“Big Pandas” - Dask from the Inside

PyData Berlin, 30 June 2017

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https://github.com/stevesimmons/pydata-berlin2017-pandas-and-dask-from-the-inside

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

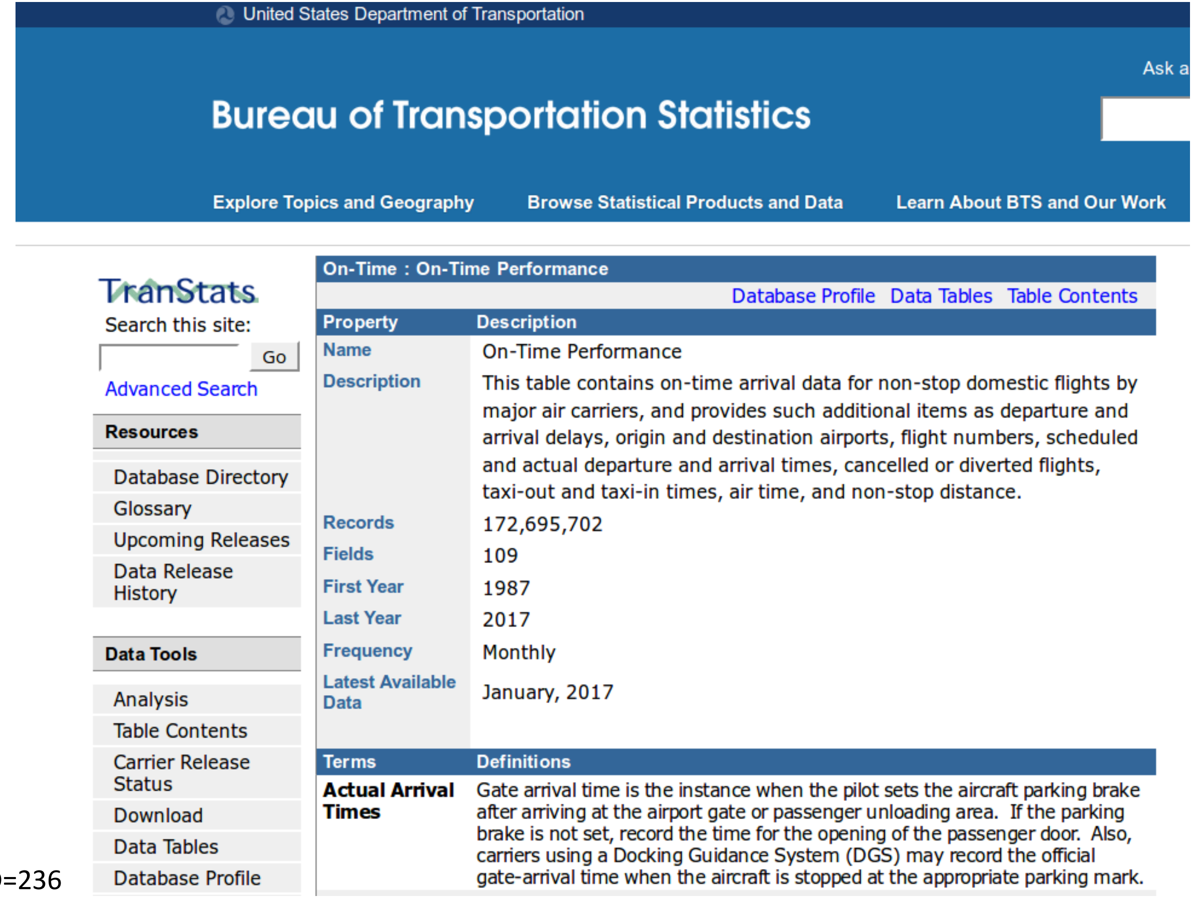
(Note: Examples here all designed to run on a local machine)

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)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Resources

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Data Tools

- Analysis
- Table Contents
- Carrier Release Status
- Download
- Data Tables
- Database Profile

