

pandas / polars

Lecture 09

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Filtering rows

The `query()` method can be used for filtering rows, it evaluates a string expression in the context of the data frame.

```
1 df.query('date == "2022-02-01"')
```

Empty DataFrame

Columns: [id, weight, height, date]

Index: []

```
1 df.query('weight > 50')
```

	id	weight	height	date
anna	202	79.477217	162.607949	2025-02-01
bob	535	97.369002	175.888696	2025-02-02
carol	960	51.663463	156.062230	2025-02-03
dave	370	67.517056	171.197477	2025-02-04

```
1 df.query('weight > 50 & height < 165')
```

	id	weight	height	date
anna	202	79.477217	162.607949	2025-02-01
carol	960	51.663463	156.062230	2025-02-03

```
1 qid = 202
2 df.query('id == @qid')
```

	id	weight	height	date
anna	202	79.477217	162.607949	2025-02-01

Selecting Columns

Beyond the use of `loc()` and `iloc()` there is also the `filter()` method which can be used to select columns (or indices) by name with pattern matching

```
1 df.filter(items=["id","weight"])
```

	id	weight
anna	202	79.477217
bob	535	97.369002
carol	960	51.663463
dave	370	67.517056
erin	206	29.780742

```
1 df.filter(regex="ght$")
```

	weight	height
anna	79.477217	162.607949
bob	97.369002	175.888696
carol	51.663463	156.062230
dave	67.517056	171.197477
erin	29.780742	167.607252

```
1 df.filter(like = "i")
```

	id	weight	height
anna	202	79.477217	162.607949
bob	535	97.369002	175.888696
carol	960	51.663463	156.062230
dave	370	67.517056	171.197477
erin	206	29.780742	167.607252

```
1 df.filter(like="a", axis=0)
```

	id	weight	height	date
anna	202	79.477217	162.607949	2025-02-01
carol	960	51.663463	156.062230	2025-02-03
dave	370	67.517056	171.197477	2025-02-04

Adding columns

Indexing with assignment allows for inplace modification of a DataFrame, while `assign()` creates a new object (but is chainable)

```
1 df['student'] = [True, True, True, False, None]
2 df['age'] = [19, 22, 25, None, None]
3 df
```

	id	weight	height	date	student	age
anna	202	79.477217	162.607949	2025-02-01	True	19.0
bob	535	97.369002	175.888696	2025-02-02	True	22.0
carol	960	51.663463	156.062230	2025-02-03	True	25.0
dave	370	67.517056	171.197477	2025-02-04	False	NaN
erin	206	29.780742	167.607252	2025-02-05	None	NaN

```
1 df.assign(
2     student = lambda x: np.where(x.student, "yes", "no"),
3     rand = np.random.rand(5)
4 )
```

	id	weight	height	date	student	age	rand
anna	202	79.477217	162.607949	2025-02-01	yes	19.0	0.938553
bob	535	97.369002	175.888696	2025-02-02	yes	22.0	0.000779
carol	960	51.663463	156.062230	2025-02-03	yes	25.0	0.992212
dave	370	67.517056	171.197477	2025-02-04	no	NaN	0.617482
erin	206	29.780742	167.607252	2025-02-05	no	NaN	0.611653

Removing columns (and rows)

Columns or rows can be removed via the `drop()` method,

```
1 df.drop(['student'])
```

KeyError: "['student'] not found in axis"

```
1 df.drop(['student'], axis=1)
```

	id	weight	height	date	age
anna	202	79.477217	162.607949	2025-02-01	19.0
bob	535	97.369002	175.888696	2025-02-02	22.0
carol	960	51.663463	156.062230	2025-02-03	25.0
dave	370	67.517056	171.197477	2025-02-04	NaN
erin	206	29.780742	167.607252	2025-02-05	NaN

```
1 df.drop(['anna','dave'])
```

	id	weight	height	date	student	age
bob	535	97.369002	175.888696	2025-02-02	True	22.0
carol	960	51.663463	156.062230	2025-02-03	True	25.0
erin	206	29.780742	167.607252	2025-02-05	None	NaN

```
1 df.drop(columns = df.columns == "age")
```

