC LINK LABS

## Microsoft Fabric

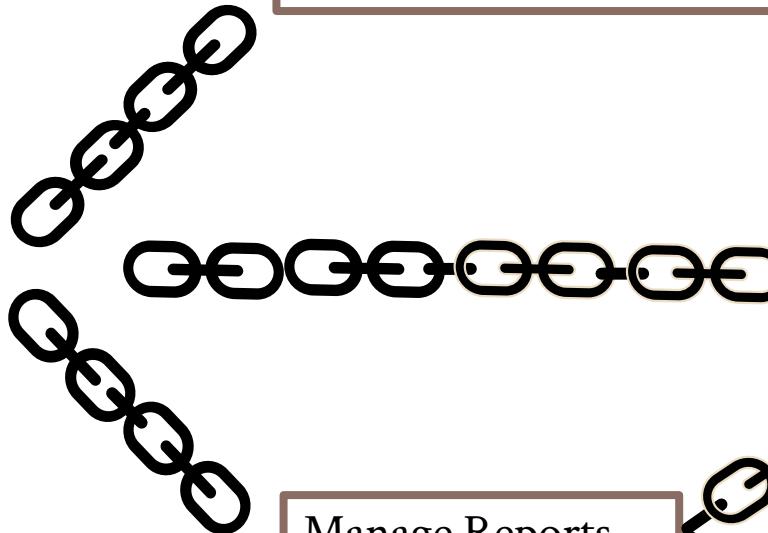


## Semantic Link

- List Tables
- List Workspaces
- List Models
- List Reports

## Semantic Link Labs

Migrate to Direct Lake



Best Practice Analyzer

View Broken Reports

Manage Reports

Rebind Reports

A close-up photograph of a person's hands against a dark background. The hands are positioned to hold a single length of red string. The string is looped and twisted, creating a complex knot or braid. The lighting highlights the texture of the string and the skin of the hands.

# Semantic Link (Labs) Demo

# Resources

## Fabric Samples

- <https://github.com/microsoft/fabric-samples>
- Semantic Link
  - <https://learn.microsoft.com/en-us/fabric/data-science/semantic-link-overview>
- Semantic Link Labs
  - <https://github.com/microsoft/semantic-link-labs>

# Resources

PySpark Book – Data Analysis with Python and PySpark

- <https://www.oreilly.com/library/view/data-analysis-with/9781617297205/>

PySpark Book – Intro to PySpark (Free HTML version)

- <https://pedropark99.github.io/Introd-pyspark/>

# Our Journey

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# Conclusion

## **Powerful and Scalable Platform**

Apache Spark in Microsoft Fabric Notebooks provides a robust and scalable solution for handling big data analytics tasks efficiently.

## **User-Friendly Tools**

The platform offers intuitive and practical tools that simplify data analysis for professionals of all skill levels.

## **Unlocking Valuable Insights**

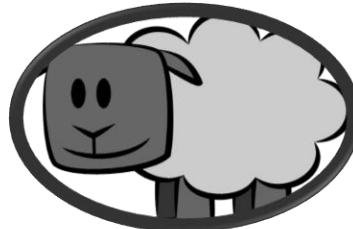
Understanding core concepts and leveraging these tools enables data professionals to extract meaningful insights effectively.

# Thank you

**Jason Romans**

**thedaxshepherd@gmail.com**

**www.thedaxshepherd.com**



**The Dax Shepherd**

