Scaling up pandas with the Beam DataFrame API

By Brian Hulette (bhulette@apache.org)

https://s.apache.org/beam-dataframes-2022

BEAM SUMMIT Austin, 2022

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Apache Arrow **Committer**
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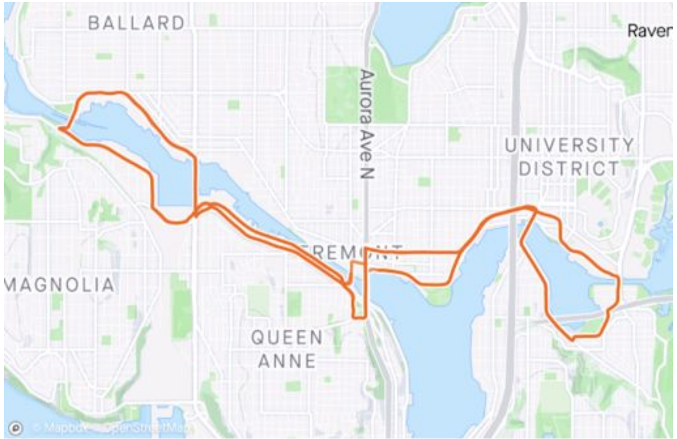
Brian Hulette



Agenda

- What are pandas DataFrames? Why put them in Beam?
- Tour of the Beam DataFrame API
- How it works
- Lessons Learned and Future Work

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```
In [1]: import pandas as pd

In [2]: df = pd.DataFrame(
   ....:     {
   ....:         "A": ["foo", "bar", "foo", "bar", "foo", "bar", "foo", "foo"],
   ....:         "B": ["one", "one", "two", "three", "two", "two", "one", "three"],
   ....:         "C": np.random.randn(8),
   ....:         "D": np.random.randn(8),
   ....:     }
   ....: )
   ....:

In [3]: df
Out[3]:
     A      B         C         D
0  foo    one  1.346061 -1.577585
1  bar    one  1.511763  0.396823
2  foo    two  1.627081 -0.105381
3  bar  three -0.990582 -0.532532
4  foo    two -0.441652  1.453749
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In [4]: df.groupby("A").sum()
Out[4]:
            C         D
A
bar  1.732707  1.073134
foo  2.824590 -0.574779
```

```
In [5]: df.C
Out[5]:
0    0.359797
1    0.371583
2   -1.849233
3   -1.880074
4   -0.689943
5   -1.024726
6   -1.492432
7   -0.650677
Name: C, dtype: float64

In [6]: df.C.mean()
Out[6]: -0.8569631996465763
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DataFrame

```
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```

Series

```
In [3]: df[df.B == 'one']
Out[3]:
     A      B         C         D
0   foo    one  1.346061 -1.577585
1   bar    one  1.511763  0.396823
6   foo    one  0.268520 -0.080952

In [4]: df.groupby("A").agg({
   ....:    'C': 'sum',
   ....:    'D': 'mean',
   ....: })
Out[4]:
            C         D
A
bar  1.732707  1.073134
foo  2.824590 -0.574779
```

```
In [5]: df.new = df.C.abs() > df.D.abs()

In [6]: df
Out[6]:
     A      B         C         D    new
0   foo    one  1.346061 -1.577585 False
1   bar    one  1.511763  0.396823  True
2   foo    two  1.627081 -0.105381  True
3   bar  three -0.990582 -0.532532  True
4   foo    two -0.441652  1.453749 False
5   bar    two  1.211526  1.208843  True
6   foo    one  0.268520 -0.080952  True
7   foo  three  0.024580 -0.264610 False
```

Used interactively in Notebooks

Dataset: Stanford Open Policing Project (video) ¶

https://openpolicing.stanford.edu/

In [3]:
```
# ri stands for Rhode Island
ri = pd.read_csv('police.csv')
```

In [4]:
```
# what does each row represent?
ri.head()
```

Out[4]:

	stop_date	stop_time	county_name	driver_gender	driver_age_raw	driver_age	driver_race	violation_raw	violati
0	2005-01-02	01:55	NaN	M	1985.0	20.0	White	Speeding	Speedi
1	2005-01-18	08:15	NaN	M	1965.0	40.0	White	Speeding	Speedi
2	2005-01-23	23:15	NaN	M	1972.0	33.0	White	Speeding	Speedi
3	2005-02-20	17:15	NaN	M	1986.0	19.0	White	Call for Service	Oth
4	2005-03-14	10:00	NaN	F	1984.0	21.0	White	Speeding	Speedi

In [5]:
```
# what do these numbers mean?
```

2. Do men or women speed more often? (video)

In [13]:
```
# when someone is stopped for speeding, how often is it a man or woman?
ri[ri.violation == 'Speeding'].driver_gender.value_counts(normalize=True)
```

Out[13]:
```
M    0.680527
F    0.319473
Name: driver_gender, dtype: float64
```

In [14]:
```
# alternative
ri.loc[ri.violation == 'Speeding', 'driver_gender'].value_counts(normalize=True)
```

Out[14]:
```
M    0.680527
F    0.319473
Name: driver_gender, dtype: float64
```

In [15]:
```
# when a man is pulled over, how often is it for speeding?
ri[ri.driver_gender == 'M'].violation.value_counts(normalize=True)
```

Out[15]:
```
Speeding               0.524350
Moving violation       0.207012
Equipment              0.135671
Other                  0.057668
Registration/plates    0.038461
Seat belt              0.036839
Name: violation, dtype: float64
```

https://nbviewer.jupyter.org/github/justmarkham/pycon-2018-tutorial/blob/master/tutorial.ipynb

Why make a pandas compatible API?

- Efficient implementation
- Declarative, concise API
- Familiar API for Python users

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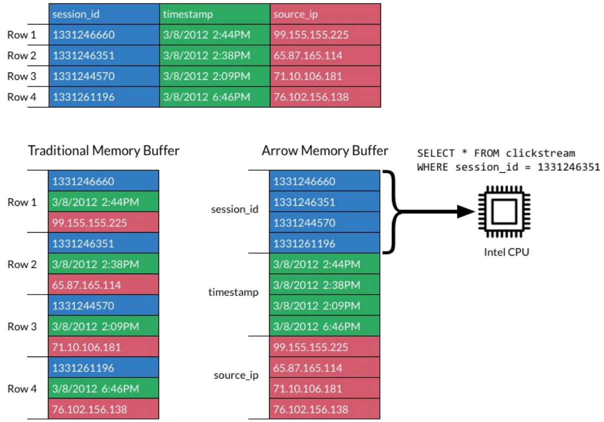
1. Efficient Implementation

- Columnar memory layout
- Implemented in C
- Can be re-used to compute partial results on workers



2. pandas has a declarative, concise API