KeyError: '[False, False, False, False, False, True] not found in axis'

```
1 df.drop(columns = df.columns[df.columns == "age"])
```

	id	weight	height	date	student
anna	202	79.477217	162.607949	2025-02-01	True
bob	535	97.369002	175.888696	2025-02-02	True
carol	960	51.663463	156.062230	2025-02-03	True
dave	370	67.517056	171.197477	2025-02-04	False
erin	206	29.780742	167.607252	2025-02-05	None

```
1 df.drop(columns = df.columns[df.columns.str.contains("ght")])
```

	id	date	student	age
anna	202	2025-02-01	True	19.0
bob	535	2025-02-02	True	22.0
carol	960	2025-02-03	True	25.0
dave	370	2025-02-04	False	NaN
erin	206	2025-02-05	None	NaN

Sorting

DataFrames can be sorted on one or more columns via `sort_values()`,

```
1 df
```

	id	weight	height	date	student	age
anna	202	79.477217	162.607949	2025-02-01	True	19.0
bob	535	97.369002	175.888696	2025-02-02	True	22.0
carol	960	51.663463	156.062230	2025-02-03	True	25.0
dave	370	67.517056	171.197477	2025-02-04	False	NaN
erin	206	29.780742	167.607252	2025-02-05	None	NaN

```
1 df.sort_values(by=["student","id"], ascending=[True,False])
```

	id	weight	height	date	student	age
dave	370	67.517056	171.197477	2025-02-04	False	NaN
carol	960	51.663463	156.062230	2025-02-03	True	25.0
bob	535	97.369002	175.888696	2025-02-02	True	22.0
anna	202	79.477217	162.607949	2025-02-01	True	19.0
erin	206	29.780742	167.607252	2025-02-05	None	NaN

join vs merge vs concat

All three can be used to combine data frames,

- `concat()` stacks DataFrames on either axis, with basic alignment based on (row) indexes. `join` argument only supports “inner” and “outer”.
- `merge()` aligns based on one or more shared columns. `how` supports “inner”, “outer”, “left”, “right”, and “cross”.
- `join()` uses `merge()` behind the scenes, but prefers to join based on (row) indexes. Also has different default `how` compared to `merge()`, “left” vs “inner”.

Pivoting - long to wide

```
1 df
```

	country	year	type	count
0	A	1999	cases	0.7K
1	A	1999	pop	19M
2	A	2000	cases	2K
3	A	2000	pop	20M
4	B	1999	cases	37K
5	B	1999	pop	172M
6	B	2000	cases	80K
7	B	2000	pop	174M
8	C	1999	cases	212K
9	C	1999	pop	1T
10	C	2000	cases	213K
11	C	2000	pop	1T

```
1 df_wide = df.pivot(  
2     index=["country","year"],  
3     columns="type",  
4     values="count"  
5 )  
6 df_wide
```

	type	cases	pop
A	1999	0.7K	19M
	2000	2K	20M
B	1999	37K	172M
	2000	80K	174M
C	1999	212K	1T
	2000	213K	1T

pivot indexes

```
1 df_wide.index
```

```
MultiIndex([( 'A', 1999),  
            ( 'A', 2000),  
            ( 'B', 1999),  
            ( 'B', 2000),  
            ( 'C', 1999),  
            ( 'C', 2000)],  
           names=['country', 'year'])
```

```
1 df_wide.columns
```

```
Index(['cases', 'pop'], dtype='object',  
      name='type')
```

```
1 ( df_wide  
2   .reset_index()  
3   .rename_axis(  
4       columns=None  
5   )  
6 )
```

	country	year	cases	pop
0	A	1999	0.7K	19M
1	A	2000	2K	20M
2	B	1999	37K	172M
3	B	2000	80K	174M
4	C	1999	212K	1T
5	C	2000	213K	1T

