

Derived Data Challenges in Single-cell Profiling

Or, “I have profiles but where did the images go?”

Outline

1. Definitions
2. Pipelines and exports
3. Future
4. What if ...?



Definitions

Dagster Data Engineering Glossary:

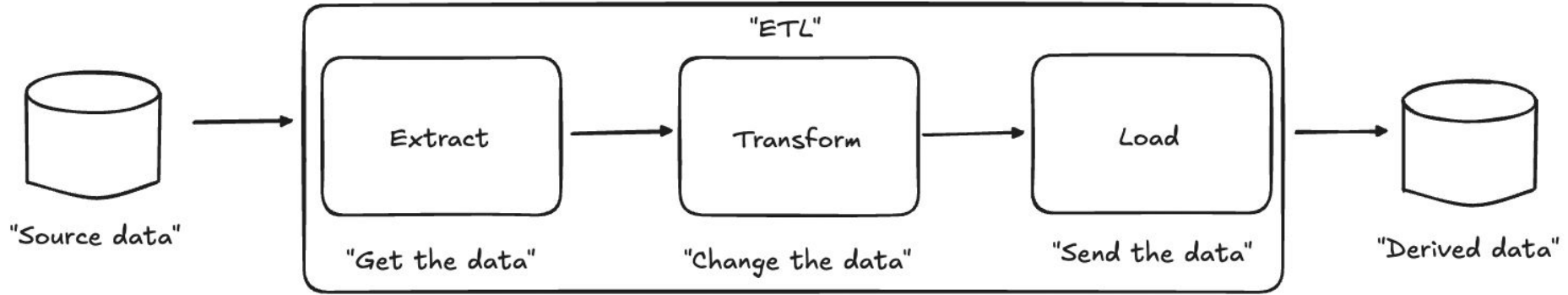
Data Derivation

Extracting, transforming, and generating new data from existing datasets.



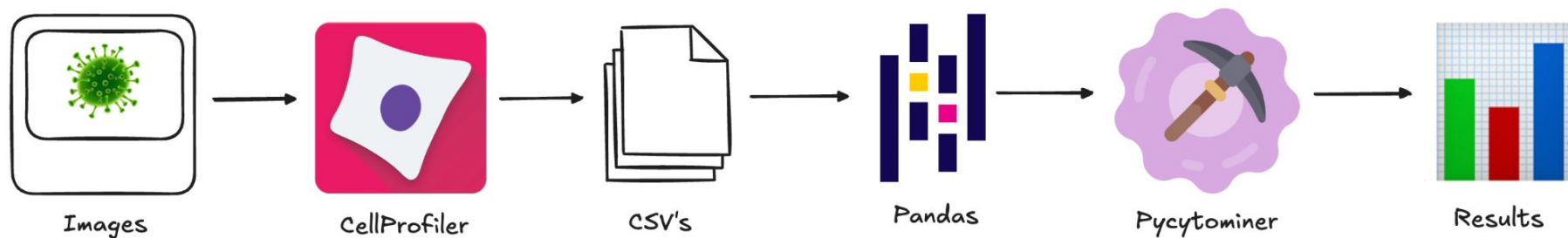
<https://dagster.io/glossary/data-derivation>

Definitions



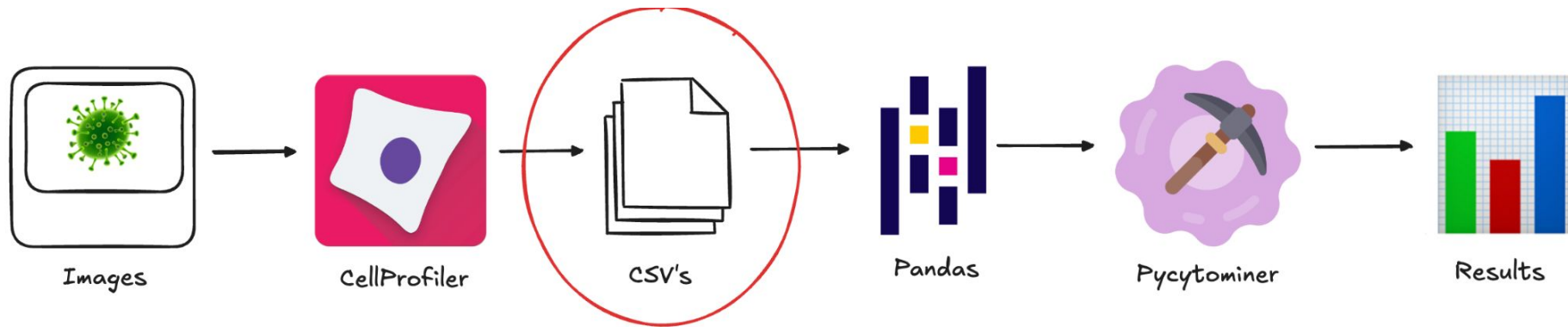
https://en.wikipedia.org/wiki/Extract,_transform,_load

Pipelines and exports



Create single-cell profiles with CellProfiler as CSV's then read them with Pandas, process with Pycytominer, and create results.

Pipelines and exports



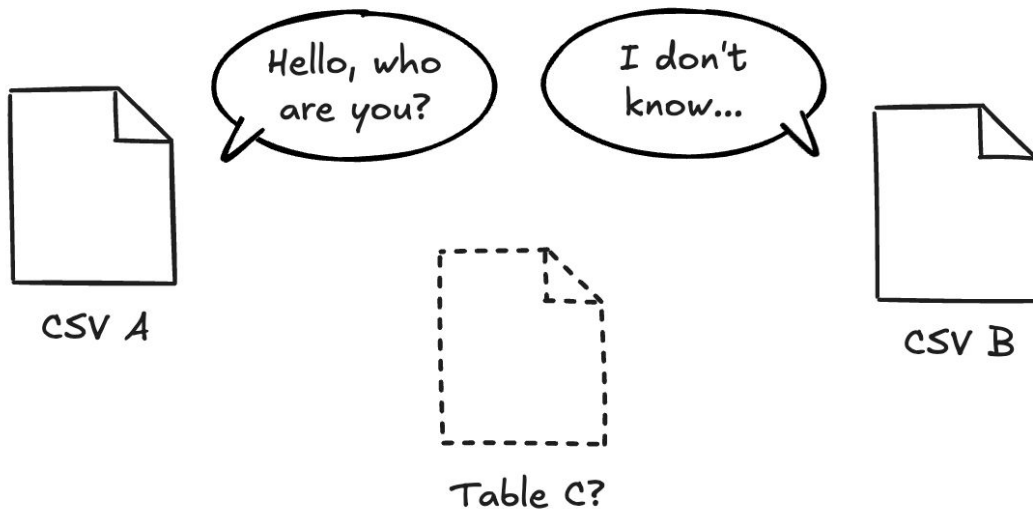
Challenge: CSV's were not built for large data operations, do not include data types, and are prone to value errors (for example, null types and floating point precision). They also have no relational model.

