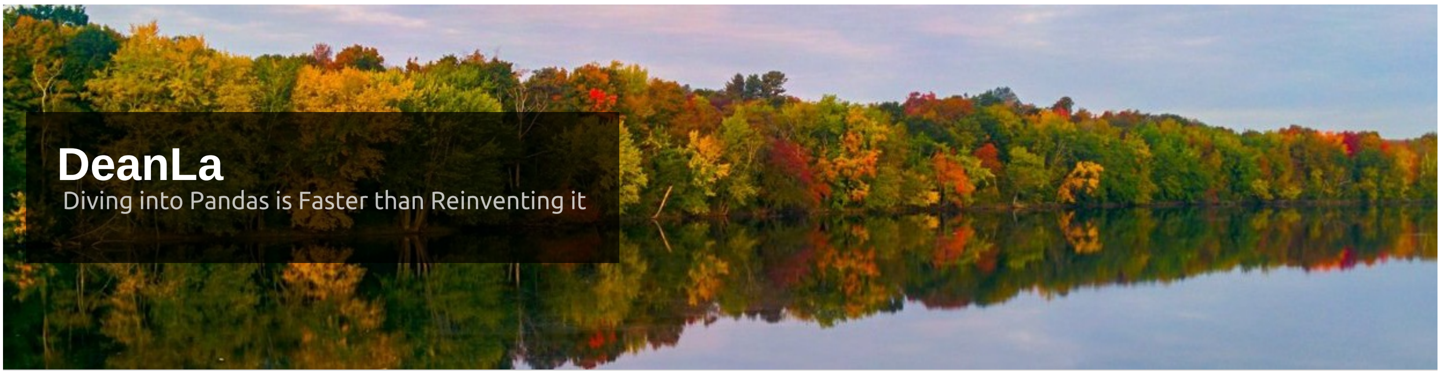
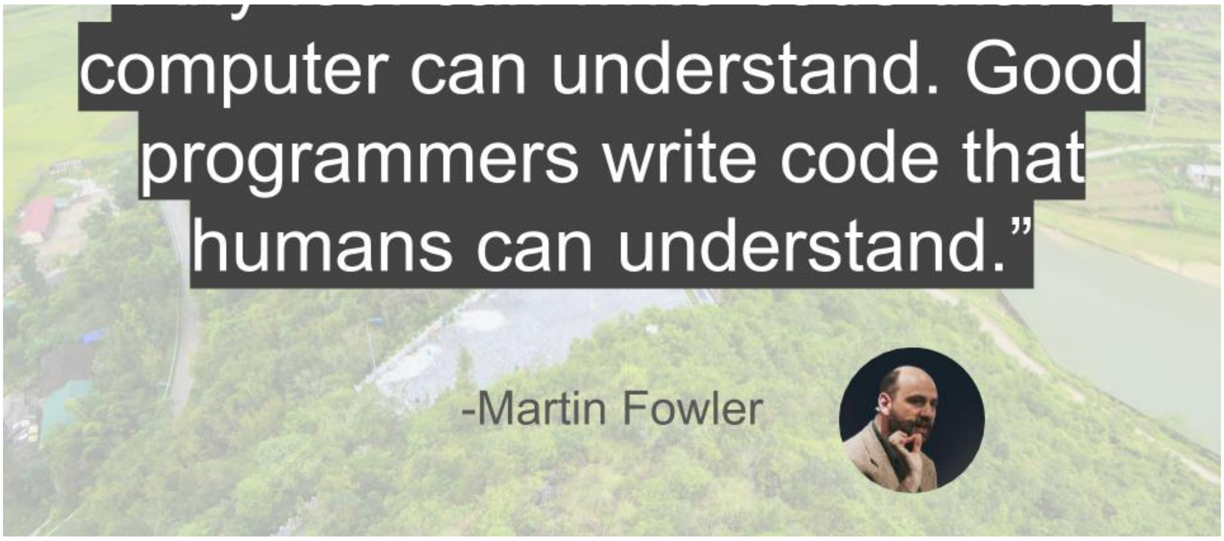


Diving into Pandas is Faster than Reinventing it

Mon 29 October 2018

The following post was first presented as a talk for the IE@DS community. It will also be presented at PyData meetup in December.
All the resources for this post, including a runable notebook, can be found in the github repo.
Let's begin

This notebook aims to show some nice ways modern Pandas makes your life easier. It is not about efficiency. I'm pretty sure using Pandas' built-in methods will be more efficient than reinventing pandas, but the main goal is to make the code easier to read, and more imoprtant - easier to write.




```
import sys
import os
sys.path.append(os.path.dirname(os.getcwd()))
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import sys
import blog
%matplotlib inline
import my_utils
blog.set_blog_style()
```

First Hacks!