Wide to long (melt)

```
1 df
```

	country	1999	2000
0	A	0.7K	2K
1	B	37K	80K
2	C	212K	213K

```
1 df_long = df.melt(  
2     id_vars="country",  
3     var_name="year",  
4     value_name="value"  
5 )  
6 df_long
```

	country	year	value
0	A	1999	0.7K
1	B	1999	37K
2	C	1999	212K
3	A	2000	2K
4	B	2000	80K
5	C	2000	213K

Exercise 1 - Tidying

How would you tidy the following data frame so that the rate column is split into cases and population columns?

```
1 df = pd.DataFrame({  
2   "country": ["A","A","B","B","C","C"],  
3   "year":    [1999, 2000, 1999, 2000, 1999, 2000],  
4   "rate":    ["0.7K/19M", "2K/20M", "37K/172M", "80K/174M", "212K/1T", "213K/1T"]  
5 })  
6 df
```

	country	year	rate
0	A	1999	0.7K/19M
1	A	2000	2K/20M
2	B	1999	37K/172M
3	B	2000	80K/174M
4	C	1999	212K/1T
5	C	2000	213K/1T

Split-Apply-Combine

cereal data

```
1 cereal = pd.read_csv("https://sta663-sp25.github.io/slides/data/cereal.csv")
2 cereal
```

	name	mfr	...	sugars	rating
0	100% Bran	Nabisco	...	6	68.402973
1	100% Natural Bran	Quaker Oats	...	8	33.983679
2	All-Bran	Kellogg's	...	5	59.425505
3	All-Bran with Extra Fiber	Kellogg's	...	0	93.704912
4	Almond Delight	Ralston Purina	...	8	34.384843
..
72	Triples	General Mills	...	3	39.106174
73	Trix	General Mills	...	12	27.753301
74	Wheat Chex	Ralston Purina	...	3	49.787445
75	Wheaties	General Mills	...	3	51.592193
76	Wheaties Honey Gold	General Mills	...	8	36.187559

[77 rows x 6 columns]

groupby

Groups can be created within a DataFrame via `groupby()` - these groups are then used by the standard summary methods (e.g. `sum()`, `mean()`, `std()`, etc.).

```
1 cereal.groupby("type")
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x119372a20>
```

```
1 cereal.groupby("type").groups
```

```
{'Cold': [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76], 'Hot': [20, 43, 57]}
```

```
1 cereal.groupby("mfr").groups
```

```
{'General Mills': [5, 7, 11, 12, 13, 14, 18, 22, 31, 36, 40, 42, 47, 51, 59, 69, 70, 71, 72, 73, 75, 76], 'Kellogg's': [2, 3, 6, 16, 17, 19, 21, 24, 25, 26, 28, 38, 39, 46, 48, 49, 50, 53, 58, 60, 62, 66, 67], 'Maltex': [43], 'Nabisco': [0, 20, 63, 64, 65, 68], 'Post': [9, 27, 29, 30, 32, 33, 34, 37, 52], 'Quaker Oats': [1, 10, 35, 41, 54, 55, 56, 57], 'Ralston Purina': [4, 8, 15, 23, 44, 45, 61, 74]}
```

groupby and aggregation methods

```
1 cereal.groupby("type").mean()
```

TypeError: agg function failed [how->mean,dtype->object]

```
1 ( cereal
2   .groupby("type")
3   .mean(numeric_only=True)
4 )
```

	calories	sugars	rating
type			
Cold	107.162162	7.175676	42.095218
Hot	100.000000	1.333333	56.737708

```
1 cereal.groupby("mfr").size()
```

mfr	
General Mills	22
Kellogg's	23
Maltex	1
Nabisco	6
Post	9
Quaker Oats	8
Ralston Purina	8
dtype:	int64