```
import pandas as pd
df = pd.read_csv(input)
agg = df.groupby('DOLocationID').passenger_count.sum()
agg.to_csv(output)
```

```
import apache_beam as beam
(p | beam.io.ReadFromText(input, skip_header_lines=1)
   | beam.Map(lambda line: line.split(','))
   # Parse CSV, create key - value pairs
   | beam.Map(lambda splits: (int(splits[8] or 0),  # DOLocationID
                              int(splits[3] or 0))) # passenger_count
   # Sum values per key
   | beam.CombinePerKey(sum)
   | beam.MapTuple(lambda loc_id, pc: f'{loc_id},{pc}')
   | beam.io.WriteToText(output))
```

3. pandas has a *Familiar* API

Among 26.9M OSS .py files from GitHub...

- `import apache_beam` 14.6k
- `import pandas` 172k (**~12x** apache_beam)

query

3. pandas has a *Familiar* API

Among 253k OSS .ipynb files from GitHub…

- `import apache_beam` 306
- `import pandas` 53k (**173x** apache_beam, **21% of corpus**)

query

3. pandas has a *Familiar* API

Among 253k OSS .ipynb files from GitHub…

- `import apache_beam` 306
- `import pandas` 53k (**173x** apache_beam, **21% of corpus**)
- `“SELECT …` 8.48k
- `import numpy` 117k
- `import matplotlib` 89k

query

3. pandas has a *Familiar* API

… but it's **in-memory only**.

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DataframeTransform

Any schema'd PCollection

```
output = input | DataframeTransform(
                     lambda df: df.groupby(...).agg(...))
```

Outputs a schema'd PCollection

A “deferred” DataFrame

Multiple Inputs

```
output = (pc1, pc2) | DataframeTransform(lambda df1, df2: ...)

output = {a: pc, ...} | DataframeTransform(lambda a, ...: ...)
```

DataFrame-PCollection Conversion

```
with beam.Pipeline() as p:
  pc = ... # A PCollection with a Schema

  df = to_dataframe(pc) # A Beam DeferredDataFrame
  result = df.groupby('foo').agg(...)
  result_pc = to_pcollection(result)

  result_pc | beam.WriteToText(...)
```

pandas IOs

```
from apache_beam.dataframe.io import read_parquet

with beam.Pipeline() as p:
  df = p | read_parquet(“gs://bucket/*.pq”)
  result = df.groupby(‘foo’).agg(...)
  result.to_csv(“gs://bucket/output.csv”)
```

Implementations use **FileIO** under the hood. Gives us distributed reads, liquid sharding, support for cloud object stores (`gs://`, `s3://`).

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All pandas objects have indexes

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All pandas objects have indexes

Unique Index

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```

Many operations use the index implicitly

```
In [6]: a
Out[6]:
0    1
1    2
2    3
dtype: int64

In [7]: b
Out[7]:
0    0
1    0
2    1
dtype: int64


In [8]: a*b
Out[8]:
0    0
1    0
2    3
dtype: int64
```

```
In [9]: c
Out[9]:
2    0
1    0
0    1
dtype: int64

In [10]: a*c
Out[10]:
0    1
1    0
2    0
dtype: int64
```

Not order sensitive!
Implicitly joined on the index.

How to make a Pipeline Graph?

```
def my_function(df):
    df['C'] = df.A + 2*df.B
    result = df.groupby('C').sum().filter('A < 0')
    return result

output = input | DataframeTransform(my_function)
```

Objective: Create a Beam Pipeline sub-graph that performs the computation described by `my_function`.

How to make a Pipeline Graph?

```
def my_function(df):
    df['C'] = df.A + 2*df.B
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```
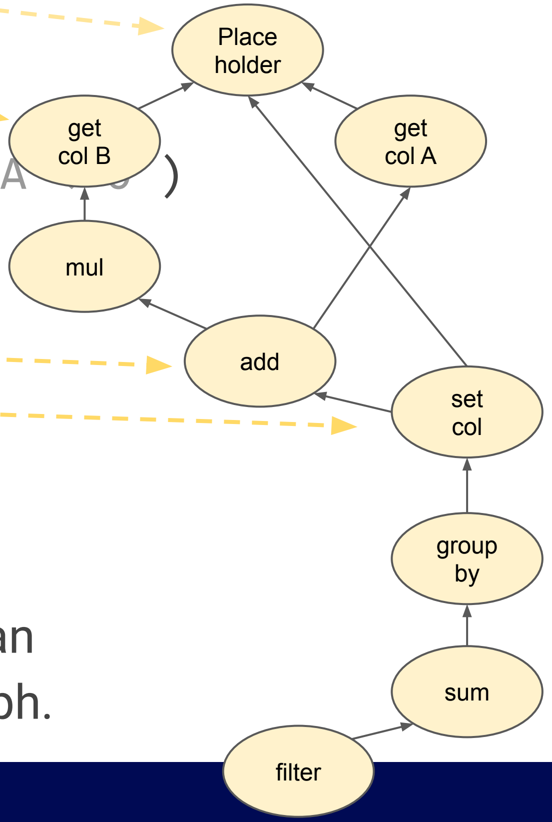

~~pd.DataFrame~~ → apache_beam.DeferredDataFrame

Call function with our own DeferredDataFrame, which has custom implementations for pandas operations.