Pipelines and exports

```
Col_A,Col B,Col_C,COL_D  
,a,"0.01"  
2,null,0.02,{'color':'blue'}
```

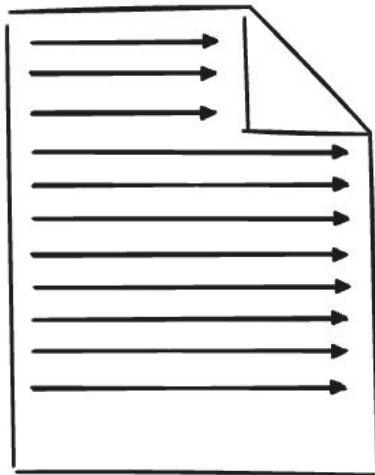
Consider the above example: multiple data types in single columns, multiple null type values, inconsistent naming, and complex data.

Pipelines and exports



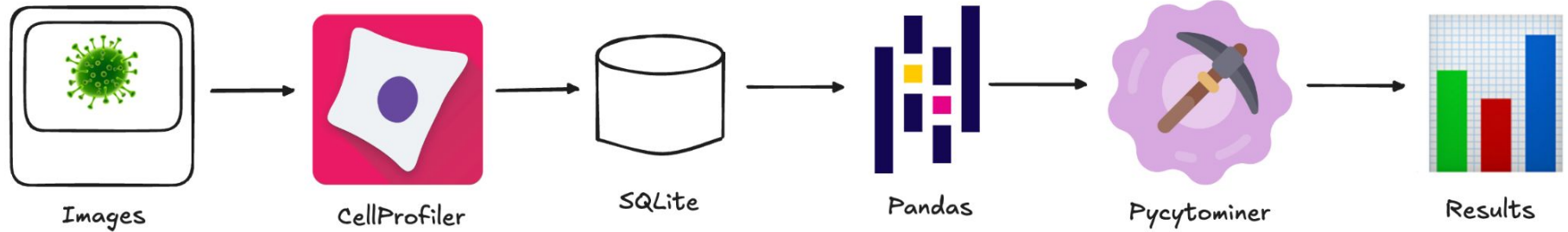
CSV's have no relational model. They're all standalone files who don't know about one another, meaning we have to infer or reinvent for any join.

Pipelines and exports



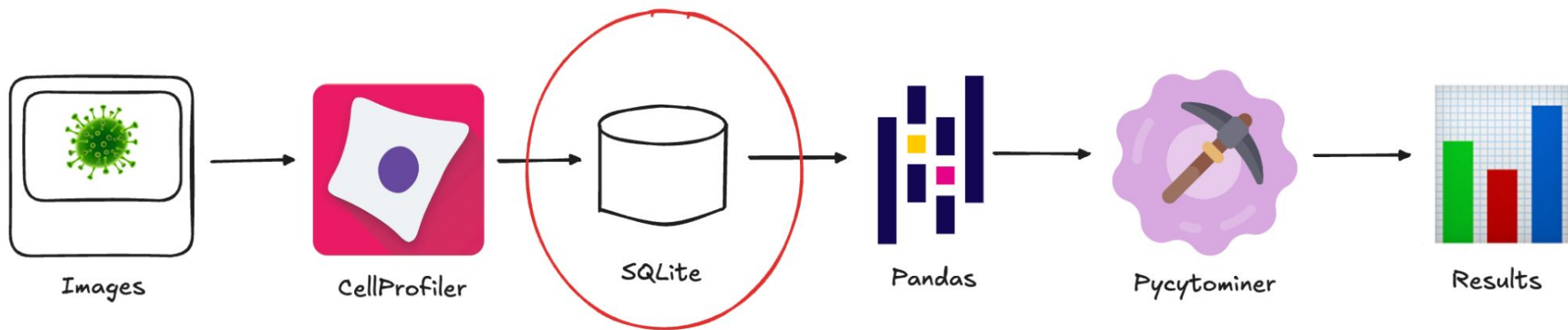
CSV's must be read sequentially when extracting data (we have to read all columns and each row when gathering things). Data types are implied and converted through the reader. This takes a long time!

Pipelines and exports



We can solve some of these problems with SQLite, an embeddable database. CSV files become **binary tables** that include **affinity types** within a **relational model**.

Pipelines and exports



Challenges: affinity types entail implied but not required, the model must also be maintained in order to be useful, and SQLite is not optimized for large data operations.

Pipelines and exports

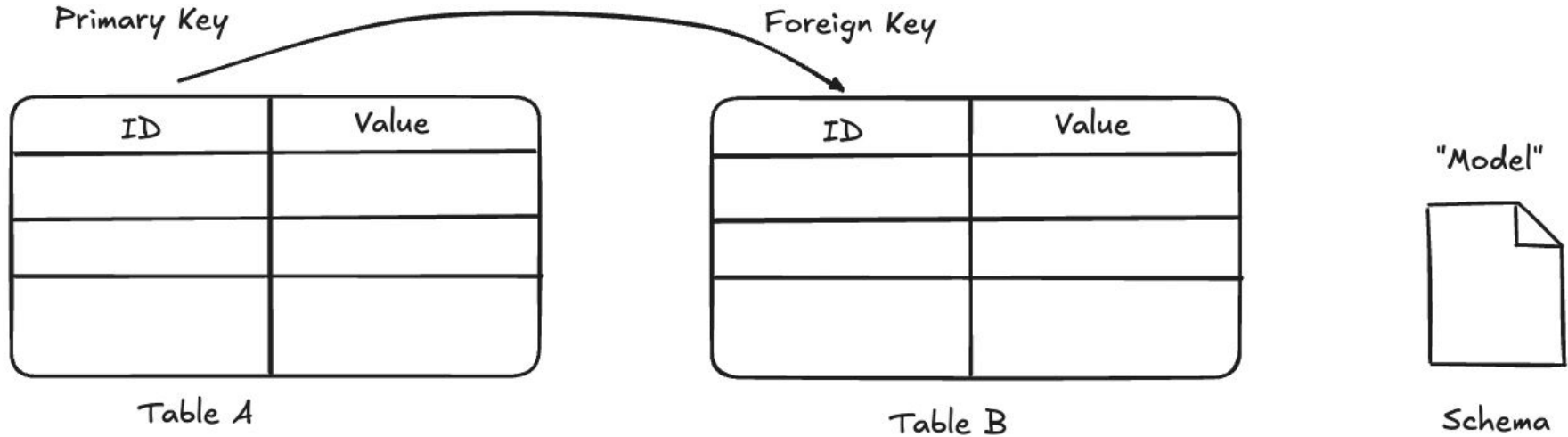
```
-- Affinity types example
-- Create the table
CREATE TABLE research_data (
  standard_column INTEGER,
  made_up_column FLUXCAPACITOR
);

-- Insert mixed values
INSERT INTO research_data (standard_column, made_up_column)
VALUES (1, 'text_value');
INSERT INTO research_data (standard_column, made_up_column)
VALUES (2, 3.14159);

SELECT * FROM research_data;

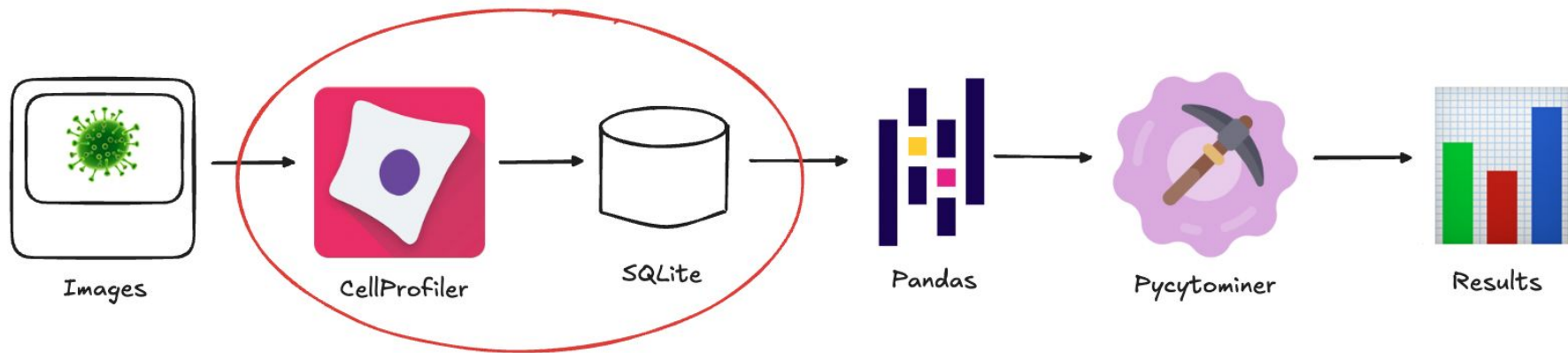
>
1|text_value
2|3.14159
```