Selecting groups

Groups can be accessed via `get_group()`

```
1 cereal.groupby("type").get_group("Hot")
```

	name	mfr	type	calories	sugars	rating
20	Cream of Wheat (Quick)	Nabisco	Hot	100	0	64.533816
43	Maypo	Maltex	Hot	100	3	54.850917
57	Quaker Oatmeal	Quaker Oats	Hot	100	1	50.828392

```
1 cereal.groupby("mfr").get_group("Post")
```

	name	mfr	...	sugars	rating
9	Bran Flakes	Post	...	5	53.313813
27	Fruit & Fibre Dates; Walnuts; and Oats	Post	...	10	40.917047
29	Fruity Pebbles	Post	...	12	28.025765
30	Golden Crisp	Post	...	15	35.252444
32	Grape Nuts Flakes	Post	...	5	52.076897
33	Grape-Nuts	Post	...	3	53.371007
34	Great Grains Pecan	Post	...	4	45.811716
37	Honey-comb	Post	...	11	28.742414
52	Post Nat. Raisin Bran	Post	...	14	37.840594

[9 rows x 6 columns]

Iterating groups

DataFrameGroupBy's can also be iterated over,

```
1 for name, group in cereal.groupby("type"):
2     print(f"# {name}\n{group}\n\n")
```

Cold

	name	mfr	...	sugars	rating
0	100% Bran	Nabisco	...	6	68.402973
1	100% Natural Bran	Quaker Oats	...	8	33.983679
2	All-Bran	Kellogg's	...	5	59.425505
3	All-Bran with Extra Fiber	Kellogg's	...	0	93.704912
4	Almond Delight	Ralston Purina	...	8	34.384843
..
72	Triples	General Mills	...	3	39.106174
73	Trix	General Mills	...	12	27.753301
74	Wheat Chex	Ralston Purina	...	3	49.787445
75	Wheaties	General Mills	...	3	51.592193
76	Wheaties Honey Gold	General Mills	...	8	36.187559

[74 rows x 6 columns]

Hot

Aggregation

The `aggregate()` function or `agg()` method can be used to compute summary statistics for each group,

```
1 cereal.groupby("mfr").agg("mean")
```

TypeError: agg function failed [how->mean,dtype->object]

```
1 cereal.groupby("mfr").agg("mean", numeric_only = True)
```

	calories	sugars	rating
mfr			
General Mills	111.363636	7.954545	34.485852
Kellogg's	108.695652	7.565217	44.038462
Maltex	100.000000	3.000000	54.850917
Nabisco	86.666667	1.833333	67.968567
Post	108.888889	8.777778	41.705744
Quaker Oats	95.000000	5.500000	42.915990
Ralston Purina	115.000000	6.125000	41.542997

Aggregation by column

```
1 cereal.groupby("mfr").agg({
2     "calories": ['min', 'max'],
3     "sugars":    ['median'],
4     "rating":    ['sum', 'count']
5 })
```

	calories		sugars	rating	
	min	max	median	sum	count
mfr					
General Mills	100	140	8.5	758.688737	22
Kellogg's	50	160	7.0	1012.884634	23
Maltex	100	100	3.0	54.850917	1
Nabisco	70	100	0.0	407.811403	6
Post	90	120	10.0	375.351697	9
Quaker Oats	50	120	6.0	343.327919	8
Ralston Purina	90	150	5.5	332.343977	8

Named aggregation

It is also possible to use special syntax to aggregate specific columns into a named output column,

```
1 cereal.groupby("mfr", as_index=False).agg(  
2     min_cal = ("calories", "min"),  
3     max_cal = ("calories", max),  
4     med_sugar = ("sugars", "median"),  
5     avg_rating = ("rating", np.mean)  
6 )
```

	mfr	min_cal	max_cal	med_sugar	avg_rating
0	General Mills	100	140	8.5	34.485852
1	Kellogg's	50	160	7.0	44.038462
2	Maltex	100	100	3.0	54.850917
3	Nabisco	70	100	0.0	67.968567
4	Post	90	120	10.0	41.705744
5	Quaker Oats	50	120	6.0	42.915990
6	Ralston Purina	90	150	5.5	41.542997

