“Big Pandas” - Dask from the Inside

PyCon UK tutorial, 27 October 2017

Stephen Simmons

mail@stevesimmons.com
stephen.e.simmons@jpmorgan.com

https://github.com/stevesimmons/pyconuk-2017-pandas-and-dask

Goals for today…

Let’s try a much bigger data set – “BTS OTP” (172m records)

Try some simple analysis

- DataFrames from dask rather than pandas
- Efficient data storage
- Calculating the dask dependency graph

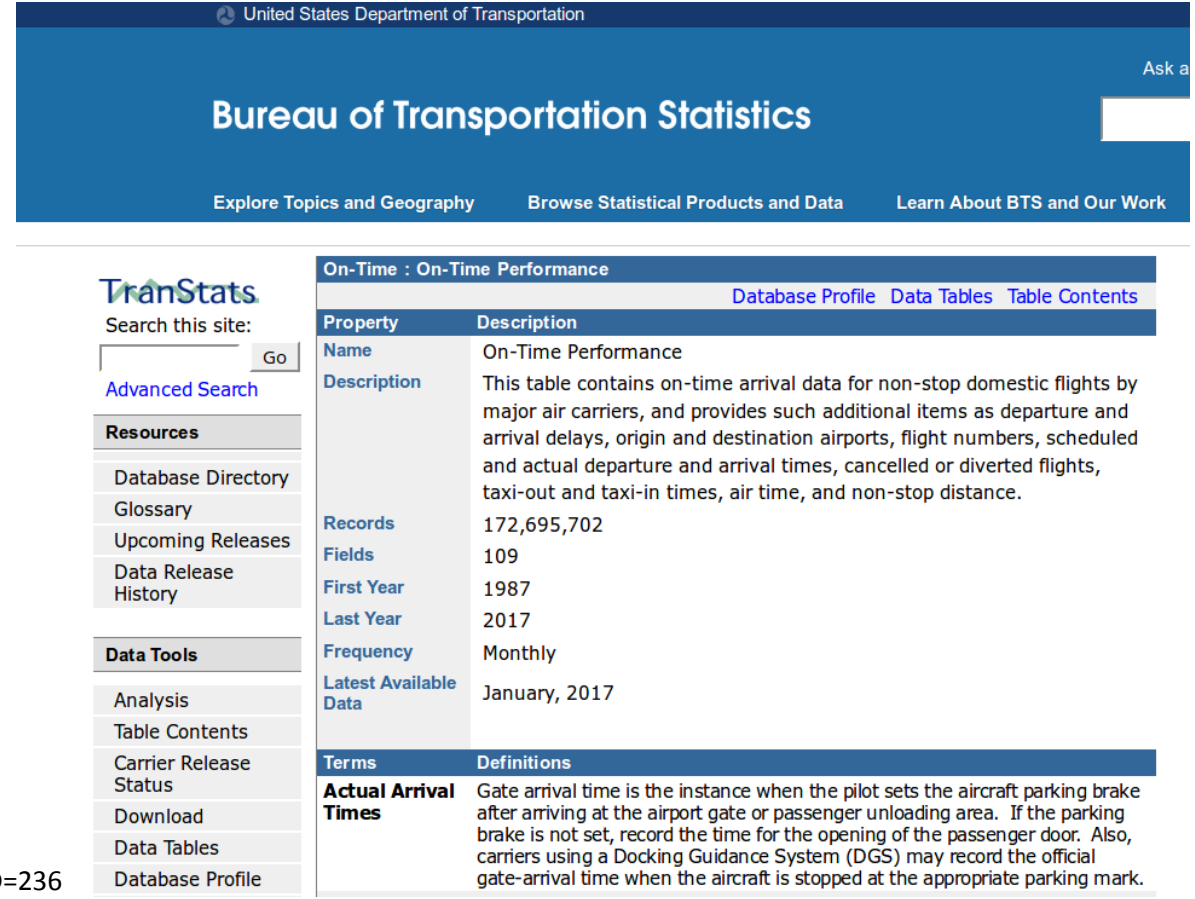
(Note: Examples here all designed to run on a local machine)

American “on-time performance” flight data

Monthly zipped csv files

Each file has
450,000 rows x 109 cols

220MB unzipped
22MB zipped
12MB with LZMA (.xz)



https://www.transtats.bts.gov/acTableInfo.asp?Table_ID=236

CONGESTION IN THE SKY ✈ Visualizing Domestic Airline Traffic with SAS® Software

Rick Wicklin, SAS Institute
Robert Allison, SAS Institute

THE DATA

Twenty years of data (120 million observations) on commercial domestic flights in the United States.

Variables

- *Dates:* day of week, date, month, year
- *Arrival and departure times:* actual and scheduled
- *Flight times:* actual and scheduled
- *Origin and destination:* airport code, latitude, longitude
- *Carrier:* American, Aloha Air, ..., United, US Air

Data are from the Research and Innovative Technology Administration (RITA) which coordinates the U.S. Department of Transportation research programs

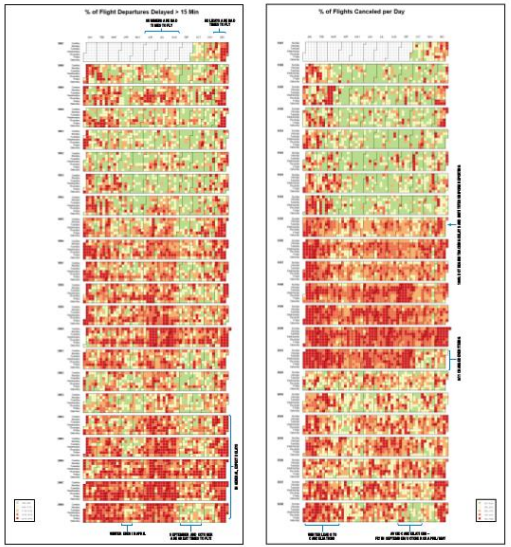
GOALS

- **Summarize data by time periods, airport, and carrier**
- **Temporal effects**
  - Are some time periods more prone to delays than others?
  - Relationships between delays and
    Seasonal factors: winter, summer, holidays
    Weather factors: blizzards and severe weather
    Daily factors: time of day, day of week
- **Spatial effects**
  - Are some airports more prone to delays than others?
  - Are there differences between flying into an airport and flying out?
- **Carrier effects**
  - Are some carriers more prone to delays than others?

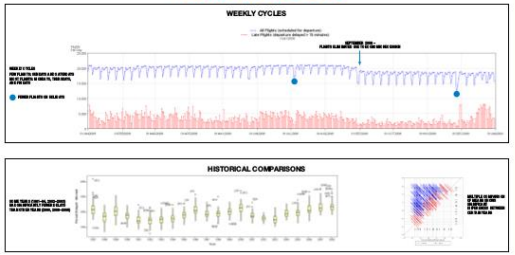
LESSONS LEARNED: TIPS FOR TRAVELERS

- Avoid flying during holidays and summer
- Fly in April, May, and September
- Watch the weather!
- Avoid airports (Newark, JFK, Chicago,...) with consistent delays
- Use carriers (Aloha, Hawaiian, Southwest,...) with superior on-time performance
- Fly early in the day
- Avoid flights that depart between 5 and 7 p.m.