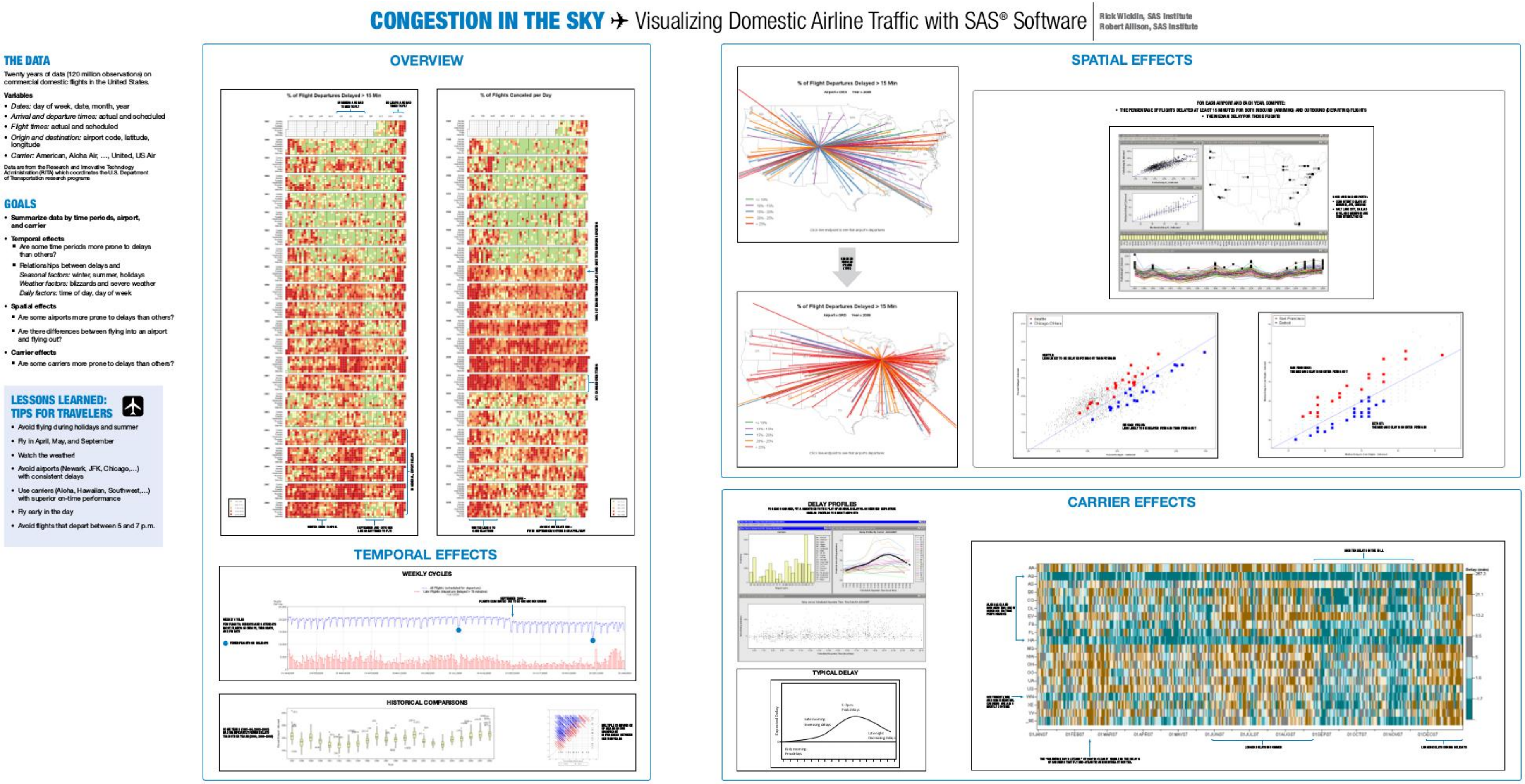
On-Time : On-Time Performance

Database Profile | Data Tables | Table Contents

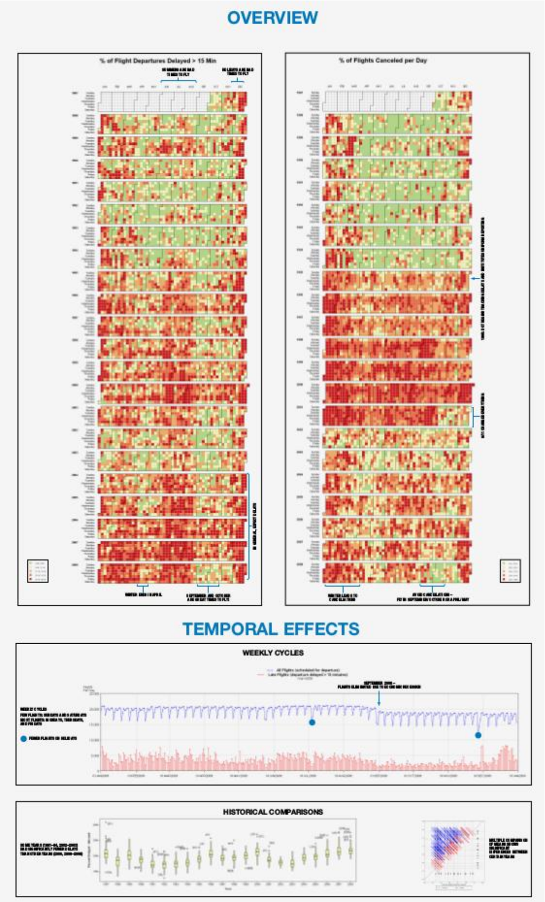
Property	Description
Name	On-Time Performance
Description	This table contains on-time arrival data for non-stop domestic flights by major air carriers, and provides such additional items as departure and arrival delays, origin and destination airports, flight numbers, scheduled and actual departure and arrival times, cancelled or diverted flights, taxi-out and taxi-in times, air time, and non-stop distance.
Records	172,695,702
Fields	109
First Year	1987
Last Year	2017
Frequency	Monthly
Latest Available Data	January, 2017

Terms	Definitions
Actual Arrival Times	Gate arrival time is the instance when the pilot sets the aircraft parking brake after arriving at the airport gate or passenger unloading area. If the parking brake is not set, record the time for the opening of the passenger door. Also, carriers using a Docking Guidance System (DGS) may record the official gate-arrival time when the aircraft is stopped at the appropriate parking mark.

