

Use with Polars

This document is a quick introduction to using datasets with Polars, with a particular focus on how to process

datasets using Polars functions, and how to convert a dataset to Polars or from Polars.

This is particularly useful as it allows fast zero-copy operations, since both datasets and Polars use Arrow under the hood.

Dataset format

By default, datasets return regular Python objects: integers, floats, strings, lists, etc.

To get Polars DataFrames or Series instead, you can set the format of the dataset to polars using Dataset.with_format():

```
>>> from datasets import Dataset
>>> data = {"col_0": ["a", "b", "c", "d"], "col_1": [0., 0., 1., 1.]}
>>> ds = Dataset.from_dict(data)
>>> ds = ds.with_format("polars")
           # pl.DataFrame
>>> ds[0]
shape: (1, 2)
| col_0 | col_1 |
| --- | ---
       f64
str
       0.0
l a
>>> ds[:2] # pl.DataFrame
shape: (2, 2)
| col_0 | col_1 |
       ---
        f64
str
       0.0
a
       0.0
b
>>> ds["data"] # pl.Series
shape: (4,)
Series: 'col_0' [str]
"a"
       "h"
       "c"
       "d"
]
```

```
This also works for IterableDataset objects obtained e.g. using load_dataset(..., streaming=True):
```

Process data

Polars functions are generally faster than regular hand-written python functions, and therefore they are a good option to optimize data processing. You can use Polars functions to process a dataset in Dataset.map() or Dataset.filter():

```
>>> import polars as pl
>>> from datasets import Dataset
>>> data = {"col_0": ["a", "b", "c", "d"], "col_1": [0., 0., 1., 1.]}
>>> ds = Dataset.from_dict(data)
>>> ds = ds.with format("polars")
>>> ds = ds.map(lambda df: df.with_columns(pl.col("col_1").add(1).alias("col_2")), batched=True)
>>> ds[:2]
shape: (2, 3)
str
       f64
               f64
       0.0
               1.0
       0.0
               1.0
>>> ds = ds.filter(lambda df: df["col_0"] == "b", batched=True)
>>> ds[0]
shape: (1, 3)
col_0 | col_1 | col_2
       f64
               f64
 str
       0.0
 b
               1.0
```

We use batched=True because it is faster to process batches of data in Polars rather than row by row. It's also possible to use batch_size= in map() to set the size of each df.

This also works for IterableDataset.map() and IterableDataset.filter().

Example: data extraction

Many functions are available in Polars and for any data type: string, floats, integers, etc. You can find the full list here. Those functions are written in Rust and run on batches of data which enables fast data processing.

Here is an example that shows a 5x speed boost using Polars instead of a regular python

function to extract solutions from a LLM reasoning dataset:

```
from datasets import load_dataset

ds = load_dataset("ServiceNow-AI/R1-Distill-SFT", "v0", split="train")

# Using a regular python function
pattern = re.compile("boxed\\{(.*)\\}")
result_ds = ds.map(lambda x: {"value_solution": m.group(1) if (m:=pattern.search(x["solution"])) e
# Time: 10s

# Using a Polars function
expr = pl.col("solution").str.extract("boxed\\{(.*)\\}").alias("value_solution")
result_ds = ds.with_format("polars").map(lambda df: df.with_columns(expr), batched=True)
# Time: 2s
```

Import or Export from Polars

To import data from Polars, you can use <code>Dataset.from_polars()</code>:

```
ds = Dataset.from_polars(df)
```

And you can use Dataset.to_polars() to export a Dataset to a Polars DataFrame:

```
df = Dataset.to_polars(ds)
```