Pipelines and exports



We can store the data relationships as a model within the SQLite schema.

Pipelines and exports



We have to modify the model upstream (it's defined by CellProfiler exports).

Pipelines and exports

Correct and enhance SQLite database export foreign keys #4949

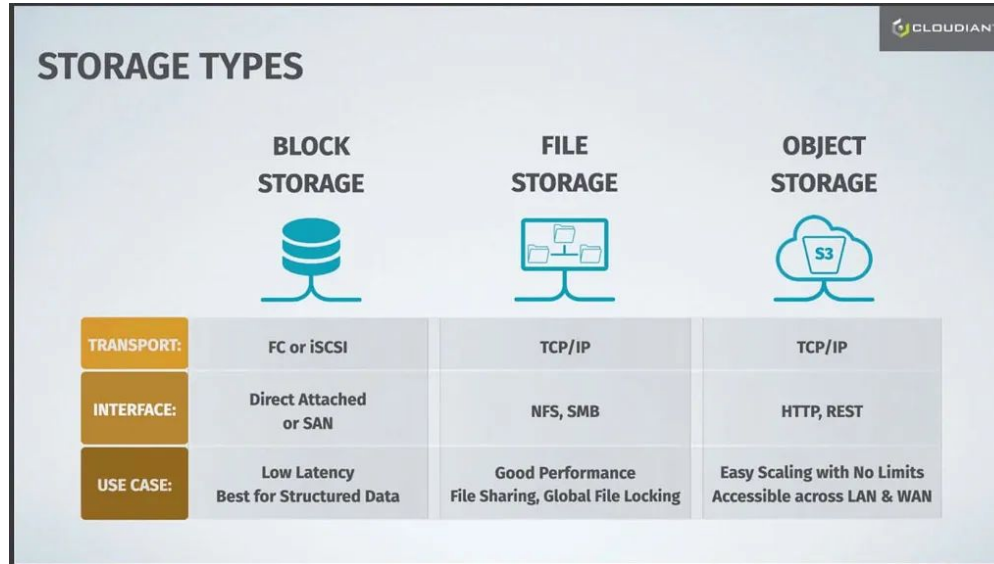


d33bs opened this issue on Sep 30 · 0 comments

- **ImageNumber columns in compartment tables:** Compartment tables often label the `ImageNumber` column as a primary key but not a foreign key (`ImageNumber` may be referenced from the `Per_Image` table).
- **Parent object columns in compartment tables:** Compartment tables such as `Per_Cells` do not currently label `Cells_Parent_Nuclei` as foreign keys (`Nuclei_Number_Object_Number` may be referenced for these).

<https://github.com/CellProfiler/CellProfiler/issues/4949>

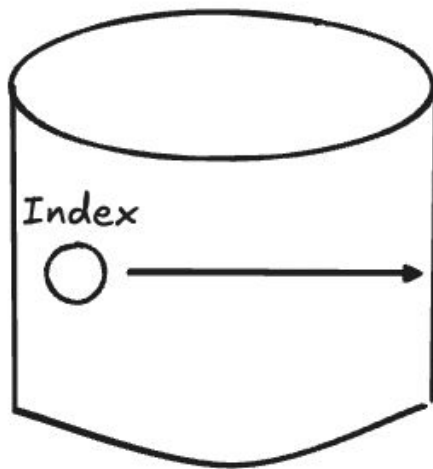
Pipelines and exports



SQLite uses block storage through a filesystem.

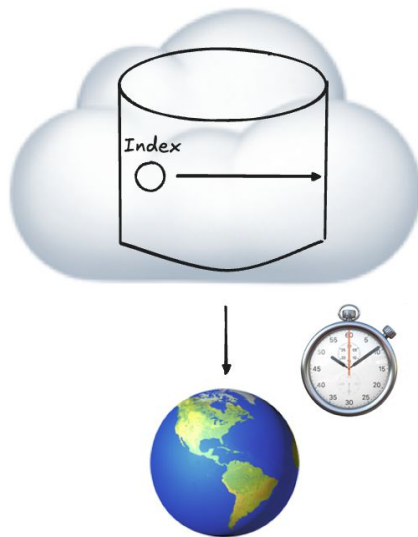
<https://cloudian.com/blog/object-storage-care/>

Pipelines and exports



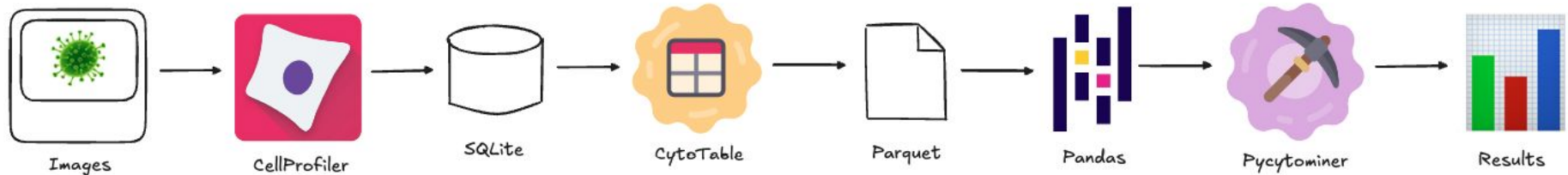
SQLite enables quicker data extraction through indexes, meaning we don't need to read sequentially for many cases. Much faster than CSV's.