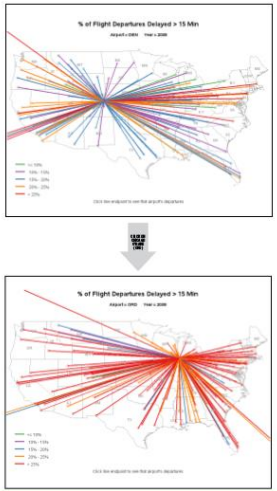
OVERVIEW

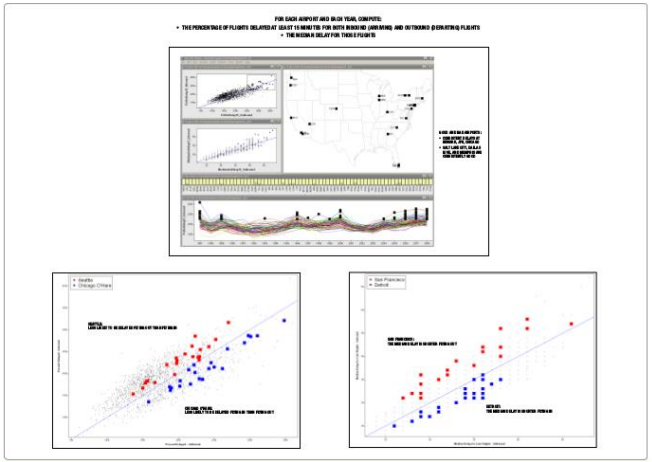


TEMPORAL EFFECTS

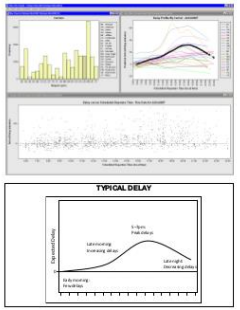


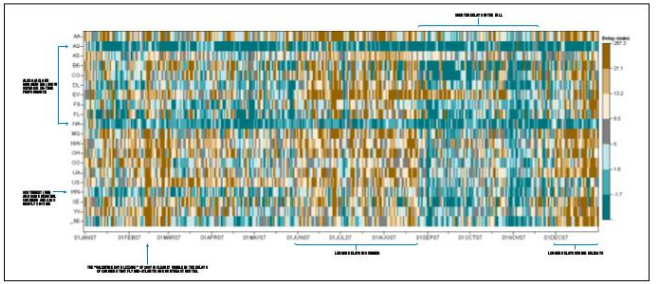
SPATIAL EFFECTS



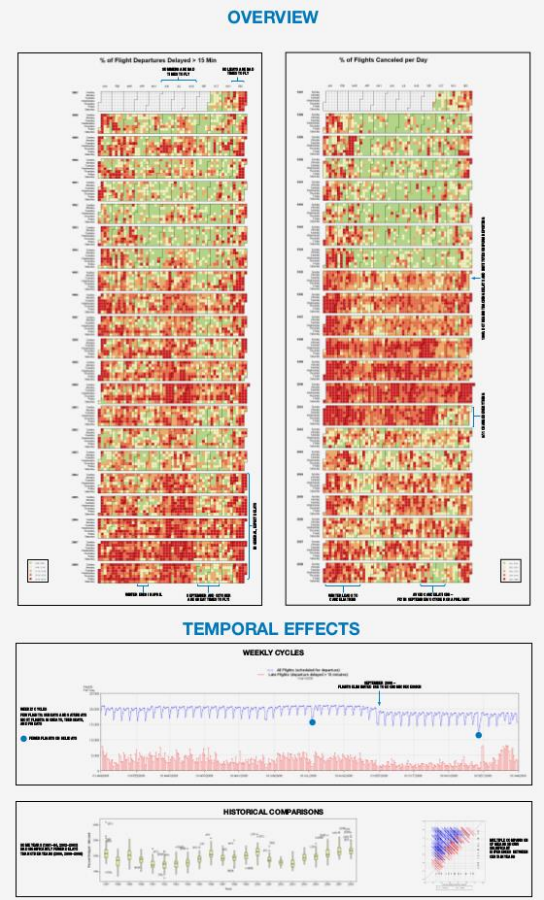


CARRIER EFFECTS





http://stat-computing.org/dataexpo/2009



Our analysis goals…

Calculate % of flights cancelled per day

- by date / date range
- by origin / destination
- by carrier
- by state

http://stat-computing.org/dataexpo/2009

```
df = pd.read_csv('flights-2016-01.xz', nrows=4, dialect="excel")
```

```
> df.T
```

Year	2016	2016	2016	2016
Quarter	1	1	1	1
Month	1	1	1	1
DayofMonth	6	7	8	9
DayOfWeek	3	4	5	6
FlightDate	2016-01-06	2016-01-07	2016-01-08	2016-01-09
UniqueCarrier	AA	AA	AA	AA
AirlineID	19805	19805	19805	19805
Carrier	AA	AA	AA	AA
TailNum	N4YBAA	N434AA	N541AA	N489AA
FlightNum	43	43	43	43
...				
Origin	DFW	DFW	DFW	DFW
...				
Dest	DTW	DTW	DTW	DTW
...				
CRSDepTime	1100	1100	1100	1100
DepTime	1057	1056	1055	1102
DepDelay	-3	-4	-5	2
...				
TaxiOut	15	14	21	13
WheelsOff	1112	1110	1116	1115
WheelsOn	1424	1416	1431	1424
TaxiIn	8	10	14	9
CRSArrTime	1438	1438	1438	1438
ArrTime	1432	1426	1445	1433
ArrDelay	-6	-12	7	-5
...				
Cancelled	0	0	0	0
CancellationCode	NaN	NaN	NaN	NaN
Diverted	0	0	0	0
CRSElapsedTime	158	158	158	158
ActualElapsedTime	155	150	170	151
AirTime	132	126	135	129
Flights	1	1	1	1
Distance	986	986	986	986
...				

```
[110 rows x 4 columns]
```

Pandas DataFrames don’t scale well

```
> df = pd.read_csv('flights-2016-01.xz',
                           dialect="excel")
```

```
DtypeWarning: Columns (77) have mixed types.
Specify dtype option on import or set low_memory=False.
```

```
CPU times: user 5.48 s, sys: 1.36 s, total: 6.83 s
Wall time: 6.83 s
```

```
> df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 445827 entries, 0 to 445826
Columns: 110 entries, Year to Unnamed: 109
dtypes: float64(71), int64(21), object(18)
memory usage: 374.2+ MB
```

```
> df.memory_usage(deep=True).sum() / 2**20
745.2
```

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RangeIndex: 445827 entries, 0 to 445826
Columns: 110 entries, Year to Unnamed: 109
dtypes: float64(71), int64(21), object(18)
memory usage: 374.2+ MB
```

```
> df.memory_usage(deep=True).sum() / 2**20
745.2
```

```
> df = pd.concat([
        pd.read_csv('flights-%s.xz' % m,
                    dialect="excel")
        for m in ['2015-12','2016-01','2016-02']
    ])
```

```
DtypeWarning: Columns (48,76,77,84,85) have mixed types.
DtypeWarning: Columns (77) have mixed types.
DtypeWarning: Columns (77,84) have mixed types.
Specify dtype option on import or set low_memory=False.
```

```
CPU times: user 18.4 s, sys: 6.66 s, total: 25.1 s
Wall time: 1min 26s
```

```
> df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1348946 entries, 0 to 423888
Columns: 110 entries, Year to Unnamed: 109
dtypes: float64(69), int64(21), object(20)
memory usage: 1.1+ GB
```

```
> df.memory_usage(deep=True).sum() / 2**20
2326.9
```

Need to scale up in multiple places…

Data storage format

Load data in parallel

Parallelize intermediate calculations

Run on multiples core/machines

Effort required to write/optimize correct parallel code

And we still want to use Python and Pandas!

Dask is a ‘drop-in’ replacement for pandas*

```
> import dask.dataframe as dd

> paths = [ 'flights-%s.xz' % dt.strftime('%Y-%m')
            for dt in pd.date_range('2015-12', '2016-03', freq='M') ]