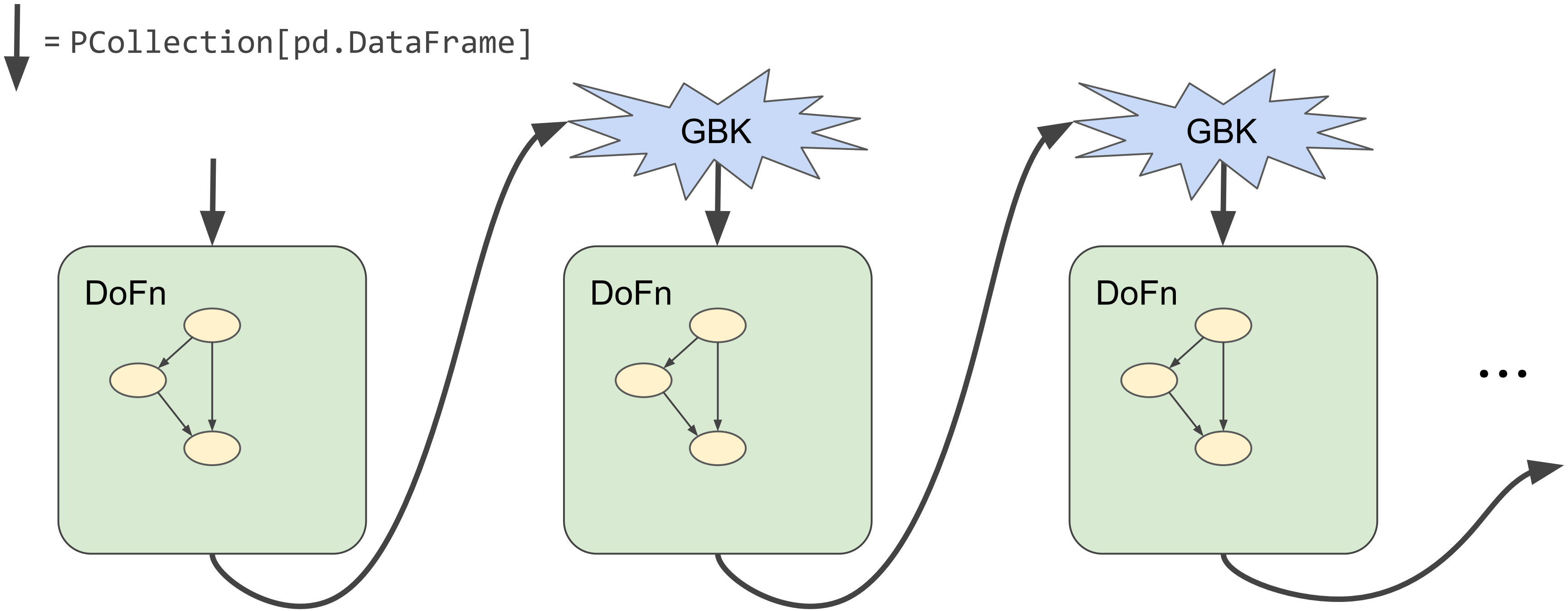
Build an expression tree

```
def my_function(df):
    df['C'] = df.A + 2*df.B
    result = df.groupby('C').sum().filter('A …')
    return result
```



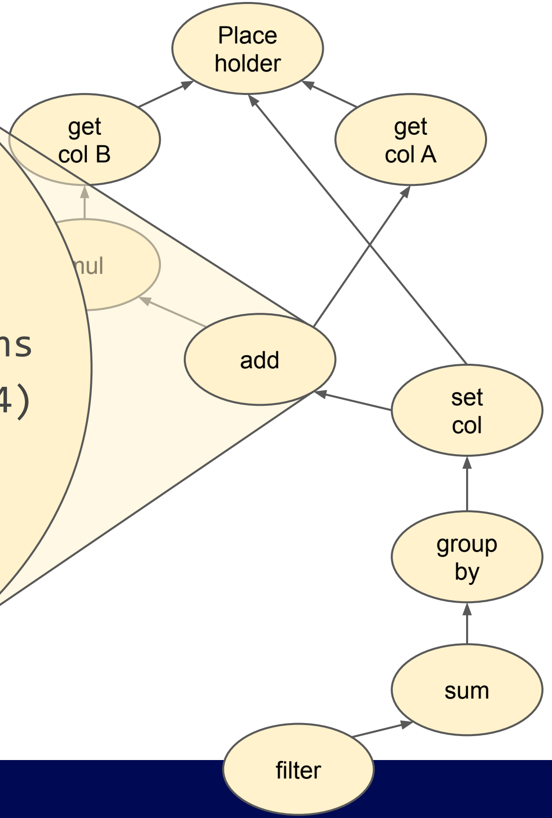
DeferredDataFrame operations record and validate an **Expression Tree**. Note this is *not* a Beam pipeline graph.

Goal: A Beam Pipeline Graph



Expression Metadata

```
name  = “add”
args  = [mul, get_col_a]
fn    = lambda lhs, rhs: lhs + rhs
proxy = Series([], dtype: float64)
requires_partition_by = Index()
preserves_partition_by = Index()
```



Expression Metadata - fn, args

Input expressions

At execution time, **fn** is called with **pd.Series** or **pd.DataFrame** representing a partition of the full dataset.

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```

Expression Metadata - proxy

An *empty* **`pd.Series`** or **`pd.DataFrame`** with the same shape that we expect to see at execution time.