Pipelines and exports



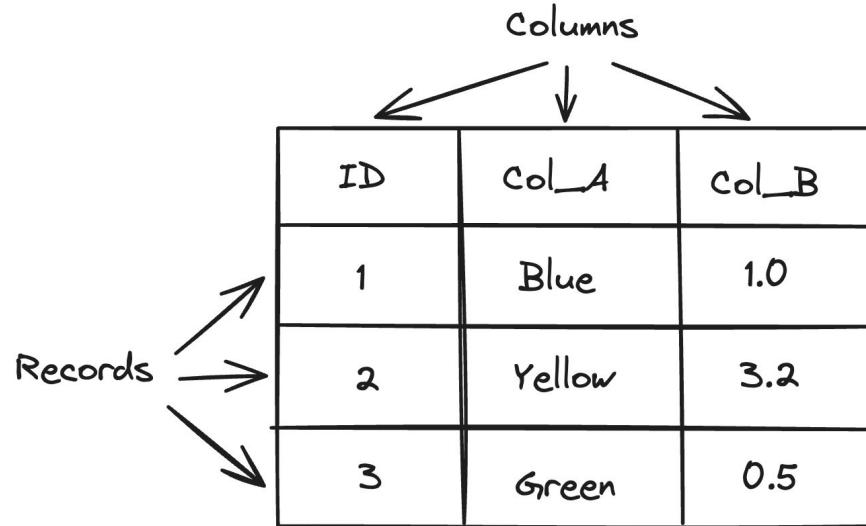
We can only gain that benefit through the local filesystem (we have to download the entire file from cloud storage).

Pipelines and exports



We can use CytoTable to create data which is purpose built for large data operations (incl. cloud), has strict data types, and use single-cell records as a model.

Pipelines and exports



A diagram illustrating a table structure. The word "Columns" is positioned above the table, with three arrows pointing down to the column headers: "ID", "col_A", and "col_B". The word "Records" is positioned to the left of the table, with three arrows pointing right to the row indices: "1", "2", and "3". The table contains three rows of data.

ID	col_A	col_B
1	Blue	1.0
2	Yellow	3.2
3	Green	0.5

We use one table to imply the relationship among all columns through rows (records) of single-cell objects. This reduces complexity without losing a model.

Pipelines and exports

```
# prompt: Create an example pyarrow table with 3 columns, export to parquet, then read the parquet file and show

!pip install pyarrow

import pyarrow as pa
import pyarrow.parquet as pq

# Create an example table
data = {'col1': [1, 2, 3], 'col2': ['a', 'b', 'c'], 'col3': [1.0, 2.0, 3.0]}
table = pa.table(data)

# Export to parquet
pq.write_table(table, 'example.parquet')

# Read the parquet file
read_table = pq.read_table('example.parquet')

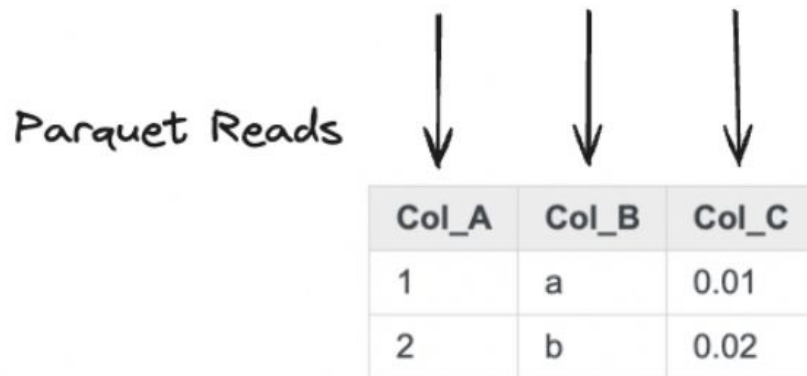
# Show the schema
read_table.schema
```

Requirement already satisfied: pyarrow in /usr/local/lib/python3.10/dist-packages (17.0.0)
Requirement already satisfied: numpy>=1.16.6 in /usr/local/lib/python3.10/dist-packages (from pyarrow) (1.26.4)
col1: int64
col2: string
col3: double

Parquet columns and values are strict: column and value types must exist and must match.

https://colab.research.google.com/drive/1pkitILmbp_JlNSp1UIISafY8NjNvtrkc?authuser=0#scrollTo=vJ1kjYjIcUDR

Pipelines and exports



Parquet reads are “columnar” meaning we don’t need to scan each row and we gain efficiencies.

Pipelines and exports

"file1.parquet"

Col_A	Col_B	Col_C
1	a	0.01

"file2.parquet"

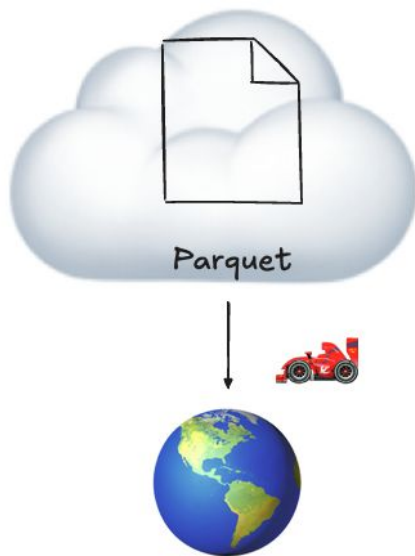
Col_A	Col_B	Col_C
2	b	0.02

"Parquet dataset"

Col_A	Col_B	Col_C
1	a	0.01
2	b	0.02

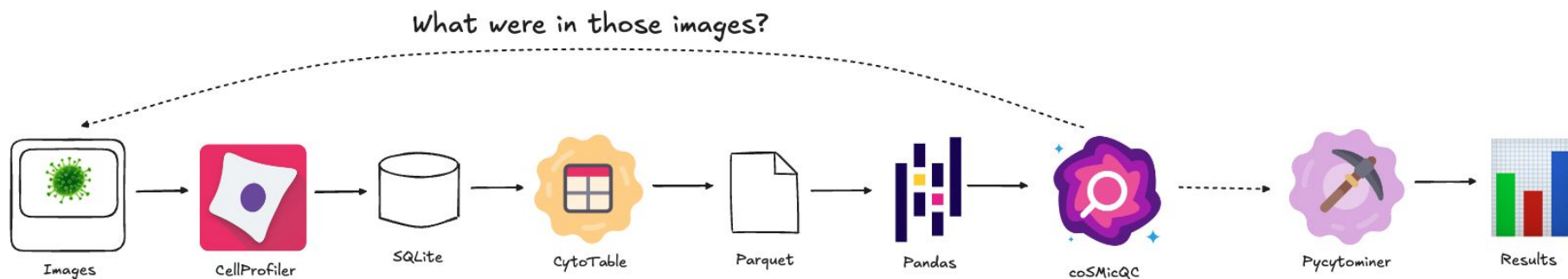
Parquet tables can be composed of one or many individual files (we aren't constrained to a single file). Multi-file Parquet tables are called "datasets".