> cols = ['FlightDate', 'Origin', 'Dest', 'OriginState', 'DestState',
          'Carrier', 'FlightNum', 'TailNum', 'CRSDepTime', 'CRSArrTime',
          'DepDelay', 'ArrDelay', 'Flights', 'Cancelled', 'Diverted', ]

> ddf = dd.read_csv(
              paths,
              dialect="excel", encoding='latin-1',
              header=0, usecols=cols,
              compression='xz', blocksize=None,
              parse_dates=['FlightDate'],
              dtype={'FlightNum': str}, )
```

* … for a subset of pandas DataFrame operations

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> import dask.dataframe as dd

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> ddf = dd.read_csv(
            paths,
            dialect="excel", encoding='latin-1',
            header=0, usecols=cols,
            compression='xz', blocksize=None,
            parse_dates=['FlightDate'],
            dtype={'FlightNum': str}, )


> ddf[['Carrier','Flights','Cancelled']].groupby('Carrier').sum()
CPU times: user 16 ms, sys: 0 ns, total: 16 ms
Wall time: 18.3 ms
```

* … for a subset of pandas DataFrame operations

Dask is a ‘drop-in’ replacement for pandas*

```
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> paths = [ 'flights-%s.xz' % dt.strftime('%Y-%m')
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          'DepDelay', 'ArrDelay', 'Flights', 'Cancelled', 'Diverted', ]

> ddf = dd.read_csv(
              paths,
              dialect="excel", encoding='latin-1',
              header=0, usecols=cols,
              compression='xz', blocksize=None,
              parse_dates=['FlightDate'],
              dtype={'FlightNum': str}, )


> ddf[['Carrier','Flights','Cancelled']].groupby('Carrier').sum()
CPU times: user 16 ms, sys: 0 ns, total: 16 ms
Wall time: 18.3 ms

> _.compute()
CPU times: user 13.9 s, sys: 2.22 s, total: 16.1 s
Wall time: 9.62 s
```

Carrier	Flights	Cancelled
AA	223582.0	5001.0
AS	42063.0	311.0
B6	68137.0	1522.0
DL	208121.0	1472.0
EV	126036.0	4409.0
F9	21865.0	266.0
HA	18390.0	12.0
MQ	20993.0	805.0
NK	32072.0	894.0
OO	140825.0	3471.0
UA	122148.0	2470.0
VX	15859.0	241.0
WN	308855.0	5677.0

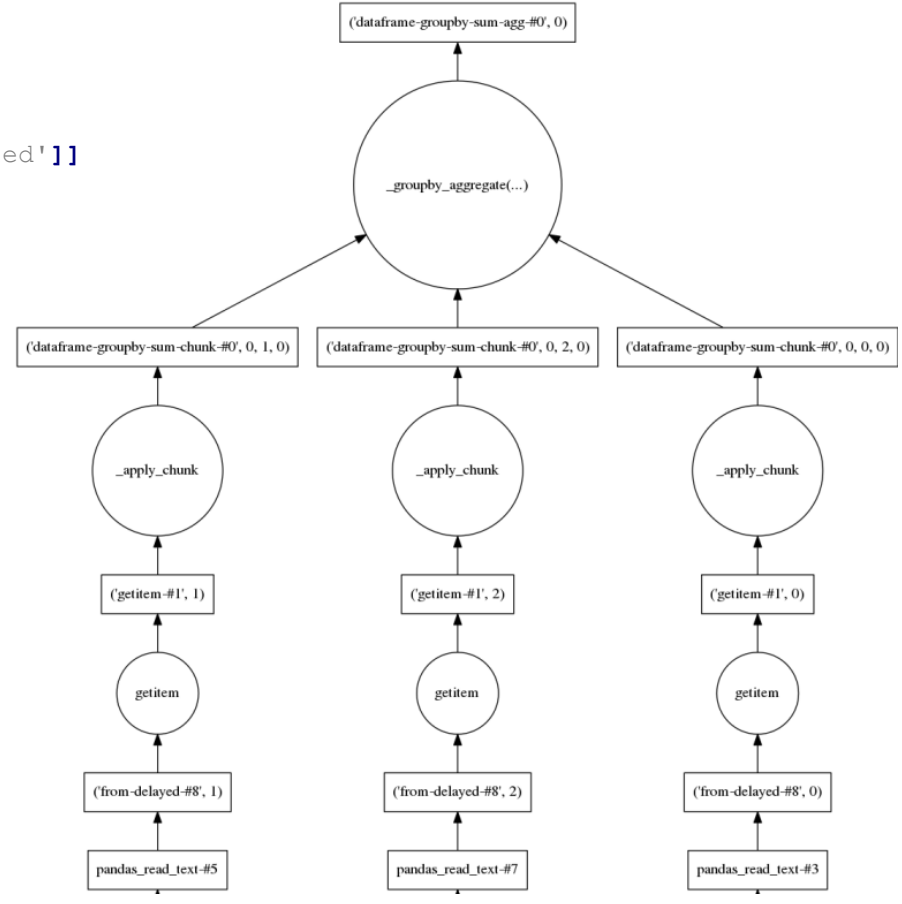
* … for a subset of pandas DataFrame operations

Expressions build a dependency graph…

```
> task = ddf[['Carrier', 'Flights','Cancelled']]
    .groupby('Carrier')
    .sum()
```

```
> task.compute()
CPU times: user 13.9 s,
sys: 2.22 s, total: 16.1 s
Wall time: 9.62 s
```

```
> task.visualize()
```