Used for:

- Validation
- Authentic error messages
- Data types, mapping to Beam Schemas

```
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Expression Metadata - partitioning

Type of partitioning this expression requires in its inputs to be computed correctly.

Type of partitioning guaranteed to be preserved in the expression's outputs.

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Partitioning Requirements

- Index()
  - Shuffle using a hash of the index modulo N to co-locate like indexes into N partitions.
- Singleton()
  - Collect all data onto a single node.
  - Some operations require it.
  - Used internally if we know data volume is small.
- Arbitrary()
  - No partitioning guarantees whatsoever.

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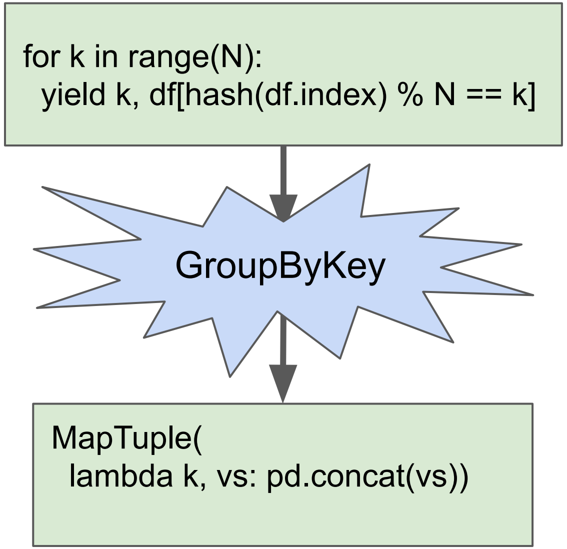

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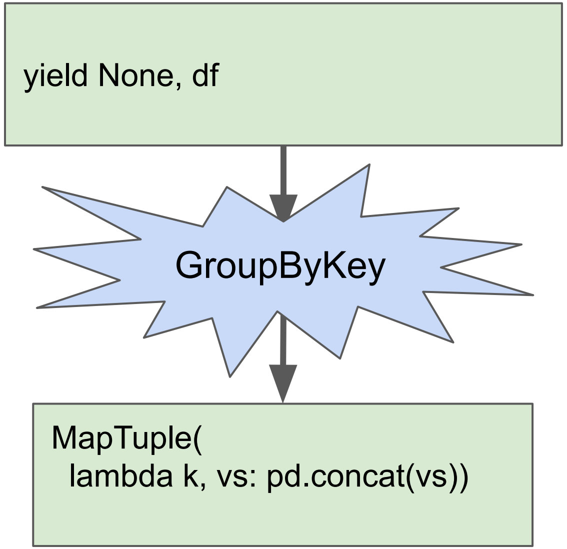

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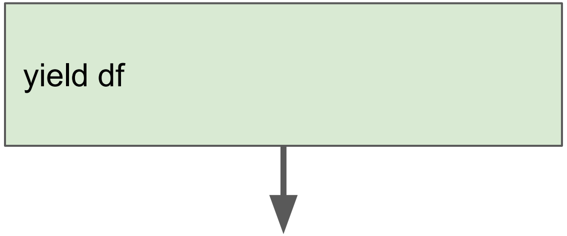
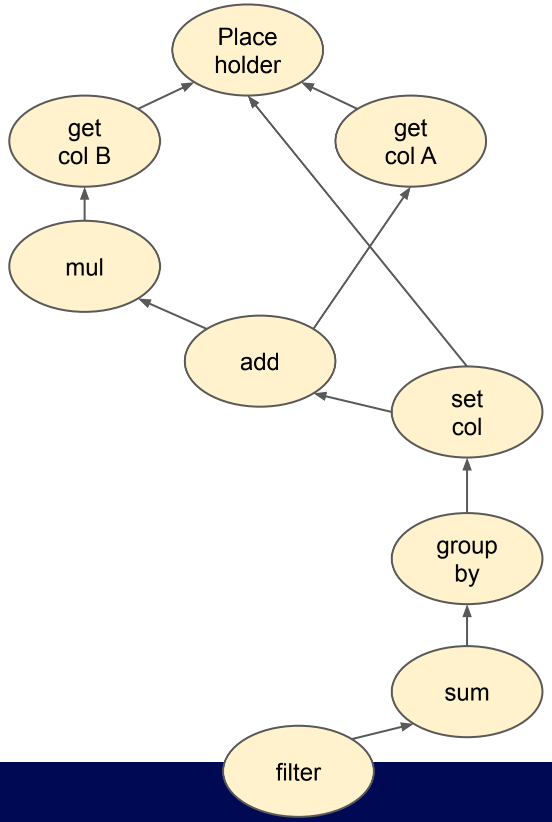


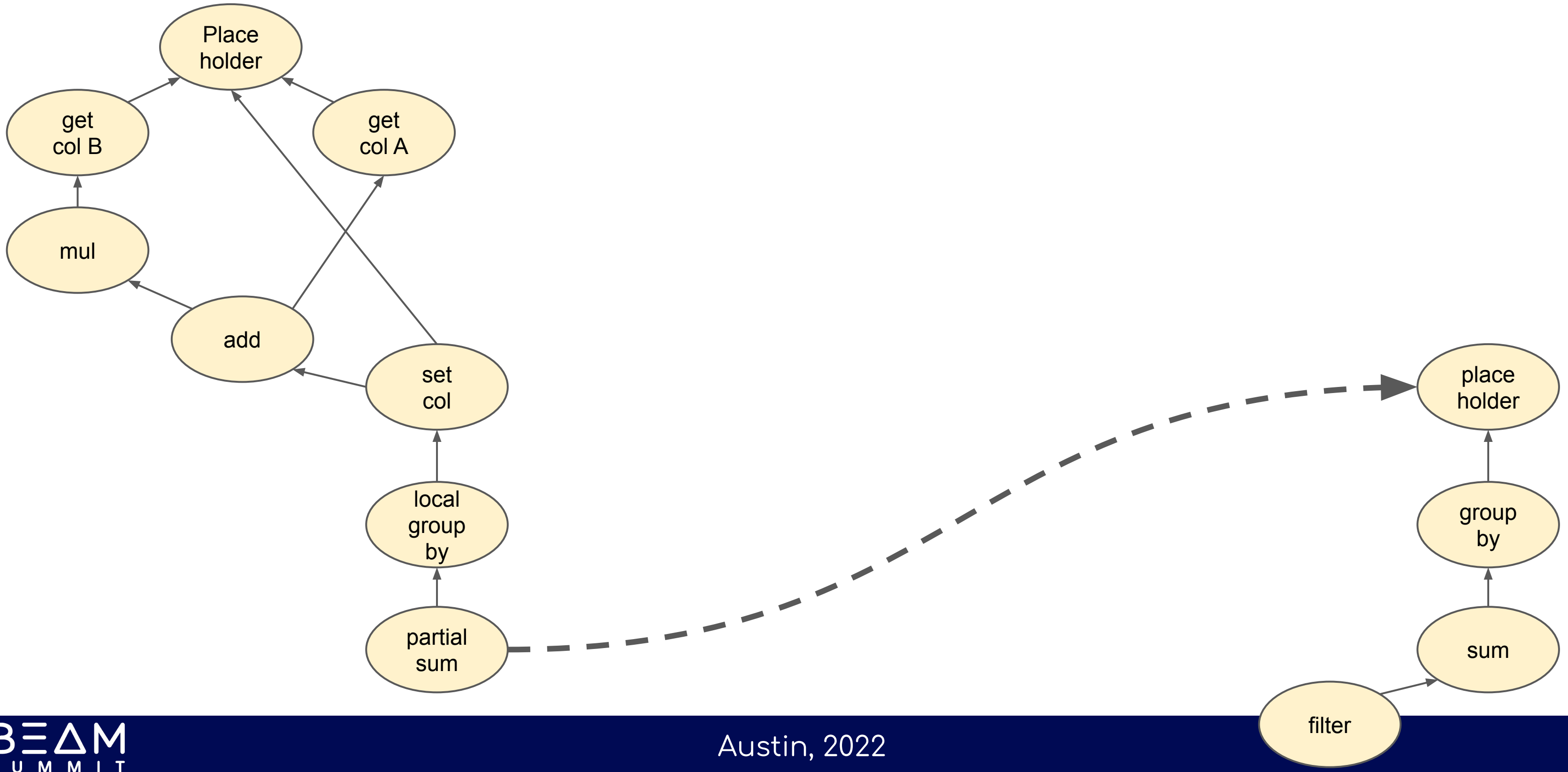
Expression Tree to Pipeline Graph