Pipelines and exports



Parquet is optimized for cloud storage, meaning we have greater flexibility when it comes to storage and distribution.

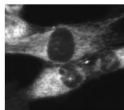
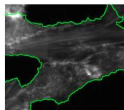
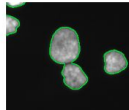
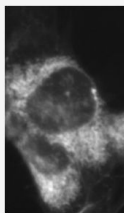
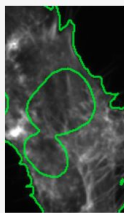
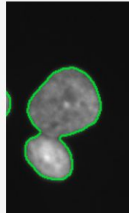
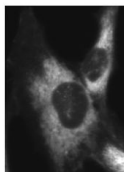
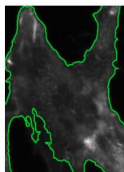
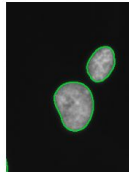
Pipelines and exports



What if we need to go back to where the data was derived from (the images)?

<https://github.com/WayScience/coSMicQC>

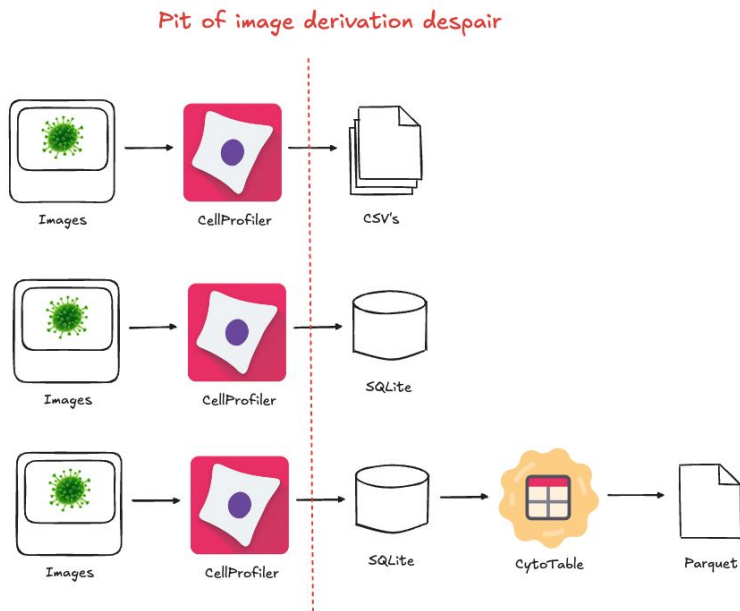
Pipelines and exports

Metadata_ImageNumber	Metadata_Cells_Number_Object_Number	cqc.large_nuclei.is_outlier	Image_FileName_GFP	Image_FileName_RFP	Image_FileName_DAPI	
699	50	2	True			
1557	113	10	True			
568	45	9	False			

We can view image data alongside the profiles if the image data are available.

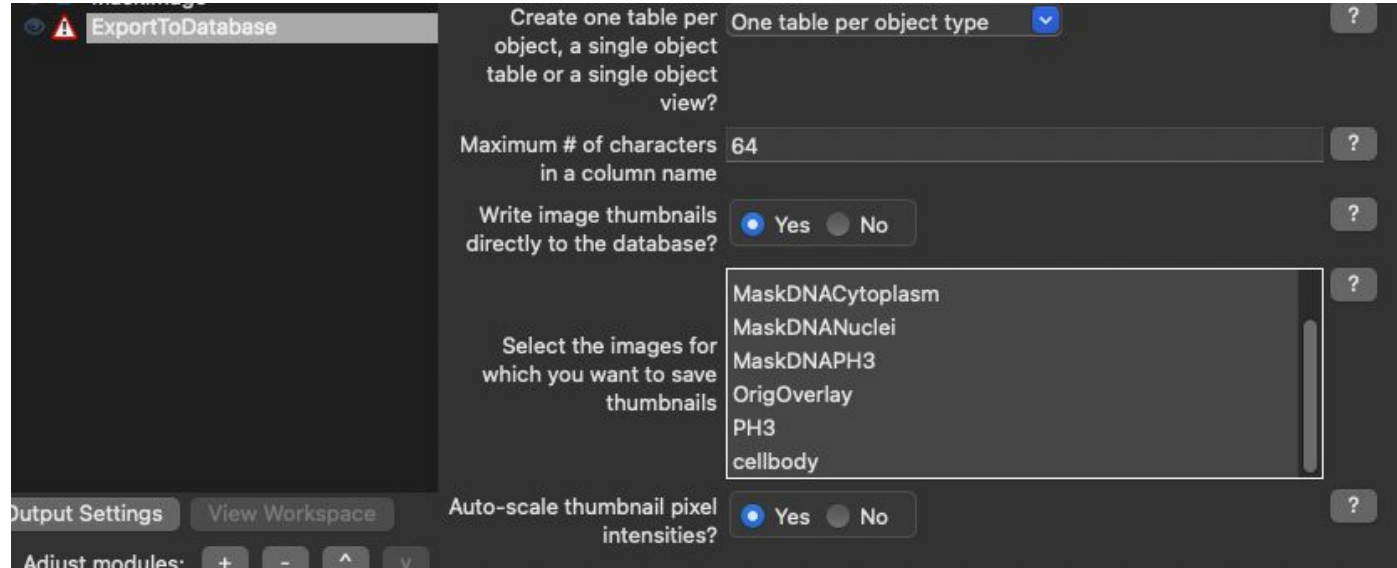
<https://github.com/WayScience/CytoDataFrame>