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



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

```python
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
```

Pandas DataFrames don’t scale well

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

DtypeWarning: Columns (77) have mixed types.
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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

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}, )


> 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*

```
> 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') ]

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        '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}, )


> 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
```

```
              Flights  Cancelled
Carrier
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
```

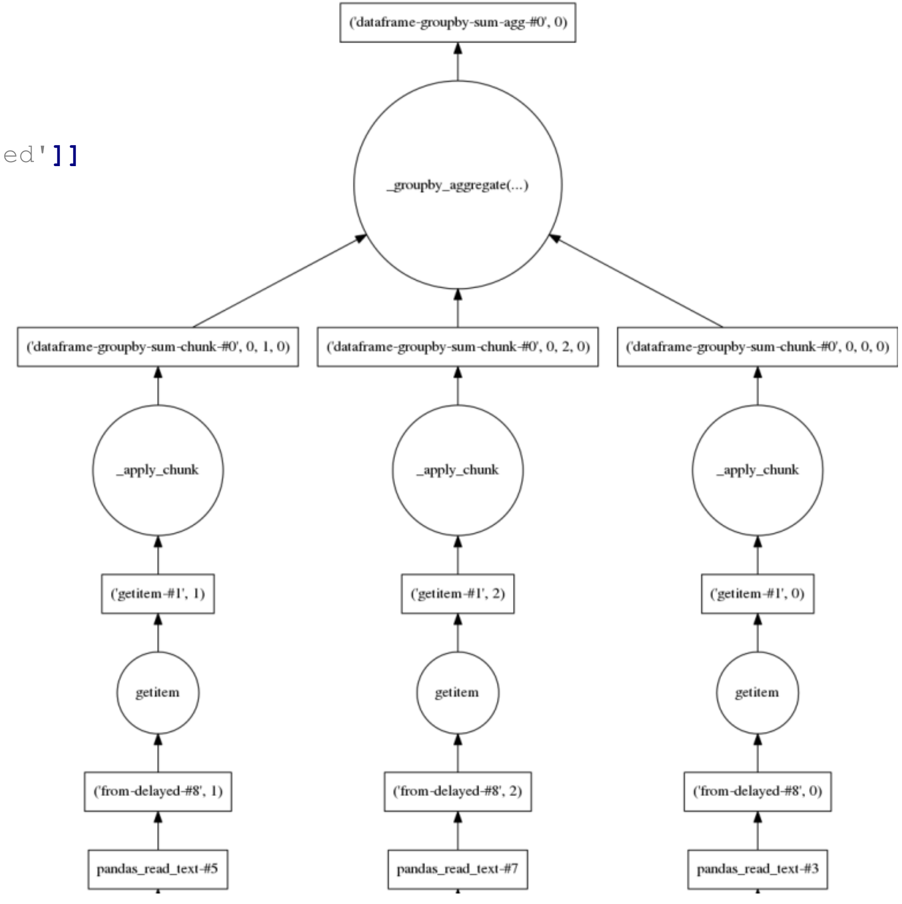
* … for a subset of pandas DataFrame operations