The expression tree is broken up into a minimal number of stages, i.e. **DoFns** interleaved with **partitioning shuffles**.

We determine where to shuffle based on the nodes' partitioning requirements.



Expression Tree to Pipeline Graph



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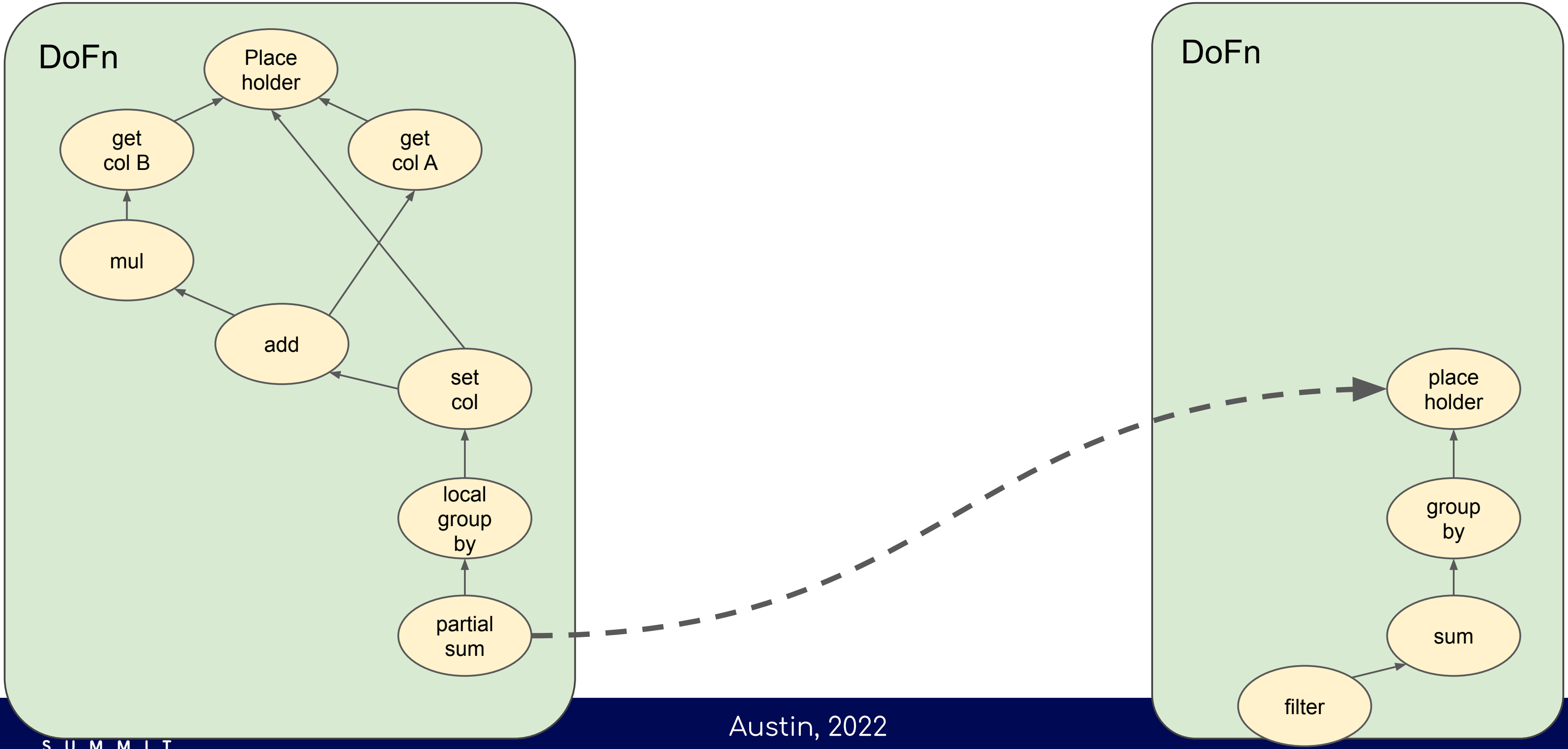
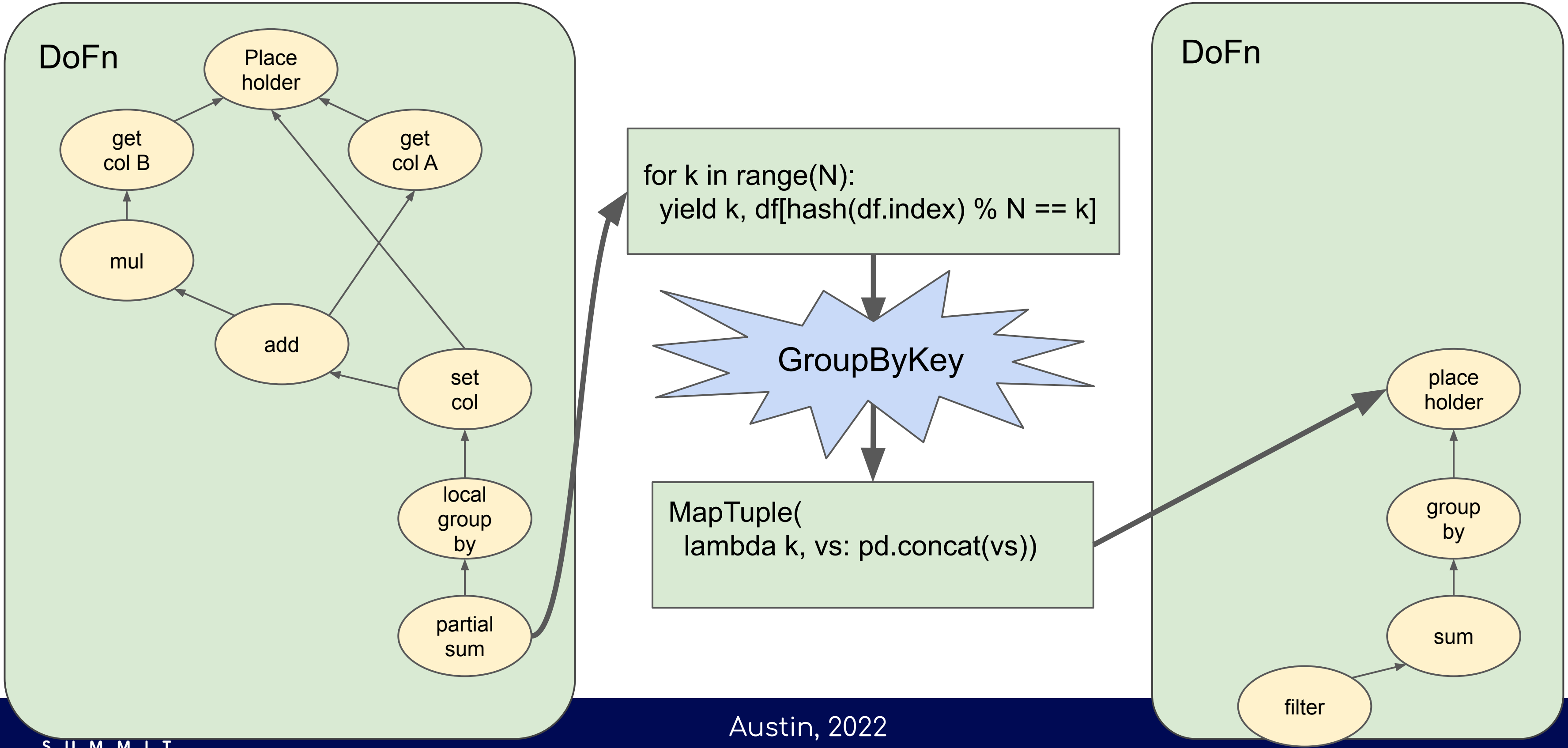
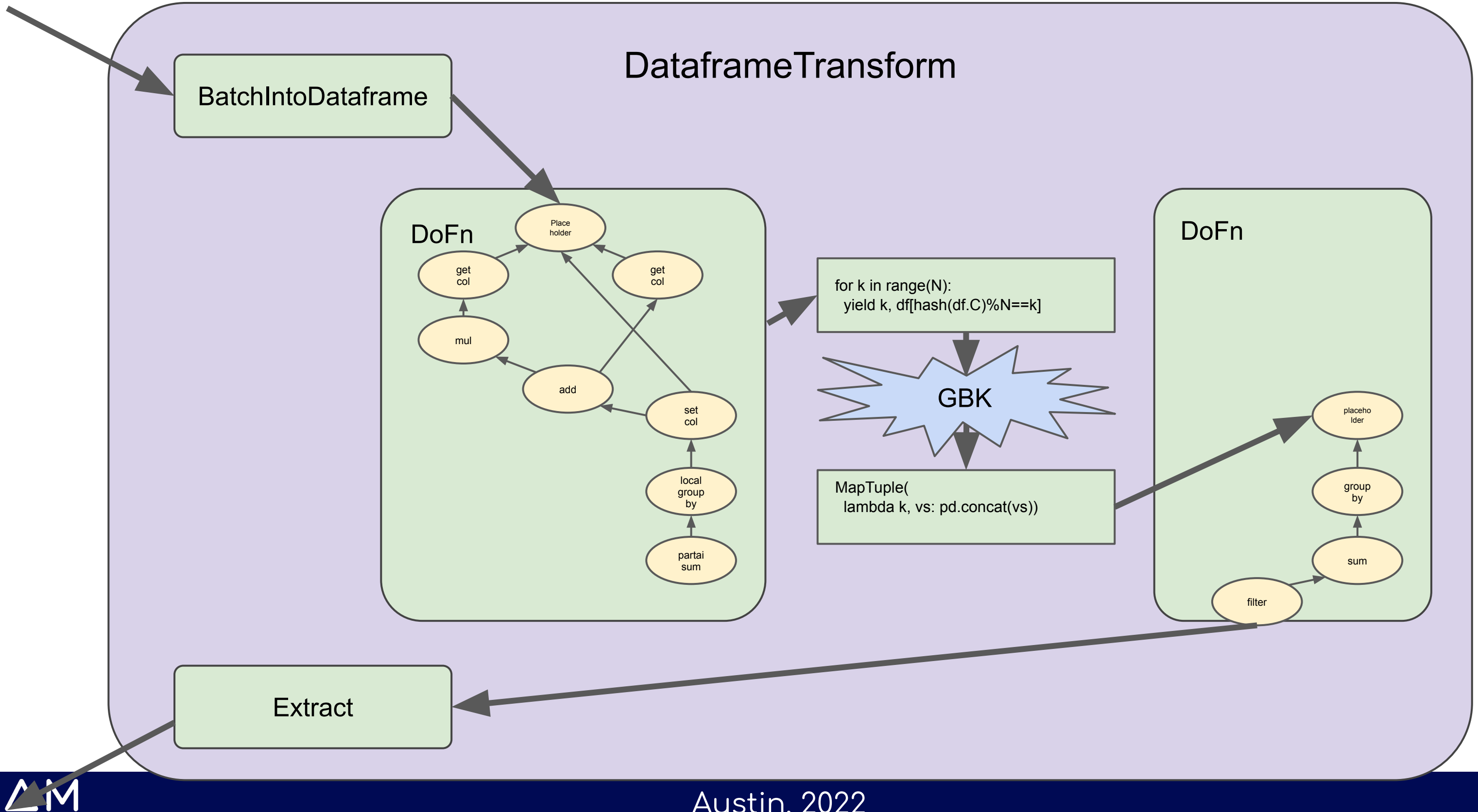


Expression Tree to Pipeline Graph



Batching and Unbatching



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Python needs more schema'd sources! 