Pipelines and exports



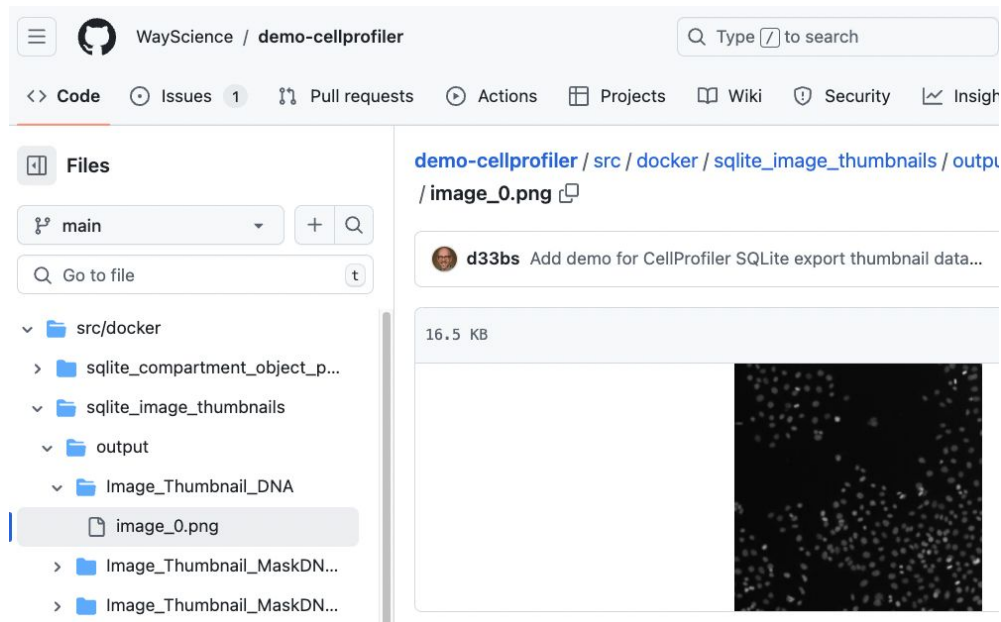
Pit of image derivation despair: we're leaving behind the images with potentially no provenance back.

Pipelines and exports



Can we export images through CellProfiler module settings?

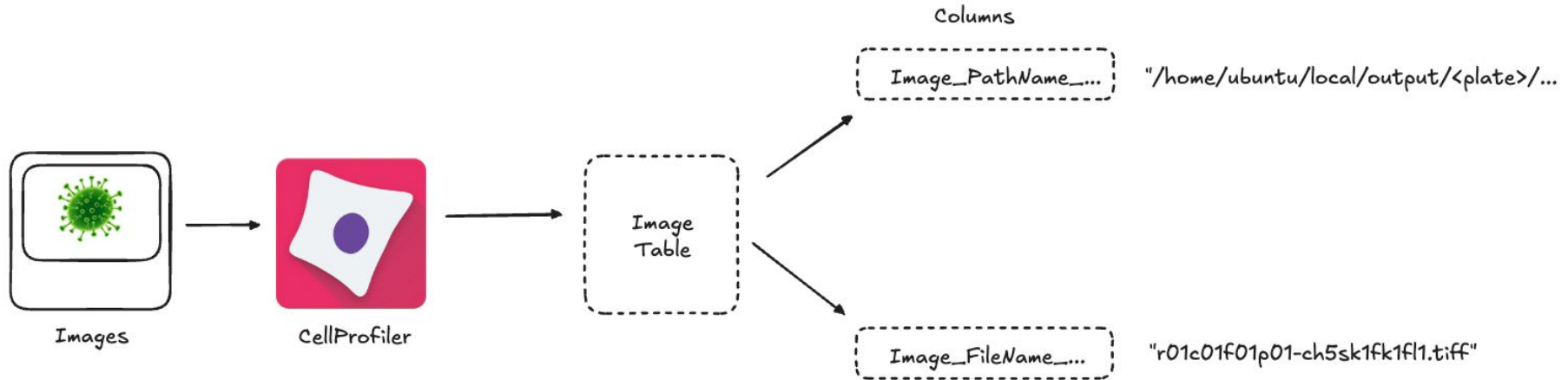
Pipelines and exports



The screenshot shows a GitHub repository page for 'demo-cellprofiler' by 'WayScience'. The file path is `demo-cellprofiler / src / docker / sqlite_image_thumbnails / output / image_0.png`. The file size is 16.5 KB. The thumbnail image shows a dark field with many small, bright, irregular shapes, likely representing cell nuclei or other biological structures. The file is named `image_0.png`.

No. 😞

Pipelines and exports



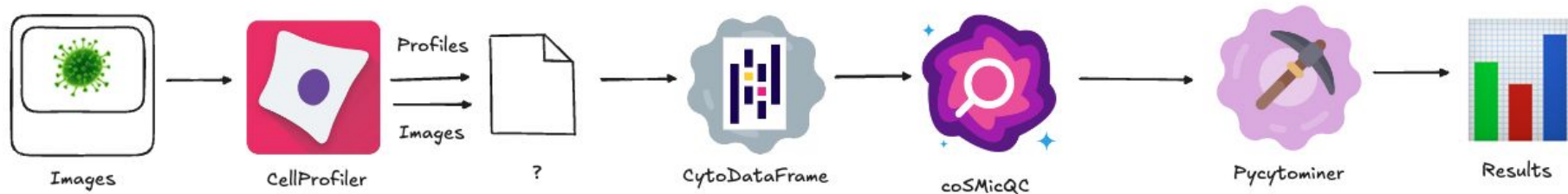
CellProfiler Image table output includes some clues.
Derivational data stored through “Image_FileName_...” column values.

Pipelines and exports

```
df[s3_column_name] = (  
    df[pathname_col].str.replace(  
        "/home/ubuntu/local_input/projects/2019_07_11_JUMP-CP/2020_11_04_CPJUMP1/",  
        (  
            "s3://cellpainting-gallery/cpg0000-jump-pilot/source_4/"  
            "images/2020_11_04_CPJUMP1/"  
        ),  
        regex=False,  
    )  
    + "/"  
    + df[filename_col]  
)
```

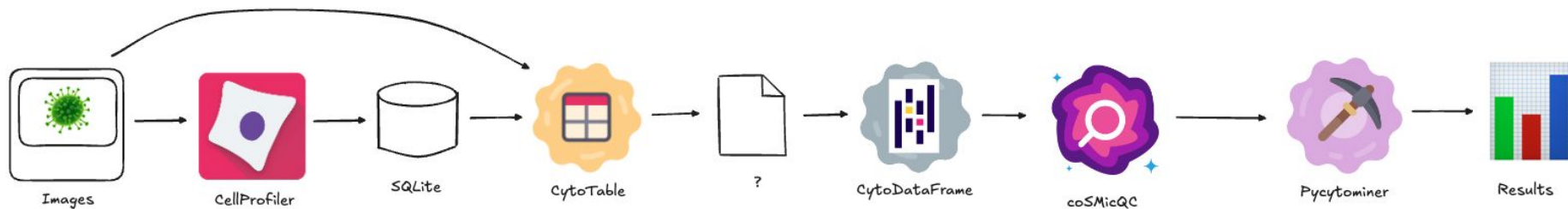
We can fix this, but it's ugly and will result in bespoke solutions every time.