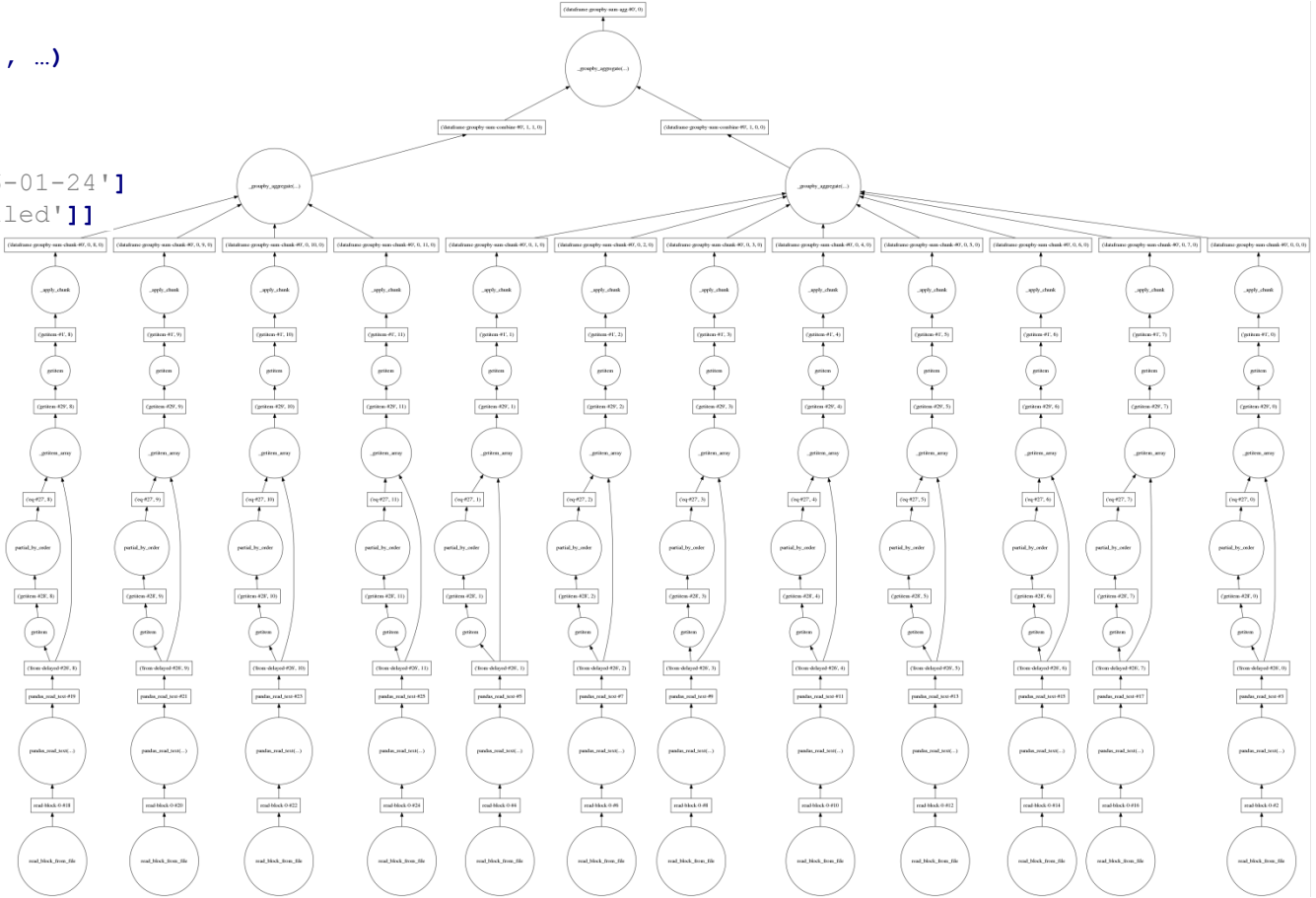


… that can get arbitrarily complex

```
> ddf = dd.read_csv('flights-*.xz', …)
```

```
> task = ddf[ddf.FlightDate=='2016-01-24']
    [['Carrier', 'Flights','Cancelled']]
    .groupby('Carrier')
    .sum()
```

```
> task.visualize()
```



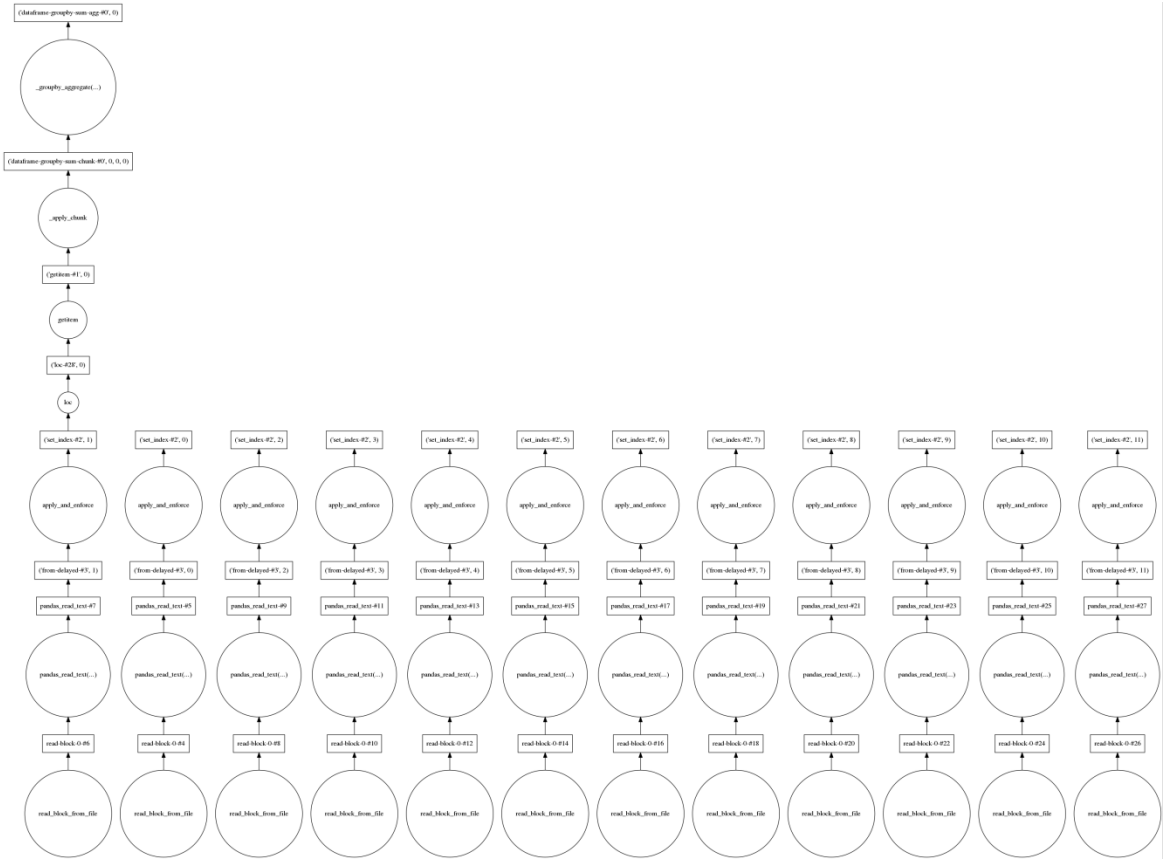
Dask prunes the graph where it can

```
> ddf = dd.read_csv('flights-*.xz', …)

> ddf = ddf.set_index('FlightDate')

> task = ddf['2016-01-24']
    [['Carrier', 'Flights','Cancelled']]
    .groupby('Carrier')
    .sum()


> task.visualize()
```



Storage formats like parquet are faster than csv

```
ddf = load_data(start='2016-01', end='2017-02')

def sort_partition(df):
    return df.set_index(df.FlightDate).sort_index()

task = ddf.map_partitions(func=sort_partition)

task.to_parquet('flights.parq',
                      compression='SNAPPY')
```

```
$ ls -hs flights.parq/
```

```
total 100M
4.0K _common_metadata
 20K _metadata
8.5M part.0.parquet
8.0M part.1.parquet
7.5M part.2.parquet
...
8.2M part.11.parquet
8.2M part.12.parquet
```

Storage formats like parquet are faster than csv

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ddf = load_data(start='2016-01', end='2017-02')