Reading the data and a few housekeeping tasks. This is the first place we can make our code more readable.

```
df_io = pd.read_csv('./data.csv',index_col=0,parse_dates=['date_'])
df_io.head()
```

	val_updated	date_	event_type
0	2018-10-09 17:01:30.662390+00:00	2018-10-09 17:01:30.662389	5
1	2018-10-09 17:01:30.687675+00:00	2018-10-09 17:01:30.687675	5
2	2018-10-09 17:03:23.952848+00:00	2018-10-09 17:03:23.952847	1
3	2018-10-09 17:05:42.327744+00:00	2018-10-09 17:05:42.327744	7
4	2018-09-24 16:36:38.177661+00:00	2018-10-09 17:06:29.708909	7

```
df = df_io.copy().sort_values('date_').set_index('date_').drop(columns='val_updated')
df.head()
```

	event_type
date_	
2018-10-09 17:01:30.662389	5

2018-10-09 17:01:30.687675	5
	event_type
2018-10-09 17:03:23.952847	1
date_	
2018-10-09 17:05:42.327744	7
2018-10-09 17:06:29.708909	7

Beautiful pipes!

One line method chaining is hard to read and prone to human error, chaining each method in its own line makes it a lot more readable.

```
df_io\
.copy()\
.sort_values('date_')\
.set_index('date_')\
.drop(columns='val_updated')\
.head()
```

	event_type
date_	
2018-10-09 17:01:30.662389	5
2018-10-09 17:01:30.687675	5
2018-10-09 17:03:23.952847	1
2018-10-09 17:05:42.327744	7
2018-10-09 17:06:29.708909	7

But it has a problem. You can't comment out and even comment in between

```
# This block will result in an error
df_io\
.copy()\ # This is an inline comment
# This is a regular comment
.sort_values('date_')\
# .set_index('date_')\
.drop(columns='val_updated')\
.head()
```

```
  File "<ipython-input-11-f6a35867b44d>", line 2
    df_io.copy()\ # This is an inline comment
                                ^
SyntaxError: unexpected character after line continuation character
```

Even an unnoticeable space character may break everything

```
# This block will result in an error
df_io\
.copy()\
.sort_values('date_')\
.set_index('date_')\
.drop(columns='val_updated')\
.head()
```

```
  File "<ipython-input-12-708b932ea07a>", line 2
    df_io.copy().sort_values('date_').set_index('date_').drop(columns='val_updated')\
                                                                                     ^
SyntaxError: unexpected character after line continuation character
```

The Penny Drops

I like those "penny dropping" moments, when you realize you knew everything that is presented, yet it is presented in a new way you never thought of.

```
# We can split these value inside ()
users = (134856, 195373, 295817, 294003, 262166, 121066, 129678, 307120,
        258759, 277922, 220794, 192312, 318486, 314631, 306448, 297059,206892,
        169046, 181703, 146200, 199876, 247904, 250884, 282989, 234280, 202520,
        138064, 133577, 301053, 242157)
```

```
# Penny Drop: We can also Split here
df = (df_io
        .copy() # This is an inline comment
        # This is a regular comment
        .sort_values('date_')
        .set_index('date_')
        .drop(columns='val_updated')
)

df.head()
```

	event_type
date_	
2018-10-09 17:01:30.662389	5
2018-10-09 17:01:30.687675	5
2018-10-09 17:03:23.952847	1
2018-10-09 17:05:42.327744	7
2018-10-09 17:06:29.708909	7

Map with dict

A dict is a callable with $f(key) = value$, there for you can call `.map` with it. In this example I want to make int key codes into letter.

```
df.event_type.map(lambda x: x+3).head()
```

```
date_
2018-10-09 17:01:30.662389     8
2018-10-09 17:01:30.687675     8
2018-10-09 17:03:23.952847     4
2018-10-09 17:05:42.327744    10
2018-10-09 17:06:29.708909    10
Name: event_type, dtype: int64
```

```
# A dict is also a calleble
df['event_type'] = df.event_type.map({
    1:'A',
    5:'B',
    7:'C'
})
df.head()
```

	event_type

date_	event_type
2018-10-09 17:01:30.662389	B
2018-10-09 17:01:30.687675	B
2018-10-09 17:03:23.952847	A
2018-10-09 17:05:42.327744	C
2018-10-09 17:06:29.708909	C

Time Series

Resample

Task: How many events happen each hour?

The Old Way

```
bad = df.copy()
bad['day'] = bad.index.date
bad['hour'] = bad.index.hour
(bad
.groupby(['day','hour'])
.count()
)
```

		event_type
day	hour	
2018-10-09	17	83
	18	96
	20	91
	21	71
	22	84

- Many lines of code
- unneeded columns
- Index is not a time anymore
- **missing rows** (Did you notice?)