Future



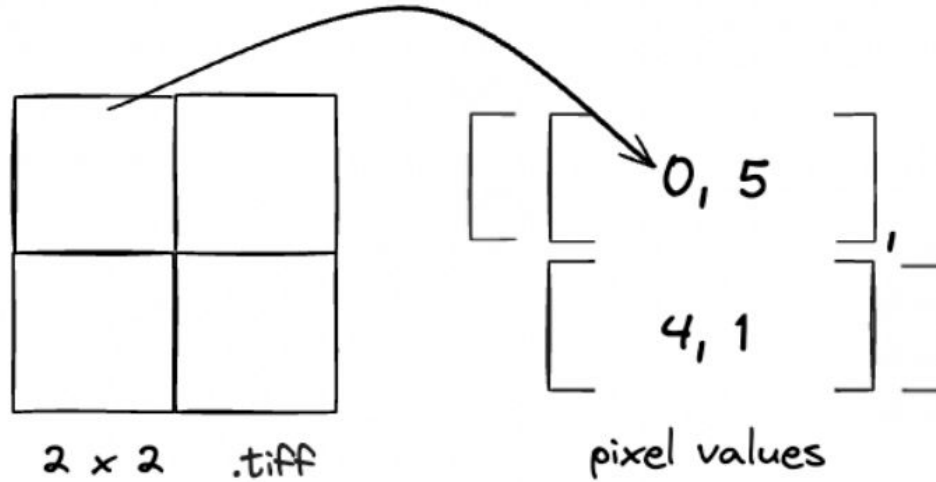
Could we build a format which retains the image data somehow? Ideally:
Strict data types, large data operable, cloud-compatible, and image data compatible.

Future



Open source science: in the meantime, we can build it!

Future



What do you mean image data compatible? Image data as arrays.

Future

Format	Extensions	Pixels	Metadata	Openness	Presence	Utility	Export	BSD	Multiple Images	Pyramid
3i SlideBook	.sld	▲	■	▼	▲	▼	✗	✗	✓	✗
3i SlideBook 7	.sldy	▲	▲	▲	▲	▲	✗	✓	✗	✗
Andor Bio-Imaging Division (ABD) TIFF	.tif	▲	▲	■	▼	■	✗	✗	✓	✗
AIM	.aim	■	▼	▼	▼	▼	✗	✗	✗	✗
Alicona 3D	.al3d	▲	▲	▲	▼	■	✗	✗	✗	✗
Amersham Biosciences Gel	.gel	▲	■	■	▼	▼	✗	✗	✗	✗
Amira Mesh	.am, .amiramesh, .grey, .hx, .labels	▲	▼	▼	▼	▼	✗	✗	✗	✗
Amnis FlowSight	.cif	■	■	■	▼	▼	✗	✓	✓	✗

Why not binary large objects (BLOBs)? Standardizing data readers for binary formats would be chaotic and voids benefits of data typing.

<https://bio-formats.readthedocs.io/en/v8.0.0/supported-formats.html>

Future

Format	Extensions	Pixels	Metadata	Openness	Presence	Utility	Export	BSD	Multiple Images	Pyramid
3i SlideBook	.sld	▲	■	▼	▲	▼	✗	✗	✓	✗
3i SlideBook 7	.sldy	▲	▲	▲	▲	▲	✗	✓	✗	✗
Andor Bio-Imaging Division (ABD) TIFF	.tif	▲	▲	■	▼	■	✗	✗	✓	✗
AIM	.aim	■	▼	▼	▼	▼	✗	✗	✗	✗
Alicona 3D	.al3d	▲	▲	▲	▼	■	✗	✗	✗	✗
Amersham Biosciences Gel	.gel	▲	■	■	▼	▼	✗	✗	✗	✗
Amira Mesh	.am, .amiramesh, .grey, .hx, .labels	▲	▼	▼	▼	▼	✗	✗	✗	✗
Amnis FlowSight	.cif	■	■	■	▼	▼	✗	✓	✓	✗

Why not binary large objects (BLOBs)? Standardizing data readers for binary formats would be chaotic and voids benefits of data typing.

<https://bio-formats.readthedocs.io/en/v8.0.0/supported-formats.html>

Future

```
-----  
ArrowInvalid                                Traceback (most recent call last)  
<ipython-input-1-e510a491ed65> in <cell line: 12>()  
    10 # Create an example table with a multi-dimensional array column  
    11 data = {'col1': array_data}  
--> 12 table = pa.table(data, schema=pa.schema([pa.field('col1', pa.list_(pa.list_(pa.int64())))) ]))  
    13  
    14  
  
----- 7 frames -----  
/usr/local/lib/python3.10/dist-packages/pyarrow/error.pxi in pyarrow.lib.check_status()  
  
ArrowInvalid: Can only convert 1-dimensional array values
```

Parquet has issues with array values.

<https://colab.research.google.com/drive/1DJ3z5zhKc5wO8rs5GYdT0h9y6cgMCWXy>

Future



Lance includes:

- Strict data typing
- Large data operation compatible
- Cloud compatibilities
- Array value handling

<https://github.com/lancedb/lance>

Future

```
!pip install pylance

import numpy as np
import lance
import pyarrow as pa
import shutil

shutil.rmtree('example.lance', ignore_errors=True)

# Create a multi-dimensional array
array_data = [np.array([[1, 2], [3, 4]]), np.array([[5, 6], [7, 8]]), np.array([[9, 10], [11, 12]])]

# Convert to a list of lists (if necessary, depending on how you want to structure it)
array_data = [array.tolist() for array in array_data]

# Create a PyArrow table
data = {'col1': array_data}
table = pa.table(data)

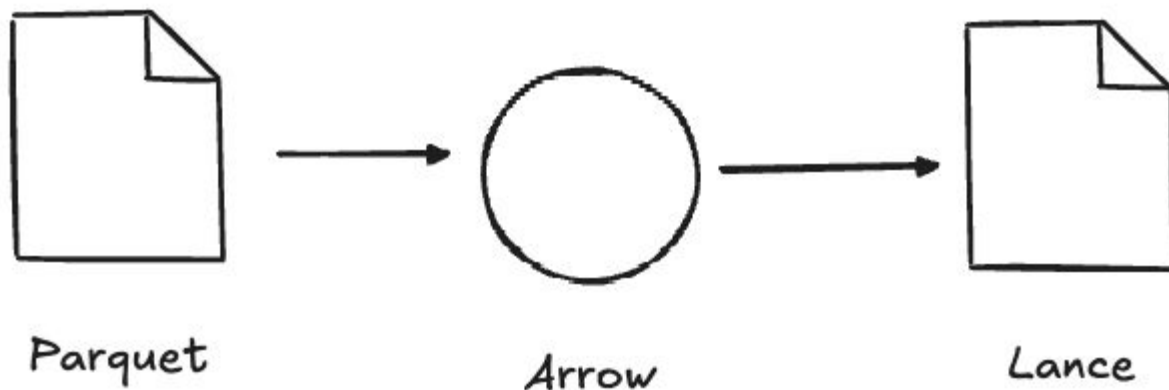
# Write the table to a Lance dataset
lance.write_dataset(table, 'example.lance')

# Read the Lance dataset back
read_table = lance.dataset('example.lance')

# Show the schema and the data
print(read_table.schema)
print(read_table.to_table().to_pandas())
```