Transformation

The `transform()` method returns a DataFrame with the aggregated result matching the size (or length 1) of the input group(s),

```
1 ( cereal
2   .groupby("mfr")
3   .transform(
4     np.mean, numeric_only=True
5   )
6 )
```

	calories	sugars	rating
0	86.666667	1.833333	67.968567
1	95.000000	5.500000	42.915990
2	108.695652	7.565217	44.038462
3	108.695652	7.565217	44.038462
4	115.000000	6.125000	41.542997
..
72	111.363636	7.954545	34.485852
73	111.363636	7.954545	34.485852
74	115.000000	6.125000	41.542997
75	111.363636	7.954545	34.485852
76	111.363636	7.954545	34.485852

[77 rows x 3 columns]

```
1 ( cereal
2   .groupby("type")
3   .transform(
4     "mean", numeric_only=True
5   )
6 )
```

	calories	sugars	rating
0	107.162162	7.175676	42.095218
1	107.162162	7.175676	42.095218
2	107.162162	7.175676	42.095218
3	107.162162	7.175676	42.095218
4	107.162162	7.175676	42.095218
..
72	107.162162	7.175676	42.095218
73	107.162162	7.175676	42.095218
74	107.162162	7.175676	42.095218
75	107.162162	7.175676	42.095218
76	107.162162	7.175676	42.095218

[77 rows x 3 columns]

Practical transformation

`transform()` will generally be most useful via a user defined function, the lambda is applied to each column of each group.

```
1 ( cereal
2   .drop(["name","type"], axis=1)
3   .groupby("mfr")
4   .transform( lambda x: (x - np.mean(x))/np.std(x, axis=0) )
5 )
```

	calories	sugars	rating
0	-1.767767	1.597191	0.086375
1	0.912871	0.559017	-0.568474
2	-1.780712	-0.582760	1.088220
3	-2.701081	-1.718649	3.512566
4	-0.235702	0.562544	-1.258442
..
72	-0.134568	-1.309457	0.528580
73	-0.134568	1.069190	-0.770226
74	-0.707107	-0.937573	1.449419
75	-1.121403	-1.309457	1.957022
76	-0.134568	0.012013	0.194681

[77 rows x 3 columns]

Filtering groups

`filter()` also respects groups and allows for the inclusion / exclusion of groups based on user specified criteria,

filter

Group sizes

```
1 ( cereal
2   .groupby("mfr")
3   .filter(lambda x: len(x) > 10)
4 )
```

	name	mfr	...	sugars	rating
2	All-Bran	Kellogg's	...	5	59.425505
3	All-Bran with Extra Fiber	Kellogg's	...	0	93.704912
5	Apple Cinnamon Cheerios	General Mills	...	10	29.509541
6	Apple Jacks	Kellogg's	...	14	33.174094
7	Basic 4	General Mills	...	8	37.038562
11	Cheerios	General Mills	...	1	50.764999
12	Cinnamon Toast Crunch	General Mills	...	9	19.823573
13	Clusters	General Mills	...	7	40.400208
14	Cocoa Puffs	General Mills	...	13	22.736446
16	Corn Flakes	Kellogg's	...	2	45.863324
17	Corn Pops	Kellogg's	...	12	35.782791
18	Count Chocula	General Mills	...	13	22.396513
19	Cracklin' Oat Bran	Kellogg's	...	7	40.448772
21	Crispix	Kellogg's	...	3	46.895644
22	Crispy Wheat & Raisins	General Mills	...	10	36.176196
24	Froot Loops	Kellogg's	...	13	32.207582
25	Frosted Flakes	Kellogg's	...	11	31.425072



polars

Polars is a blazingly fast DataFrame library for manipulating structured data. The core is written in Rust, and available for Python, R and NodeJS.