A Better Way

```
df.resample('H').count() # H is for Hour
```

	event_type
date_	
2018-10-09 17:00:00	83

2018-10-09 18:00:00	96
	event_type
2018-10-09 19:00:00	0
date_	
2018-10-09 20:00:00	91
2018-10-09 21:00:00	71
2018-10-09 22:00:00	84

But it's even better on non-round intervals

```
rs = df.resample('10T').count()
# T is for Minute, and pandas understands 10 T, it will also under stand 11T if you wonder
rs.head()
```

	event_type
date_	
2018-10-09 17:00:00	7
2018-10-09 17:10:00	12
2018-10-09 17:20:00	16
2018-10-09 17:30:00	13
2018-10-09 17:40:00	15

[Complete list of Pandas' time abbrevations]

Slice Easily

Pandas will automatically make string into timestamps, and it will understand what you want it to do.

```
# Take only timestamp in the hour of 21:00.
rs.loc['2018-10-09 21',:]
```

	event_type
date_	
2018-10-09 21:00:00	11
2018-10-09 21:10:00	18
2018-10-09 21:20:00	16
2018-10-09 21:30:00	9
2018-10-09 21:40:00	7
2018-10-09 21:50:00	10

```
# Take all time stamps berfore 18:31
rs.loc[:'2018-10-09 18:31',:]
```

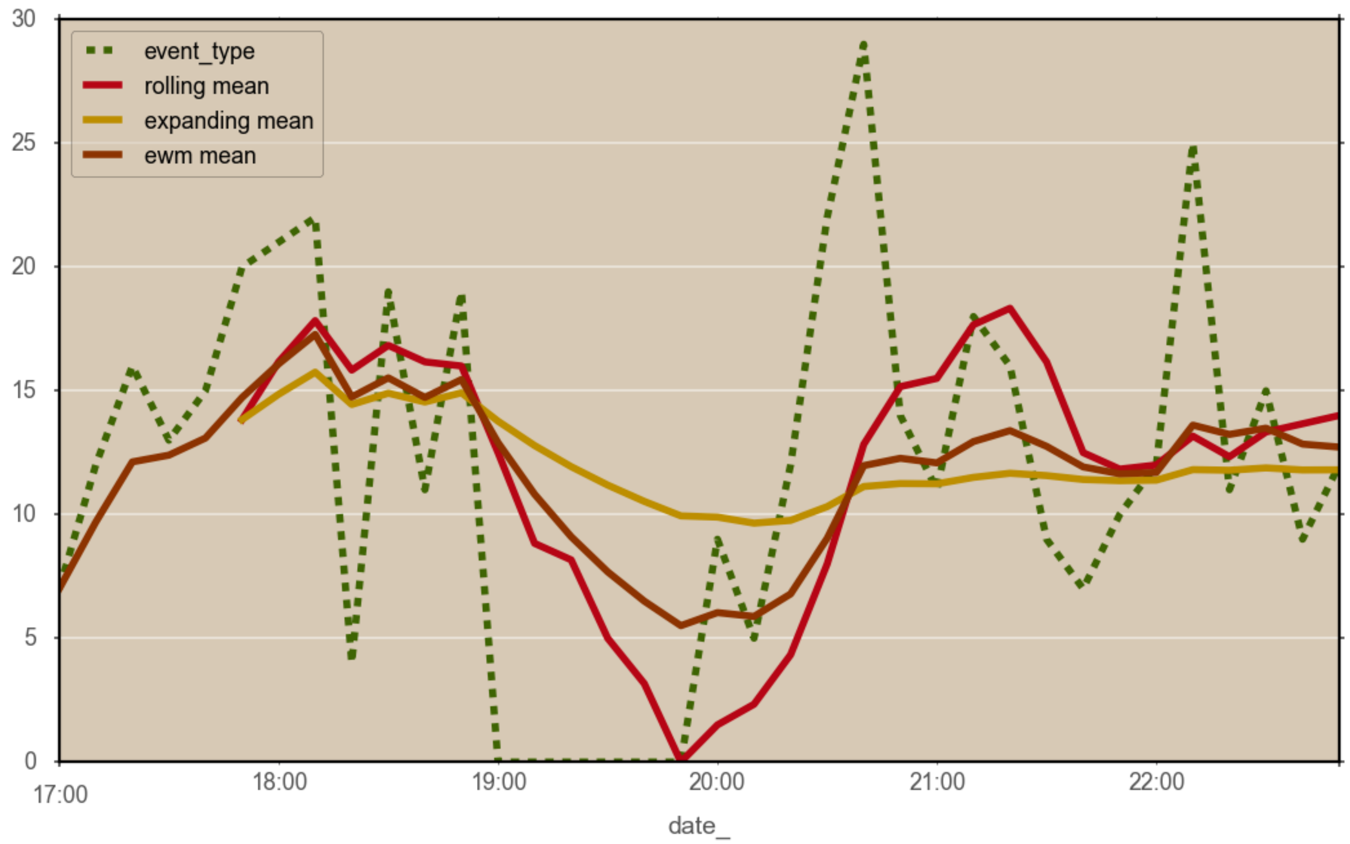
	event_type
date_	
2018-10-09 17:00:00	7

date_	event_type
2018-10-09 17:10:00	12
2018-10-09 17:20:00	16
2018-10-09 17:30:00	13
2018-10-09 17:40:00	15
2018-10-09 17:50:00	20
2018-10-09 18:00:00	21
2018-10-09 18:10:00	22
2018-10-09 18:20:00	4
2018-10-09 18:30:00	19