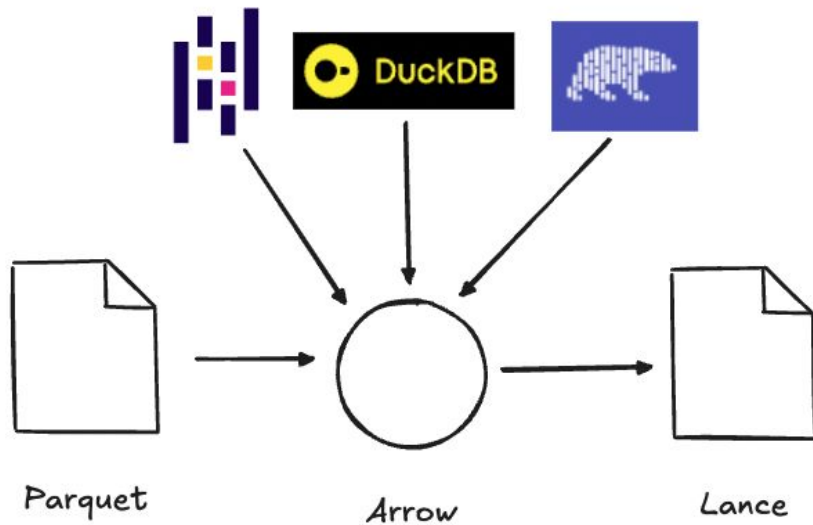
https://colab.research.google.com/drive/10dEpmtC1_pGm2qyc771DsqqVeNXnFQ85

Future



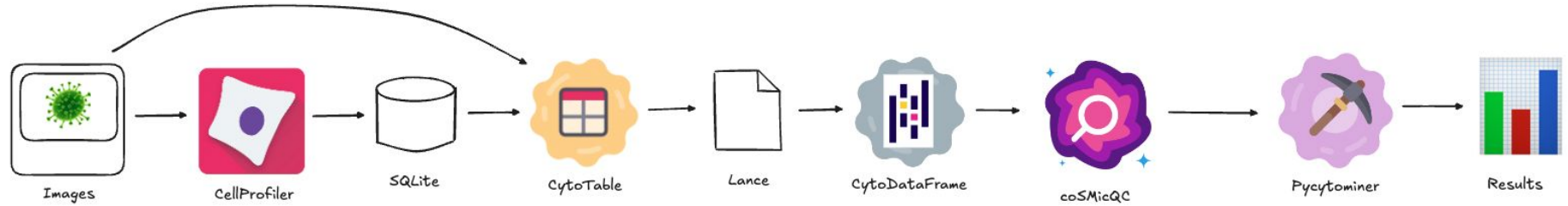
Lance uses Apache Arrow, meaning existing Parquet are backwards compatible.

Future

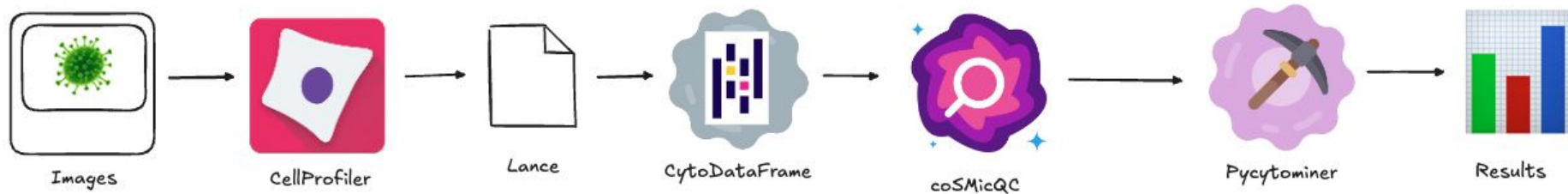


This also means we can use our favorite data analytics engines (so long as they're compatible with Apache Arrow).

What if ... ?

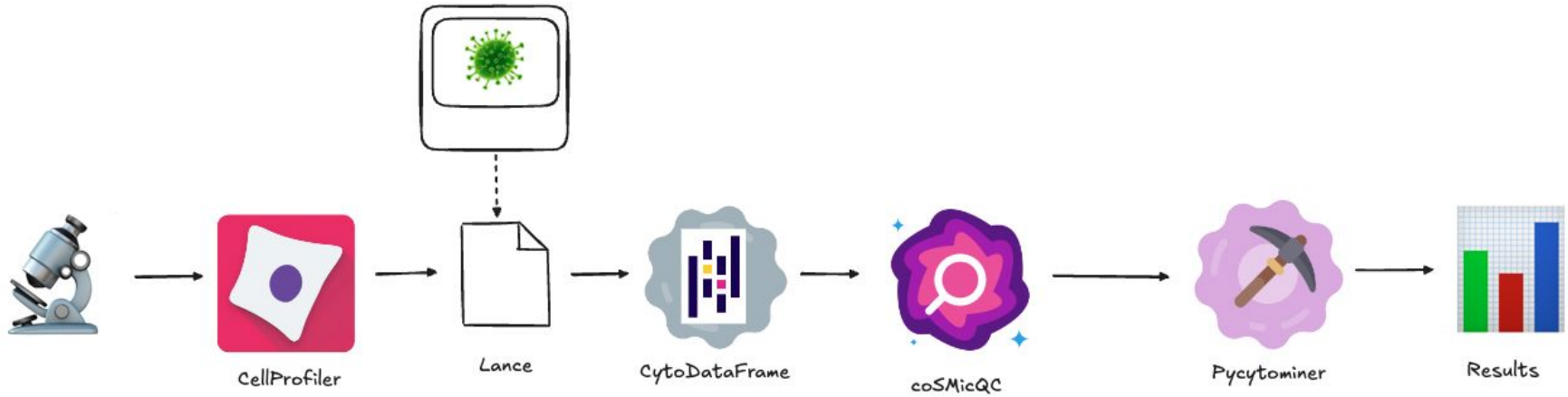


What if ... ?



This work could be a stopgap to further complexity reduction, increasing research velocity.

What if ... ?



What if ...?

Thanks! Questions / comments?