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()
```

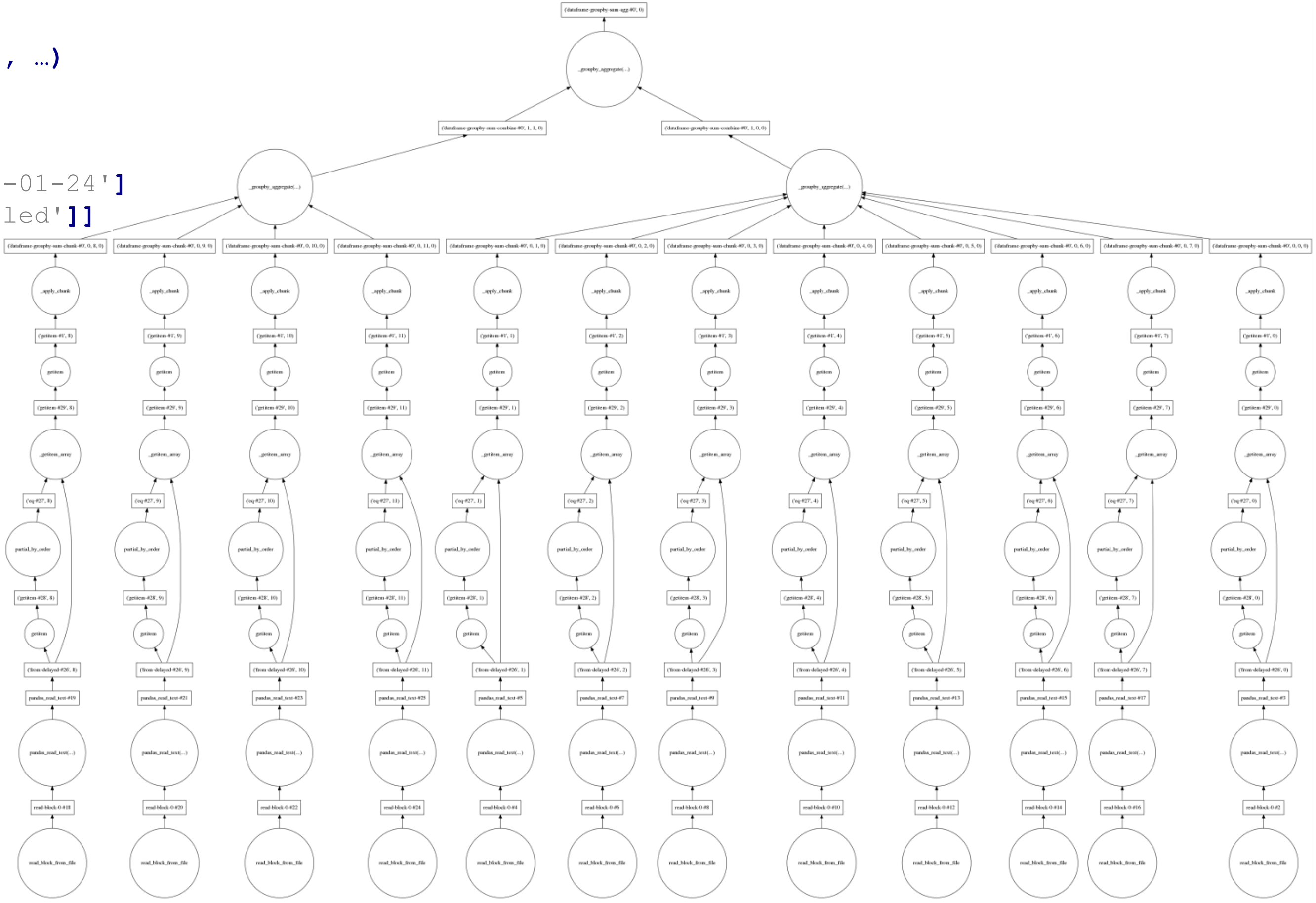


… that can get arbitrarily complex

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


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


> task.visualize()
```