The goal of Polars is to provide a lightning fast DataFrame library that:

- Utilizes all available cores on your machine.
- Optimizes queries to reduce unneeded work/memory allocations.
- Handles datasets much larger than your available RAM.
- A consistent and predictable API.
- Adheres to a strict schema (data-types should be known before running the query).

```
1 import polars as pl
2 pl.__version__
```

'1.21.0'

Series

Just like Pandas, Polars also has a [Series](#) type used for columns. For a complete list of polars dtypes see [here](#).

```
1 pl.Series("ints", [1, 2, 3, 4, 5])
```

shape: (5,)

ints
i64
1
2
3
4
5

```
1 pl.Series("bools", [True, False, True, False, True])
```

shape: (5,)

bools
bool
true
false
true
false
true

```
1 pl.Series("dbls", [1., 2., 3., 4., 5.])
```

shape: (5,)

dbls
f64
1.0
2.0
3.0
4.0
5.0

```
1 pl.Series("strs", ["A", "B", "C", "D", "E"])
```

shape: (5,)

strs
str
"A"
"B"
"C"
"D"
"E"

Missing values

In Polars, missing data is represented by the value `null`. This missing value `null` is used for all data types, including numerical types.

```
1 pl.Series("ints",
2   [1, 2, 3, None])
```

shape: (4,)

ints
i64
1
2
3
null

```
1 pl.Series("bools",
2   [True, False, True, None])
```

shape: (4,)

bools
bool
true
false
true
null

```
1 pl.Series("ints",
2   [1, 2, 3, np.nan])
```

TypeError: unexpected value while building Series of type Int64; found value of type Float64: NaN

Hint: Try setting ``strict=False`` to allow passing data with mixed types.

```
1 pl.Series("dbls",
2   [1., 2., 3., None])
```

shape: (4,)

dbls
f64
1.0
2.0
3.0
null

```
1 pl.Series("strs",
2   ["A", "B", "C", None])
```

shape: (4,)

strs
str
"A"
"B"
"C"
null

```
1 pl.Series("dbls",
2   [1., 2., 3., np.nan])
```

shape: (4,)

dbls
f64
1.0
2.0
3.0
NaN

Missing value checking

Checking for missing values can be done via the `is_null()` method

```
1 pl.Series("ints",  
2   [1, 2, 3, None]).is_null()
```

shape: (4,)

ints

bool

false

false

false

true

```
1 pl.Series("dbls",  
2   [1., 2., 3., np.nan]).is_null()
```

shape: (4,)

dbls

bool

false

false

false

false

```
1 pl.Series("dbls",  
2   [1., 2., 3., None]).is_null()
```

shape: (4,)

dbls

bool

false

false

false

true

```
1 pl.Series("bools",  
2   [True, False, True, None]).is_null()
```

shape: (4,)

bools

bool

false

false

false

true

DataFrames

Data Frames can be constructed in the same way as Pandas,

```
1 df = pl.DataFrame(  
2     {  
3         "name":    ["anna","bob","carol", "dave", "erin"],  
4         "id":      np.random.randint(100, 999, 5),  
5         "weight":  np.random.normal(70, 20, 5),  
6         "height":  np.random.normal(170, 15, 5),  
7         "date":    pd.date_range(start='2/1/2025', periods=5, freq='D')  
8     },  
9     schema_overrides = {"id": pl.UInt16, "weight": pl.Float32}  
10 )  
11 df
```

shape: (5, 5)

name	id	weight	height	date
str	u16	f32	f64	datetime[ns]
"anna"	202	79.477219	162.607949	2025-02-01 00:00:00
"bob"	535	97.369003	175.888696	2025-02-02 00:00:00
"carol"	960	51.663464	156.06223	2025-02-03 00:00:00
"dave"	370	67.517059	171.197477	2025-02-04 00:00:00
"erin"	206	29.780743	167.607252	2025-02-05 00:00:00

Expressions

Polars makes use of lazy evaluation to improve its flexibility and computational performance.

```
1 bmi_expr = pl.col("weight") / (pl.col("height") ** 2)
2 bmi_expr
```

```
[(col("weight")) / (col("height").pow([dyn int: 2]))]
```

This represents a potential computation that can be executed later. Much of the power of Polars comes from the ability to chain together / compose these expressions.