```
# From apache_beam.examples.dataframe.flight_delays
p | 'read table' >> beam.io.ReadFromBigQuery(query="SELECT …")
  # Use beam.Select to make sure data has a schema
  # The casts in lambdas ensure data types are properly inferred
  | 'set schema' >> beam.Select(
      date=lambda x: str(x['date']),
      airline=lambda x: str(x['airline']),
      departure_airport=lambda x: str(x['departure_airport']),
      arrival_airport=lambda x: str(x['arrival_airport']),
      departure_delay=lambda x: float(x['departure_delay']),
      arrival_delay=lambda x: float(x['arrival_delay'])))
```

```
beam_df = p | read_gbq("SELECT ...")
```

Follow #20810

Compliance is key

- Too many operations raise WontImplementError
- We need to close the compliance gap
- s.apache.org/interactive-dataframe-operations ([#21638]())
  - Add a set of `df.interactive.*` operations that are eagerly executed.
  - e.g. **`df.interactive.plot`**, **`df.interactive.pivot`**
- s.apache.org/order-sensitive-dataframe-operations ([#20862]())
  - **~14%** of pandas operations are order-sensitive.
  - Proposal to support these operations, with caveats.
  - e.g. **`df.sort_values().fillna()`**

Streaming can be a differentiator

```
# Read an unbounded source into a Beam DataFrame
beam_df = p | read_kafka(topic)