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$ ls -hs flights.parq/

total 100M
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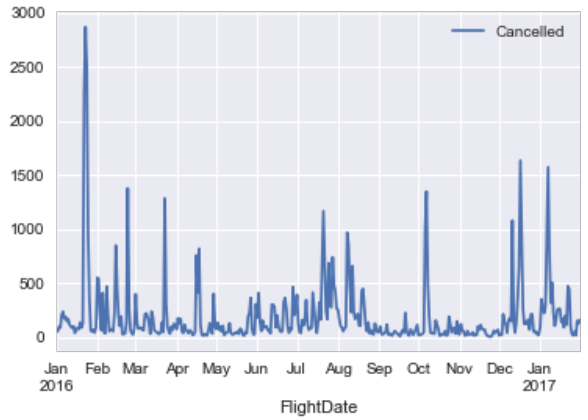
8.0M part.1.parquet
7.5M part.2.parquet
...
8.2M part.11.parquet
8.2M part.12.parquet
```

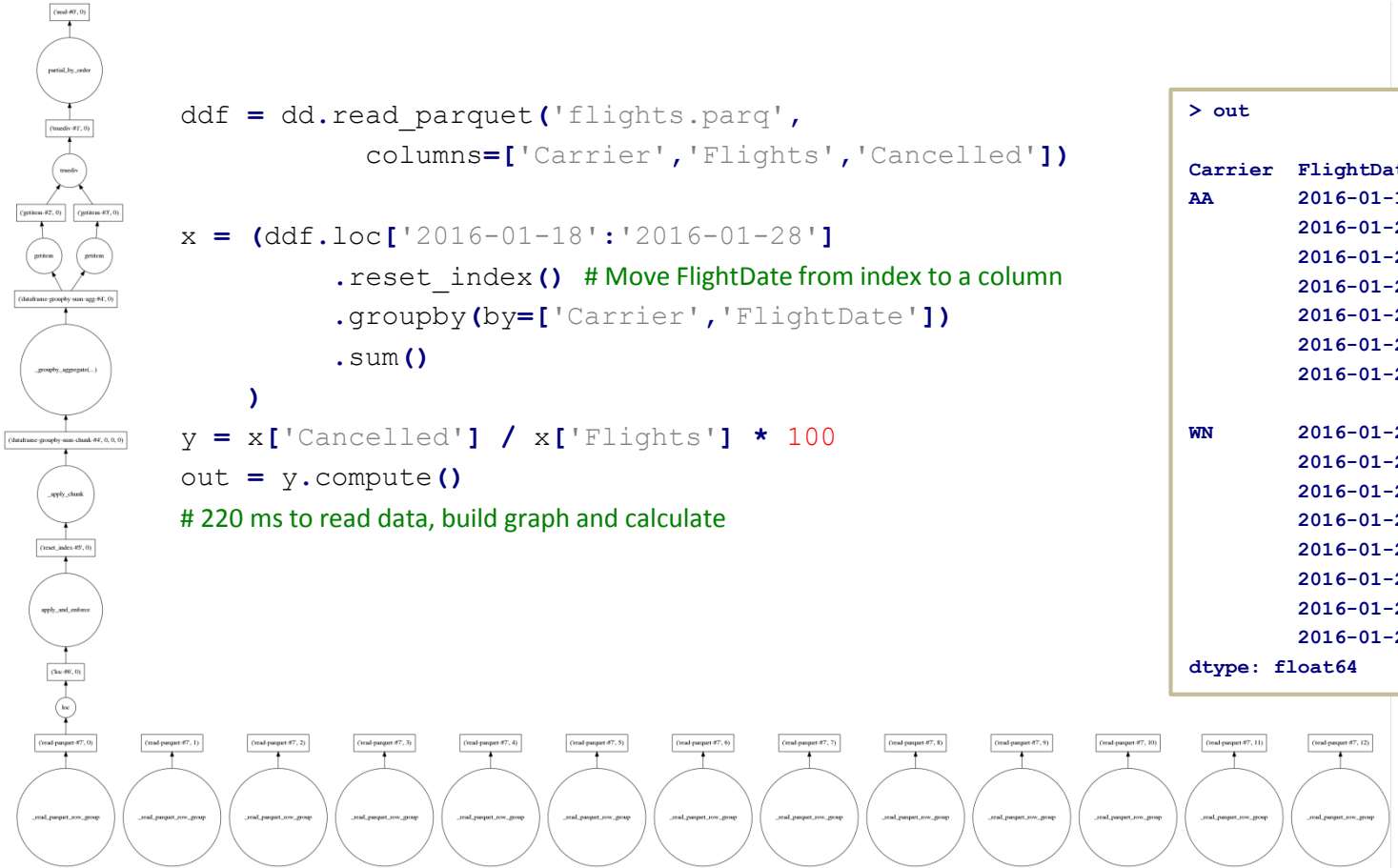
Parquet example 1 – whole dataset

```
ddf = dd.read_parquet('flights.parq',
                      columns=['Cancelled'])  # 50 ms

task = ddf.groupby(ddf.index).sum()
out = task.compute()  # 313 ms
out.plot()
```



Parquet example 2: read a subset of the partitions



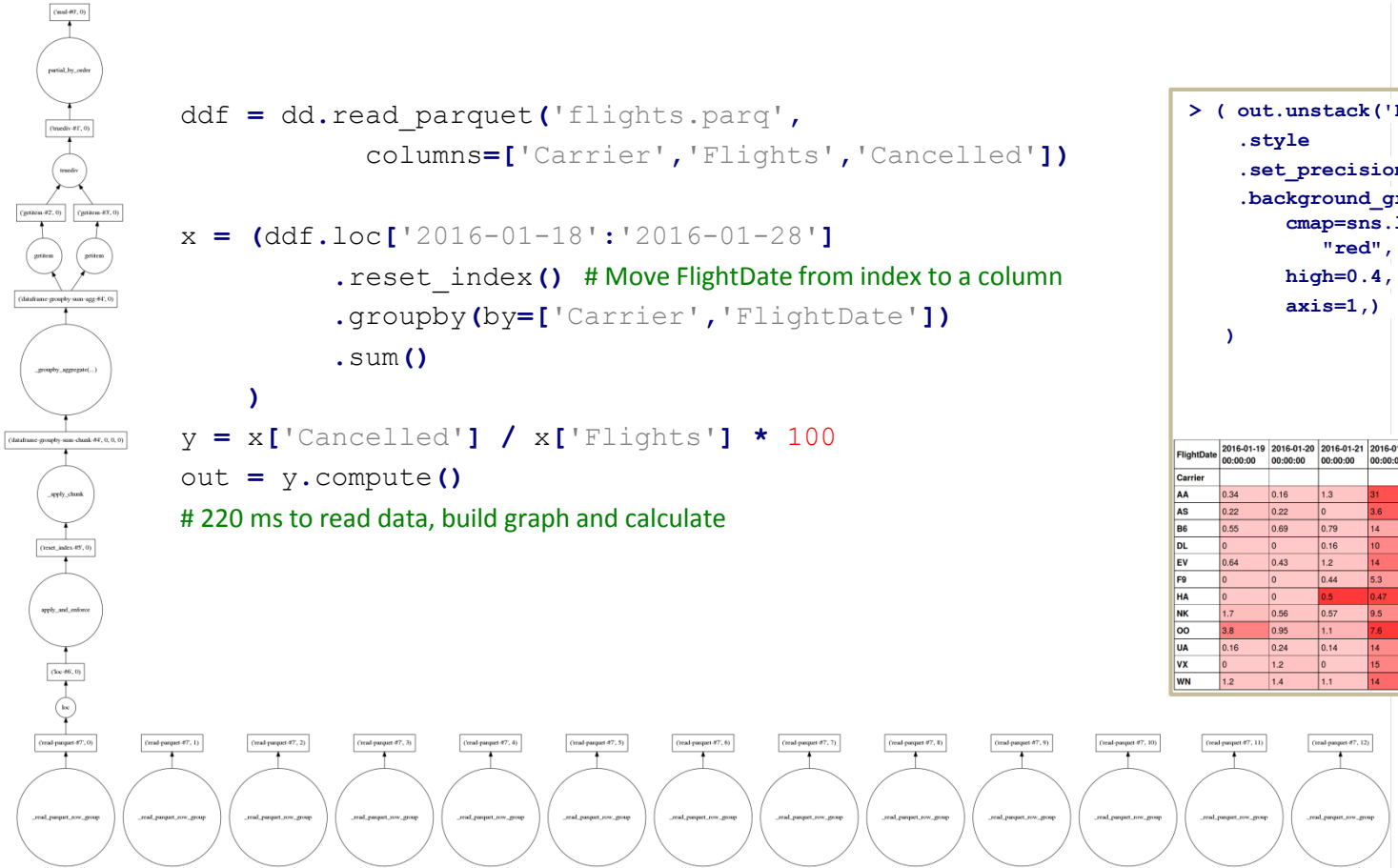
```
ddf = dd.read_parquet('flights.parq',
            columns=['Carrier','Flights','Cancelled'])

x = (ddf.loc['2016-01-18':'2016-01-28']
        .reset_index()  # Move FlightDate from index to a column
        .groupby(by=['Carrier','FlightDate'])
        .sum()
    )
y = x['Cancelled'] / x['Flights'] * 100
out = y.compute()
# 220 ms to read data, build graph and calculate
```