Contexts

Contexts are the environments in which expressions are evaluated - examples of common contexts include: `select`, `with_columns`, `filter`, and `group_by`.

```
1 df.select(bmi = bmi_expr)
```

shape: (5, 1)

bmi
f64
0.003006
0.003147
0.002121
0.002304
0.00106

```
1 df.with_columns(bmi = bmi_expr)
```

shape: (5, 6)

name	id	weight	height	date	bmi
str	u16	f32	f64	datetime[ns]	f64
"anna"	202	79.477219	162.607949	2025-02-01 00:00:00	0.003006
"bob"	535	97.369003	175.888696	2025-02-02 00:00:00	0.003147
"carol"	960	51.663464	156.06223	2025-02-03 00:00:00	0.002121
"dave"	370	67.517059	171.197477	2025-02-04 00:00:00	0.002304
"erin"	206	29.780743	167.607252	2025-02-05 00:00:00	0.00106

filter()

```
1 df.filter(  
2     pl.col("height") > 160,  
3     pl.col("id") < 500  
4 )
```

shape: (3, 5)

name	id	weight	height	date
str	u16	f32	f64	datetime[ns]
"anna"	202	79.477219	162.607949	2025-02-01 00:00:00
"dave"	370	67.517059	171.197477	2025-02-04 00:00:00
"erin"	206	29.780743	167.607252	2025-02-05 00:00:00

```
1 df.filter(  
2     (pl.col("height") > 160) |  
3     (pl.col("id") < 500)  
4 )
```

shape: (4, 5)

name	id	weight	height	date
str	u16	f32	f64	datetime[ns]
"anna"	202	79.477219	162.607949	2025-02-01 00:00:00
"bob"	535	97.369003	175.888696	2025-02-02 00:00:00
"dave"	370	67.517059	171.197477	2025-02-04 00:00:00
"erin"	206	29.780743	167.607252	2025-02-05 00:00:00

group_by() & agg()

```
1 df.groupby(  
2     id_range = pl.col("id") - pl.col("id") % 100  
3 ).agg(  
4     pl.len(),  
5     pl.col("name"),  
6     bmi_expr.alias("bmi"),  
7     pl.col("weight", "height").mean().name.prefix("avg_"),  
8     med_height = pl.col("height").median()  
9 )
```

shape: (4, 7)

id_range	len	name	bmi	avg_weight	avg_height	med_height
u16	u32	list[str]	list[f64]	f32	f64	f64
900	1	["carol"]	[0.002121]	51.663464	156.06223	156.06223
500	1	["bob"]	[0.003147]	97.369003	175.888696	175.888696
300	1	["dave"]	[0.002304]	67.517059	171.197477	171.197477
200	2	["anna", "erin"]	[0.003006, 0.00106]	54.628983	165.107601	165.107601

More expression expansion

```
1 num_cols = pl.col(pl.Float64, pl.Float32)
2
3 df.with_columns(
4     ((num_cols - num_cols.mean())/num_cols.std()).name.suffix("_std")
5 )
```

shape: (5, 7)

name	id	weight	height	date	weight_std	height_std
str	u16	f32	f64	datetime[ns]	f32	f64
"anna"	202	79.477219	162.607949	2025-02-01 00:00:00	0.552878	-0.529878
"bob"	535	97.369003	175.888696	2025-02-02 00:00:00	1.243865	1.201382
"carol"	960	51.663464	156.06223	2025-02-03 00:00:00	-0.521299	-1.383169
"dave"	370	67.517059	171.197477	2025-02-04 00:00:00	0.090973	0.589841
"erin"	206	29.780743	167.607252	2025-02-05 00:00:00	-1.366417	0.121824