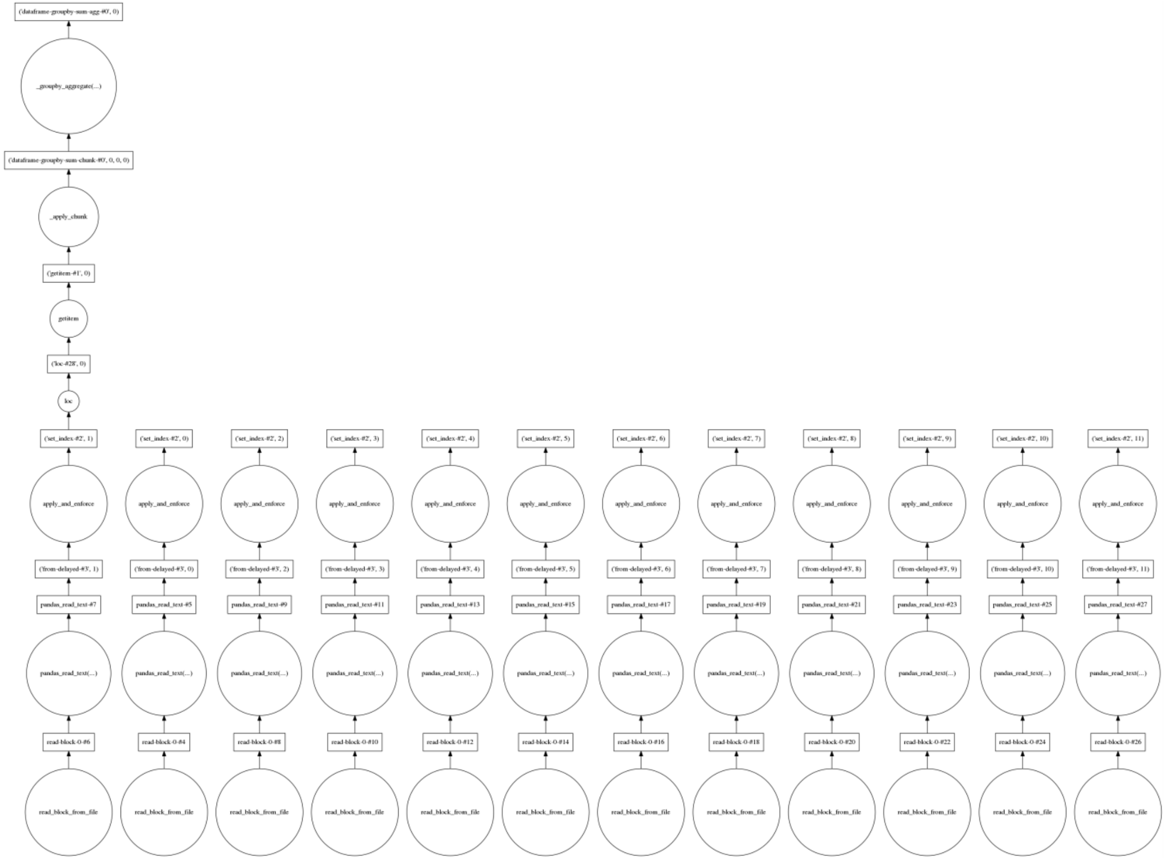
Dask prunes the graph where it can

```
> 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

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

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

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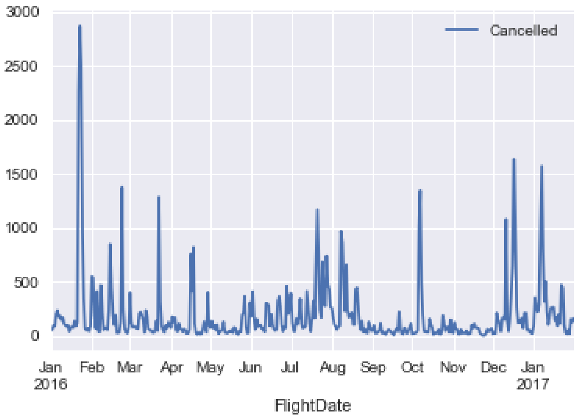
```
$ ls -hs flights.parq/