```
> out

Carrier  FlightDate
AA       2016-01-19     0.339992
         2016-01-20     0.160064
         2016-01-21     1.327606
         2016-01-22    30.712339
         2016-01-23    36.307838
         2016-01-24    25.588114
         2016-01-25     8.853119
                            ...
WN       2016-01-21     1.133787
         2016-01-22    14.436219
         2016-01-23    21.369961
         2016-01-24    17.904074
         2016-01-25     4.630682
         2016-01-26     1.394422
         2016-01-27     0.910643
         2016-01-28     0.597610
dtype: float64
```

Parquet example 2: read a subset of the partitions



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        .groupby(by=['Carrier','FlightDate'])
        .sum()
    )
y = x['Cancelled'] / x['Flights'] * 100
out = y.compute()
# 220 ms to read data, build graph and calculate
```

```
> ( out.unstack('FlightDate')
    .style
    .set_precision(2)
    .background_gradient(
        cmap=sns.light_palette(
           "red", as_cmap=True),
        high=0.4, low=0.2,
        axis=1,)
  )
```

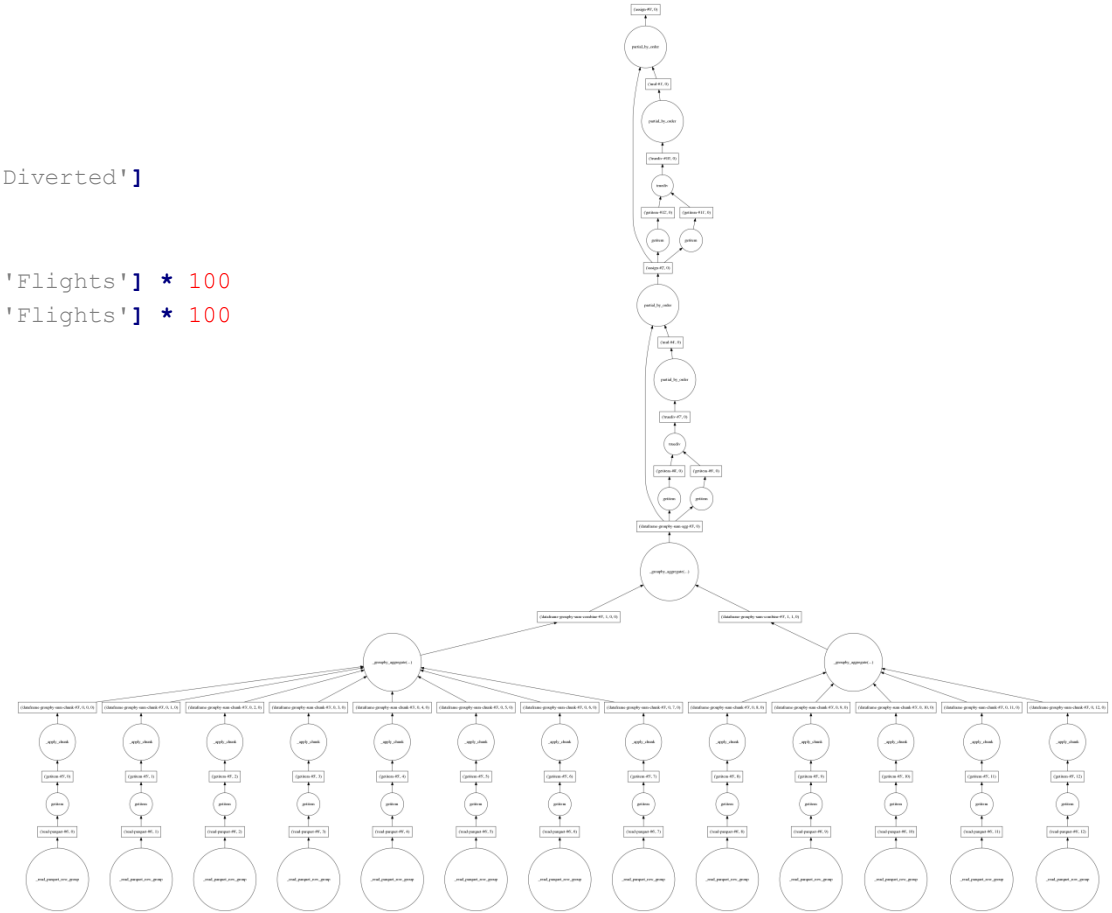
FlightDate	2016-01-19 00:00:00	2016-01-20 00:00:00	2016-01-21 00:00:00	2016-01-22 00:00:00	2016-01-23 00:00:00	2016-01-24 00:00:00	2016-01-25 00:00:00	2016-01-26 00:00:00	2016-01-27 00:00:00	2016-01-28 00:00:00
Carrier										
AA	0.34	0.16	1.3	31	36	26	8.9	0.68	0.36	0.59
AS	0.22	0.22	0	3.6	4.9	4.1	1.3	0.22	0.22	0.21
B6	0.55	0.69	0.79	14	63	33	2.5	0	0.14	0.13
DL	0	0	0.16	10	22	12	0.88	0	0	0.16
EV	0.64	0.43	1.2	14	23	20	15	12	0.5	0.27
F9	0	0	0.44	5.3	16	8	0.45	0	0	0
HA	0	0	0.5	0.47	0.5	0	0	0	0	0
NK	1.7	0.56	0.57	9.5	22	13	2.5	0	0	0.28
OO	3.8	0.95	1.1	7.6	3.4	2.5	1.3	0.38	0.38	0.062
UA	0.16	0.24	0.14	14	29	32	19	8.4	0.47	0.14
VX	0	1.2	0	15	30	27	6.1	0	0.58	0
WN	1.2	1.4	1.1	14	21	18	4.6	1.4	0.91	0.6

Monitoring progress of a Dask calculation

```
ddf = dd.read_parquet('flights.parq')

sum_cols = ['Carrier', 'Flights', 'Cancelled', 'Diverted']
task = ddf[sum_cols].groupby('Carrier').sum()

task['CancelledPct'] = task['Cancelled'] / task['Flights'] * 100
task['DivertedPct' ] = task['Diverted' ] / task['Flights'] * 100
```



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task = ddf[sum_cols].groupby('Carrier').sum()

task['CancelledPct'] = task['Cancelled'] / task['Flights'] * 100
task['DivertedPct' ] = task['Diverted' ] / task['Flights'] * 100



from dask.diagnostics import ProgressBar


with ProgressBar():
    out = task.compute()


[                                       ] |  0% Completed |  0.0s
```

```
>
```

Monitoring progress of a Dask calculation

```
ddf = dd.read_parquet('flights.parq')

sum_cols = ['Carrier', 'Flights', 'Cancelled', 'Diverted']
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    out = task.compute()
```

```
[############################     ] | 87% Completed |  2.4s
```

```
>
```

Monitoring progress of a Dask calculation

```
ddf = dd.read_parquet('flights.parq')

sum_cols = ['Carrier', 'Flights', 'Cancelled', 'Diverted']
task = ddf[sum_cols].groupby('Carrier').sum()

task['CancelledPct'] = task['Cancelled'] / task['Flights'] * 100
task['DivertedPct' ] = task['Diverted' ] / task['Flights'] * 100



from dask.diagnostics import ProgressBar


with ProgressBar():
    out = task.compute()


[####################################] |100% Completed | 2.6s
```

```
> print(out)