# Create a 5 minute window, perform an aggregation
beam_df.rolling(‘5m’)[‘column_a’].mean()

# Write the result
beam_df.to_csv()
```

❗ Fictional API ❗

Follow #20911

How you can help

- **Try** your use case in the Beam DataFrame API
  - Let us know if doesn't work! File an issue with label `dataframe`.
- **Contribute** tests for operations/use-cases you care about
  - `apache_beam.dataframe.frames_test`
  - `self._run_test(lambda df: df.groupby('foo').sum(), df)`
- **Add** schema support to IOs
- **Add** interactive and/or order-sensitive operations

Questions?

https://s.apache.org/beam-dataframes-2022

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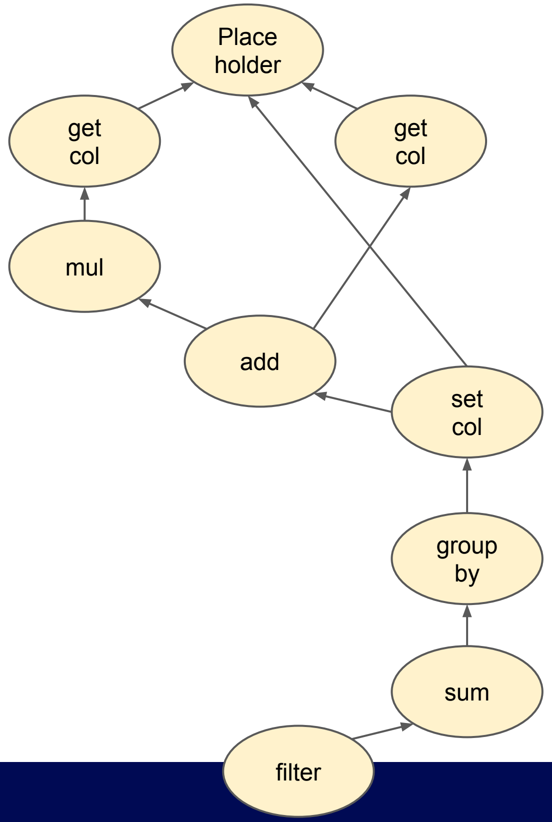
github.com/TheNeuralBit

Backup/Graveyard

Dataframe Transform - Under the Hood

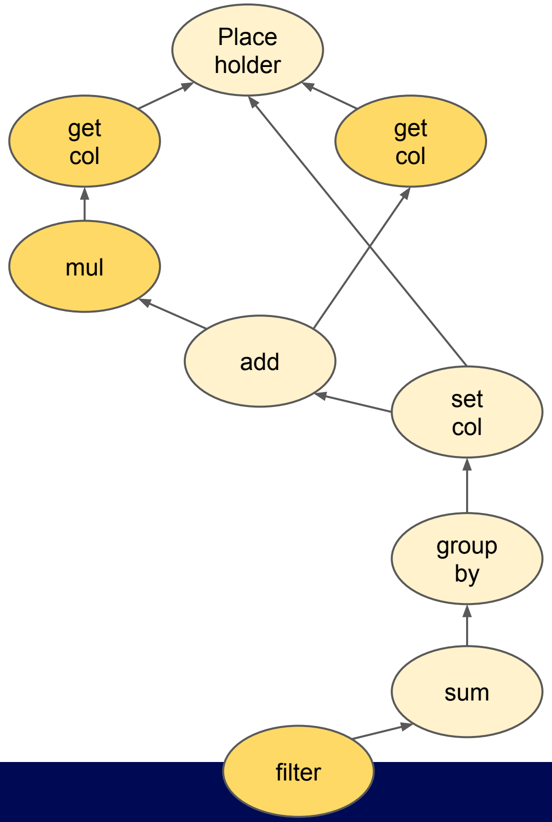
Classification of Operations

- Elementwise
- Grouping
- Zipping
- Order-sensitive



Elementwise Operations

Elementwise Operations map naturally onto ParDo operations in a distributed system, and can be executed by applying the given operation to each partition.

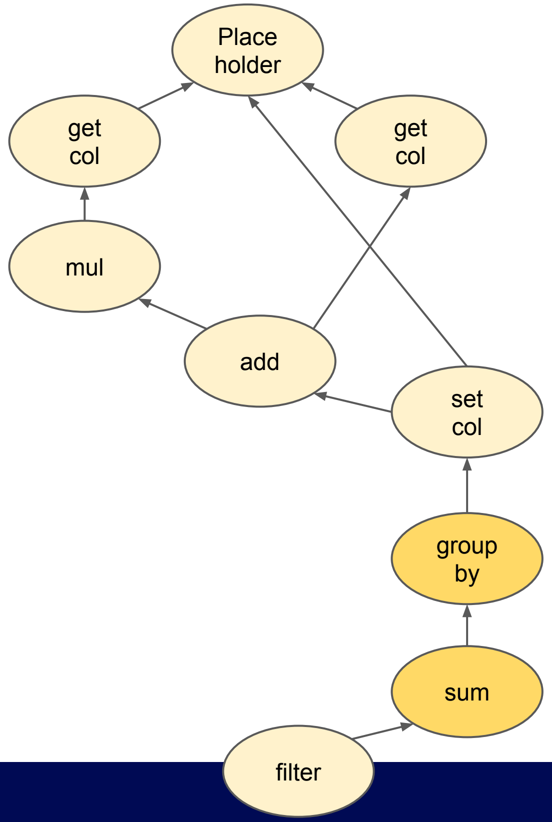


Grouping Operations

Grouping Operations collocate rows with identical values in indices/columns, analogous to the GroupByKey and Combine operations in Beam.

The key insight is that one can perform these operations locally if all required rows are in the same partition, so we inject a GroupByKey to colocate all required rows, then apply the pandas grouping operation directly.

Combining operations lifted when possible.

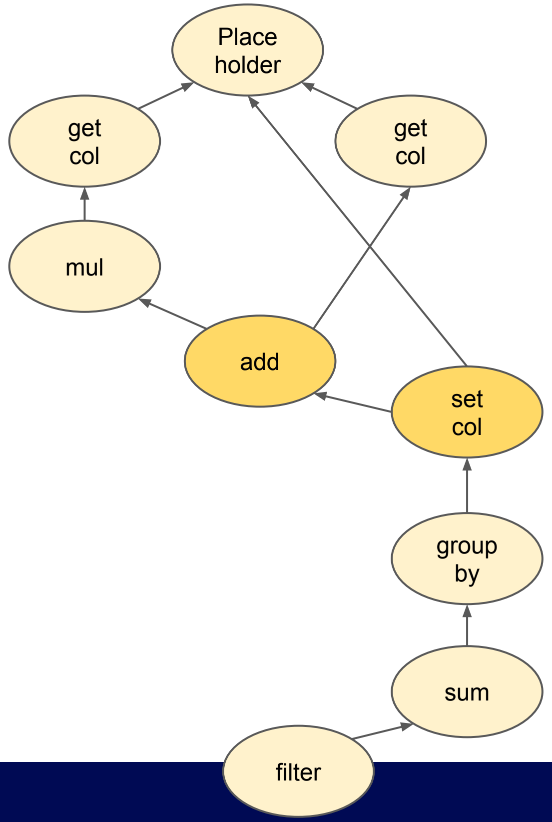


Zipping Operations

Zipping Operations take advantage of the fact that *all dataframes are keyed* giving a natural 1:1 relationship between the rows of multiple dataframes.

CoGBK or Join come the closest in Beam.

An essential optimization is avoiding shuffles when the inputs are *already* both partitioned by index (e.g. common ancestor).



Dataframe Transform - Under the Hood

Order-sensitive Operations (e.g. `iloc`) are not (yet?) supported, as PCollections are unordered and we use hash partitioning for good distributions.

We have considered doing this in the future for DataFrames whose order has been explicitly declared (e.g. via a sort). This may have performance implications.