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
```

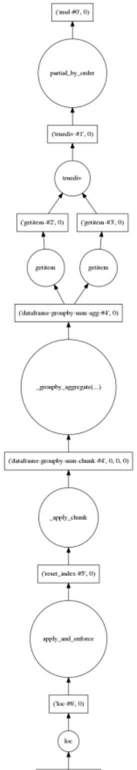
Parquet example 1 – whole dataset

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

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

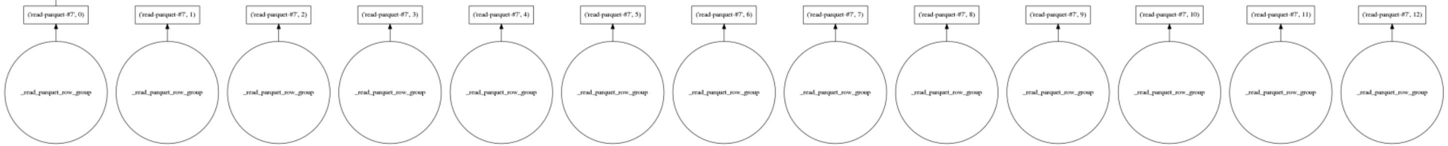


Parquet example 2: read a subset of the partitions

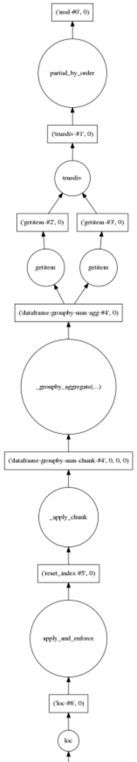


```python
ddf = dd.read_parquet('flights.parq',
                      columns=['Carrier','Flights','Cancelled'])

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
```



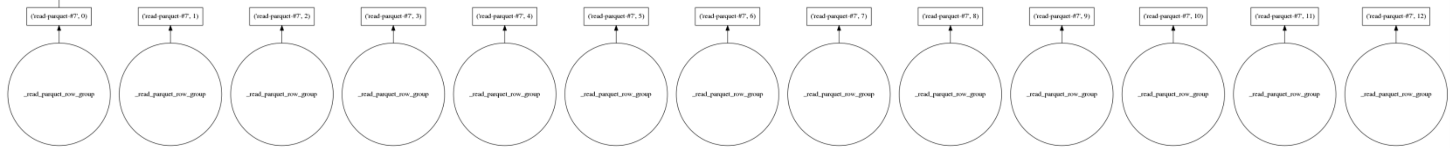
Parquet example 2: read a subset of the partitions



```
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.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