         Flights  Cancelled  Diverted  CancelledPct  DivertedPct
Carrier
AA      987627.0    11847.0    2421.0      1.199542     0.245133
AS      191991.0     1072.0     520.0      0.558360     0.270846
B6      307075.0     4322.0     774.0      1.407474     0.252056
DL      992559.0     4898.0    1923.0      0.493472     0.193742
EV      526027.0    13048.0    1723.0      2.480481     0.327550
F9      102881.0     1341.0     169.0      1.303448     0.164267
HA       83065.0      136.0      91.0      0.163727     0.109553
NK      150769.0     3070.0     218.0      2.036228     0.144592
OO      656079.0    10326.0    2181.0      1.573896     0.332429
UA      587470.0     5702.0    1522.0      0.970603     0.259077
VX       74903.0      806.0     272.0      1.076058     0.363136
WN     1407229.0    18179.0    3324.0      1.291830     0.236209
```

Profiling a Dask calculation

```
ddf = dd.read_parquet('flights.parq')

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task = ddf[sum_cols].groupby('Carrier').sum()

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task['DivertedPct' ] = task['Diverted' ] / task['Flights'] * 100
```

```
from dask.diagnostics import Profiler, ResourceProfiler, CacheProfiler
from cachey import nbytes

with (Profiler() as prof, ResourceProfiler(dt=0.25) as rprof,
                CacheProfiler(metric=nbytes) as cprof):
    df = task.compute()
```

Profiling a Dask calculation

```
ddf = dd.read_parquet('flights.parq')

sum_cols = ['Carrier', 'Flights', 'Cancelled', 'Diverted']
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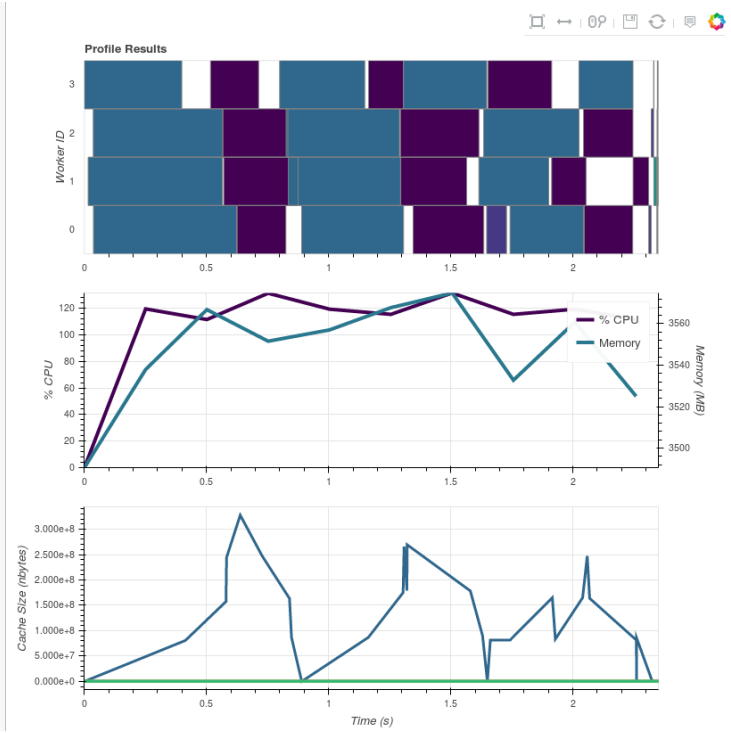
task['DivertedPct' ] = task['Diverted' ] / task['Flights'] * 100
```

```
from dask.diagnostics import Profiler, ResourceProfiler, CacheProfiler
from cachey import nbytes

with (Profiler() as prof, ResourceProfiler(dt=0.25) as rprof,
                  CacheProfiler(metric=nbytes) as cprof):
    df = task.compute()

dask.diagnostics.visualize([prof, rprof, cprof], save=False, show=True)
```



So what exactly is a Dask DataFrame?

```
> print(dd.DataFrame.__doc__)

  Implements out-of-core DataFrame as a sequence of pandas DataFrames




    Parameters
    ----------
    dask: dict
        The dask graph to compute this DataFrame
    name: str
        The key prefix that specifies which keys in the dask
        comprise this particular DataFrame
    meta: pandas.DataFrame
        An empty ``pandas.DataFrame`` with names, dtypes, and
        index matching the expected output.
    divisions: tuple of index values
        Values along which we partition our blocks on the index
```

```
def from_pandas(data, npartitions=None, chunksize=None, sort=True, name=None):
    """
    Construct a Dask DataFrame from a Pandas DataFrame

    This splits an in-memory Pandas dataframe into several parts and constructs
    a dask.dataframe from those parts on which Dask.dataframe can operate in
    parallel.

    Note that, despite parallelism, Dask.dataframe may not always be faster
    than Pandas.  We recommend that you stay with Pandas for as long as
    possible before switching to Dask.dataframe.

    Parameters
    ----------
    data : pandas.DataFrame or pandas.Series
        The DataFrame/Series with which to construct a Dask DataFrame/Series
    npartitions : int, optional
        The number of partitions of the index to create. Note that depending on
        the size and index of the dataframe, the output may have fewer
        partitions than requested.
    chunksize : int, optional
        The size of the partitions of the index.
    sort: bool
        Sort input first to obtain cleanly divided partitions or don't sort and
        don't get cleanly divided partitions
    name: string, optional
        An optional keyname for the dataframe.  Defaults to hashing the input

    Returns
    -------
    dask.DataFrame or dask.Series
        A dask DataFrame/Series partitioned along the index
```

The simplest Dask DataFrame

```
>>> df = pd.DataFrame([[1,2,3],[4,5,6],[7,8,9],
                       [10,11,12],[13,14,15]], columns=['a','b','c'])
    a   b   c
0   1   2   3
1   4   5   6
2   7   8   9
3  10  11  12
4  13  14  15

>>> ddf = dd.from_pandas(df, npartitions=1)

                a      b      c
npartitions=1   int64  int64  int64
0               ...    ...    ...
4               ...    ...    ...
Dask Name: from_pandas, 2 tasks


>>> ddf.divisions
(0, 4)

>>> ddf._meta
Empty DataFrame
Columns: [a, b, c]
Index: []
```

```
> print(dd.DataFrame.__doc__)
    dask: dict
        The dask graph to compute this DataFrame
    name: str
        The key prefix that specifies which keys in the dask
        comprise this particular DataFrame
    meta: pandas.DataFrame
        An empty ``pandas.DataFrame`` with names, dtypes, and
        index matching the expected output.
    divisions: tuple of index values
        Values along which we partition our blocks on the index
```

```
>>> ddf._name
'from_pandas-b71f6a90'

>>> ddf.dask
{
    ('from_pandas-b71f6a90', 0): df,

}

>>> ddf.visualize()
```

The next simplest Dask DataFrame

```
>>> df = pd.DataFrame([[1,2,3],[4,5,6],[7,8,9],
                       [10,11,12],[13,14,15]], columns=['a','b','c'])
    a   b   c
0   1   2   3
1   4   5   6
2   7   8   9
3  10  11  12
4  13  14  15

>>> ddf = dd.from_pandas(df, npartitions=2)

                a      b      c
npartitions=1   int64  int64  int64
0               ...    ...    ...
3               ...    ...    ...
4               ...    ...    ...
Dask Name: from_pandas, 2 tasks

>>> ddf.divisions
(0, 3, 4)

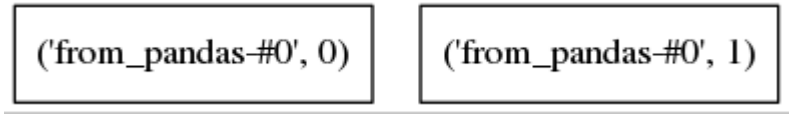
>>> ddf._meta
Empty DataFrame
Columns: [a, b, c]
Index: []
```

```
> print(dd.DataFrame.__doc__)
    dask: dict
        The dask graph to compute this DataFrame
    name: str
        The key prefix that specifies which keys in the dask
        comprise this particular DataFrame
    meta: pandas.DataFrame
        An empty ``pandas.DataFrame`` with names, dtypes, and
        index matching the expected output.
    divisions: tuple of index values
        Values along which we partition our blocks on the index
```