NYC Taxi Data

```
1 df = pl.scan_parquet(  
2     "~/Scratch/nyctaxi/*_fix.parquet"  
3 )  
4 df
```

naive plan: (run **LazyFrame.explain(optimized=True)** to see the optimized plan)

Parquet SCAN [/Users/rundel/Scratch/nyctaxi/yellow_tripdata_2020-01_fix.parquet, ... 58 other sources]

PROJECT */19 COLUMNS

```
1 df.select(pl.len()).collect()
```

shape: (1, 1)

len
171021073

```
1 df.select(pl.len()).explain()
```

```
'FAST COUNT (Parquet) [/Users/rundel/Scratch/nyctaxi/yellow_tripdata_2020-  
01_fix.parquet, ... 58 other sources] as "len"\n  DF []; PROJECT */0 COLUMNS'
```

Large lazy queries

```
1 zone_lookup = pl.read_csv(  
2     "https://d37ci6vzurychx.cloudfront.net/misc/taxi_zone_lookup.csv"  
3 ).rename(  
4     {"LocationID": "pickup_zone"}  
5 )
```

```
1 query = (  
2     df  
3     .filter(pl.col("trip_distance") > 0)  
4     .rename({"PULocationID": "pickup_zone"})  
5     .group_by("pickup_zone")  
6     .agg(  
7         num_rides = pl.len(),  
8         avg_fare_per_mile = (pl.col("fare_amount") / pl.col("trip_distance")).mean().round(2)  
9     ).join(  
10         zone_lookup.lazy(),  
11         on = "pickup_zone",  
12         how = "left"  
13     )  
14     .sort("pickup_zone")  
15 )
```

Plan

1 query

naive plan: (run **LazyFrame.explain(optimized=True)** to see the optimized plan)

SORT BY [col("pickup_zone")]

LEFT JOIN:

LEFT PLAN ON: [col("pickup_zone").strict_cast(Int64)]

AGGREGATE

[len().alias("num_rides"), [(col("fare_amount")) / (col("trip_distance"))].mean().round().alias("avg_fare_per_mile")] **BY** [col("pickup_zone")] **FROM**

RENAME

FILTER [(col("trip_distance")) > (0.0)] **FROM**

Parquet SCAN [/Users/rundel/Scratch/nyctaxi/yellow_tripdata_2020-01_fix.parquet, ... 58 other sources]

PROJECT */19 COLUMNS

RIGHT PLAN ON: [col("pickup_zone").strict_cast(Int64)]

DF ["pickup_zone", "Borough", "Zone", "service_zone"]; **PROJECT */4 COLUMNS**

END LEFT JOIN

Result

```
1 query.collect()
```

shape: (263, 6)

pickup_zone	num_rides	avg_fare_per_mile	Borough	Zone	service_zone
i32	u32	f64	str	str	str
1	6022	2205.09	"EWR"	"Newark Airport"	"EWR"
2	149	4.93	"Queens"	"Jamaica Bay"	"Boro Zone"
3	5812	11.98	"Bronx"	"Allerton/Pelham Gardens"	"Boro Zone"
4	225977	9.9	"Manhattan"	"Alphabet City"	"Yellow Zone"
5	891	20.02	"Staten Island"	"Arden Heights"	"Boro Zone"
...
261	818903	9.25	"Manhattan"	"World Trade Center"	"Yellow Zone"
262	2336728	7.93	"Manhattan"	"Yorkville East"	"Yellow Zone"
263	3531531	7.76	"Manhattan"	"Yorkville West"	"Yellow Zone"
264	1245641	22.66	"Unknown"	"N/A"	"N/A"
265	275794	66.35	"N/A"	"Outside of NYC"	"N/A"

Performance

```
1 %timeit query.collect()
```

1.14 s \pm 62 ms per loop (mean \pm std. dev. of 7 runs, 1 loop each)