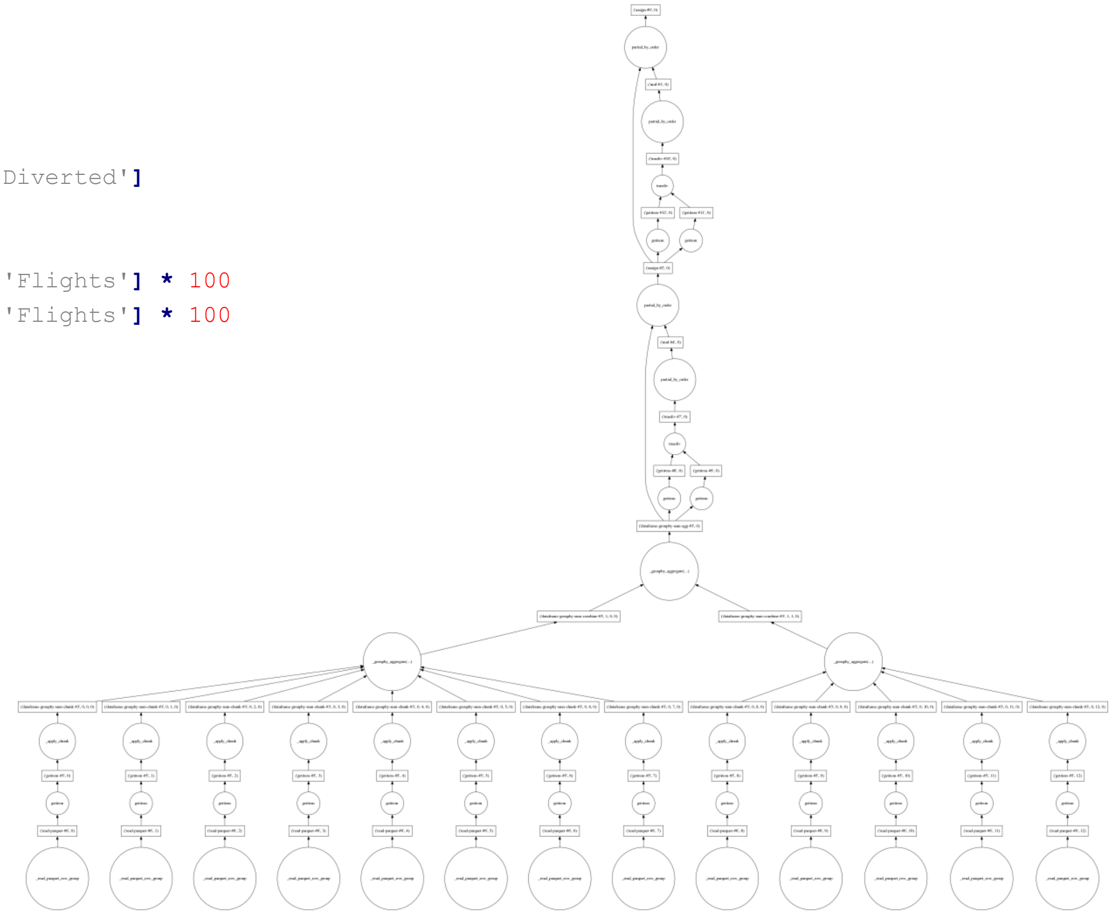


Monitoring progress of a Dask calculation

```python
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
```



Monitoring progress of a Dask calculation

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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()
```

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