```
>>> ddf._name
'from_pandas-de36e0f9'

>>> ddf.dask
{
    ('from_pandas-de36e0f9', 0): df[0:3],
    ('from_pandas-de36e0f9', 1): df[3:],
}

>>> ddf.visualize()
```



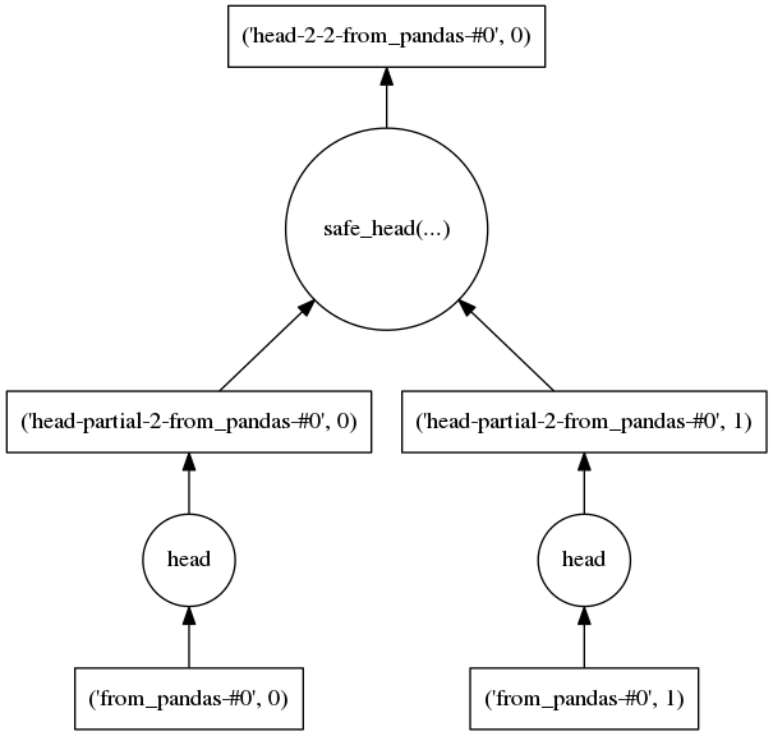
dd.DataFrame.dask

```
>>> ddf = dd.from_pandas(df, npartitions=2)
             .head(n=2, npartitions=2, compute=False)

>>> ddf._name
'head-2-2-from_pandas-de36e0f9b'

>>> ddf.dask
{
('head-2-2-from_pandas-de36e0f9b', 0):
        ( dask.dataframe.core.safe_head,
             ( function dask.dataframe.core._concat,
                 [('head-partial-2-from_pandas-de36e0f9b', 0),
                  ('head-partial-2-from_pandas-de36e0f9b', 1)]
              ), 2
         ),
('head-partial-2-from_pandas-de36e0f9b', 0):
      (<methodcaller: head>, ('from_pandas-de36e0f9b', 0), 2),
('head-partial-2-from_pandas-de36e0f9b', 1):
      (<methodcaller: head>, ('from_pandas-de36e0f9b', 1), 2),
('from_pandas-de36e0f9b', 0):    df[0:3],
('from_pandas-de36e0f9b', 1):    df[3:],
}

>>> ddf._keys()
[('head-2-2-from_pandas-de36e0f9b', 0)]
>>> ddf.compute()
```



Reimplement pandas methods lazily

```
>>> ddf = dd.from_pandas(df, npartitions=2)
              .head(n=2, npartitions=2, compute=False)

>>> ddf._name
'head-2-2-from_pandas-de36e0f9b'

>>> ddf.dask
{
('head-2-2-from_pandas-de36e0f9b', 0):
        ( dask.dataframe.core.safe_head,
             ( function dask.dataframe.core._concat,
                 [('head-partial-2-from_pandas-de36e0f9b', 0),
                  ('head-partial-2-from_pandas-de36e0f9b', 1)]
              ), 2
         ),
('head-partial-2-from_pandas-de36e0f9b', 0):
      (<methodcaller: head>, ('from_pandas-de36e0f9b', 0), 2),
('head-partial-2-from_pandas-de36e0f9b', 1):
      (<methodcaller: head>, ('from_pandas-de36e0f9b', 1), 2),
('from_pandas-de36e0f9b', 0):    df[0:3],
('from_pandas-de36e0f9b', 1):    df[3:],
}

>>> ddf._keys()
[('head-2-2-from_pandas-de36e0f9b', 0)]
>>> ddf.compute()
```

```
dask.dataframe.core._Frame (L758+):

def head(self, n=5, npartitions=1, compute=True):
    """ First n rows of the dataset"""
    if npartitions <= -1:
        npartitions = self.npartitions

    name = 'head-%d-%d-%s' % (npartitions, n, self._name)

    if npartitions > 1:
        name_p = 'head-partial-%d-%s' % (n, self._name)
        dsk = {}
        for i in range(npartitions):
            dsk[(name_p, i)] = (M.head, (self._name, i), n)
        concat = (_concat, [(name_p, i) for i in range(npartitions)])
        dsk[(name, 0)] = (safe_head, concat, n)
    else:
        dsk = {(name, 0): (safe_head, (self._name, 0), n)}

    result = new_dd_object(merge(self.dask, dsk), name, self._meta,
                [self.divisions[0], self.divisions[npartitions]])

    if compute:
        result = result.compute()
    return result
```

Now we execute the graph with ‘compute’

1. Optimize
   - Cull – remove unnecessary tasks
   - Fuse tasks – make parallelization less granular
   - Inline cheap functions
2. Get graphs keys to evaluate
3. Execute in parallel with scheduler
   - ‘get’ function
   - Sort nodes
   - Balance work between threads, processes, cores, over a cluster
4. Optionally cache intermediate results

References in dask source code:
- optimize.py, order.py and async.py

dask.dataframe.base (L139+):

```
def compute(*args, **kwargs):
    """Compute several dask collections at once.
    args     : Any dask objects are computed and the result is returned.
    traverse : Set to False to not look for dask objects in Python collections.
    get      : An optional alternative scheduler ``get`` function to use.
    optimize_graph : If True [default], optimize the graph before computation.
               Otherwise run as is. This can be useful for debugging.
    kwargs   : Extra keywords to forward to the scheduler ``get`` function.
    """
    from dask.delayed import delayed
    traverse = kwargs.pop('traverse', True)
    if traverse:
        args = tuple(delayed(a) if isinstance(a,
                             (list, set, tuple, dict, Iterator))
                                 else a for a in args)

    optimize_graph = kwargs.pop('optimize_graph', True)
    variables = [a for a in args if isinstance(a, Base)]
    if not variables:
        return args

    get = kwargs.pop('get', None) or _globals['get']
    dsk = collections_to_dsk(variables, optimize_graph, **kwargs)
    keys = [var._keys() for var in variables]
    results = get(dsk, keys, **kwargs)

    results_iter = iter(results)
    return tuple(a if not isinstance(a, Base)
                 else a._finalize(next(results_iter))
                 for a in args)
```

Conclusions

Dask is neat!

Especially in combination with parquet and
distributed schedulers

Rough edges where it isn't quite pandas…

Distributed operations have very different costs than in-memory pandas

I'd like more time to experiment with
distributed schedulers (dask/distributed, dask/dec2),
and compare storage formats (csv, Parquet, HDF5, HDFS, etc)

Conclusions

Dask is neat!

Especially in combination with parquet and
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I'd like more time to experiment with
distributed schedulers (dask/distributed, dask/dec2),
and compare storage formats (csv, Parquet, HDF5, HDFS, etc)

… but is Dask really the future of 'big pandas'?