```
>
```

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()


[#############################     ] | 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')

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

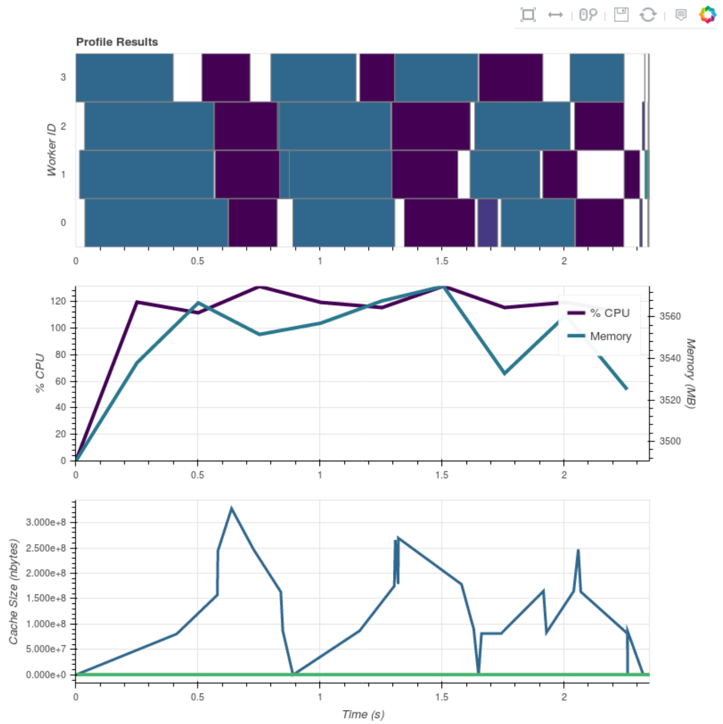
task['CancelledPct'] = task['Cancelled'] / task['Flights'] * 100
task['DivertedPct' ] = task['Diverted' ] / task['Flights'] * 100
```

```
from dask.diagnostics import 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

```python
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 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
```

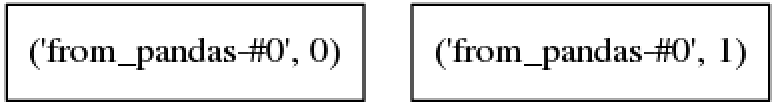
```
>>> ddf._name
'from_pandas-b71f6a90'

>>> 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: []
```

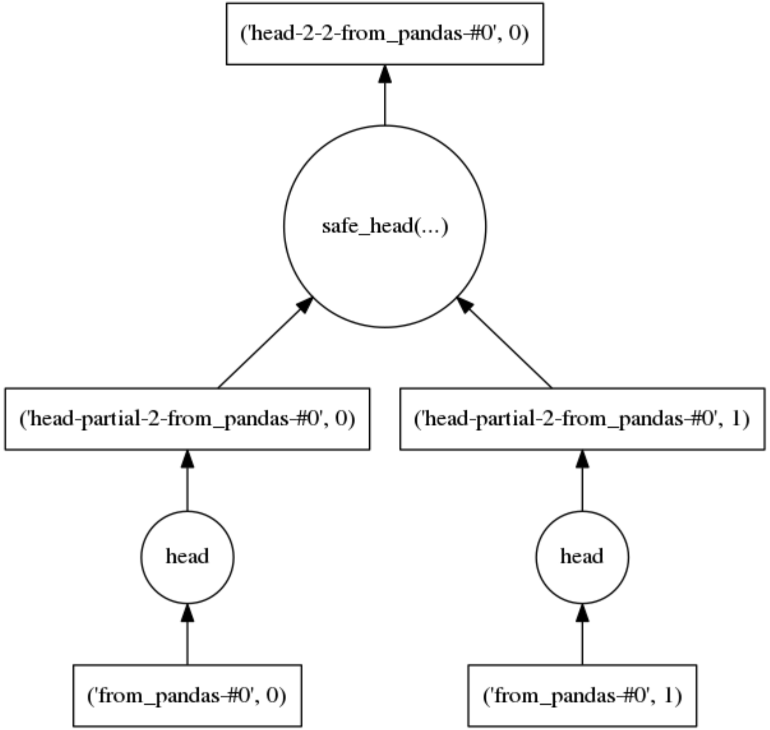
```
> print(dd.DataFrame.__doc__)
    dask: dict
        The dask graph to compute this DataFrame
    name: str
        The key prefix that specifies which keys in the dask
        comprise this particular DataFrame
    meta: pandas.DataFrame
        An empty ``pandas.DataFrame`` with names, dtypes, 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'm now going to see how far it scales, experiment with distributed schedulers (dask/distributed, dask/dec2), and compare storage formats (csv, Parquet, HDF5, HDFS, etc)