Time Windows: Rolling, Expanding, EWM

If your Dataframe is indexed on a datetime index (Which ours is), you have many options for window functions, which are again sort of "groupby" operations that in old times we used to do on our own.

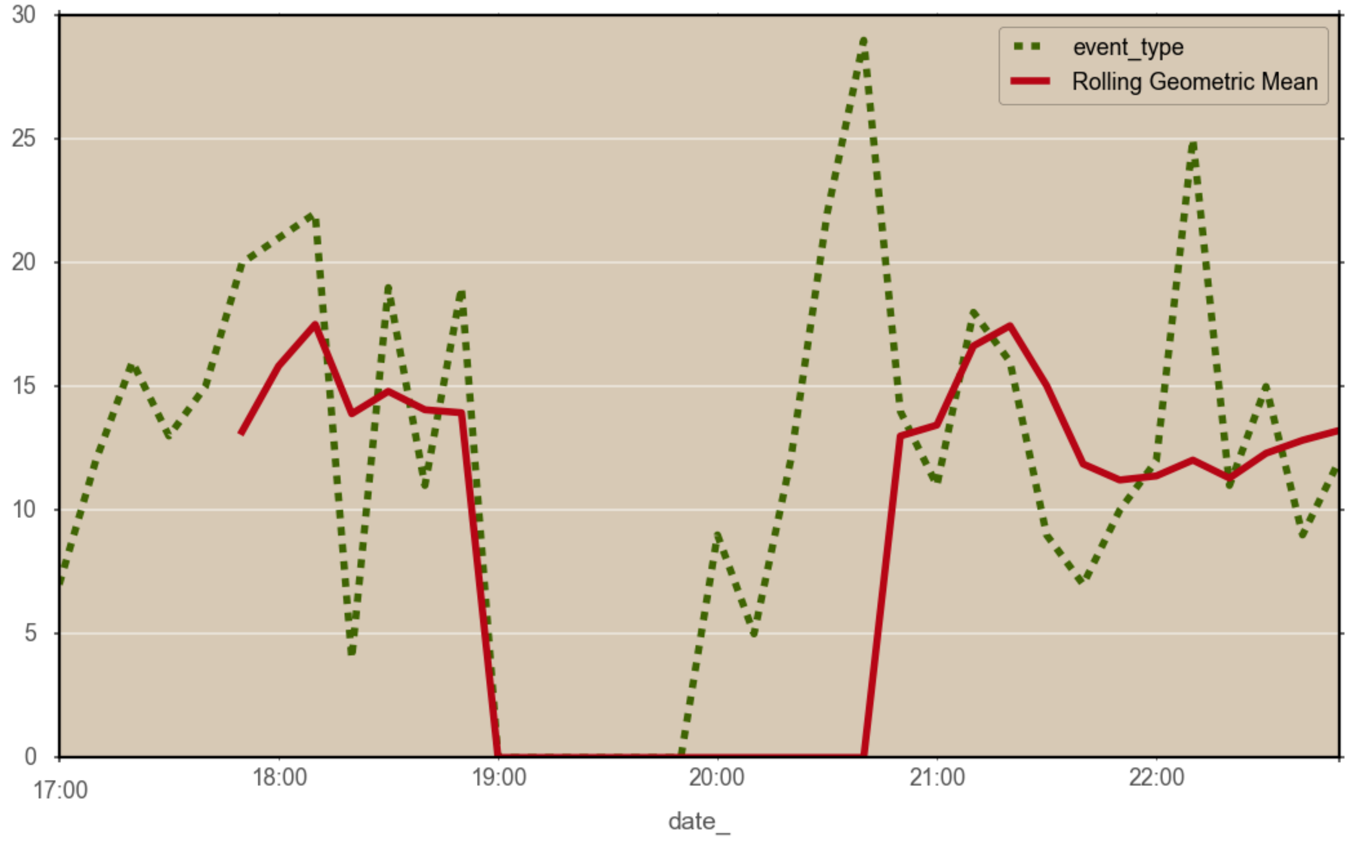
```
fig, ax = plt.subplots()
rs.plot(ax=ax,linestyle='--')
(rs
 .rolling(6)
 .mean()
 .rename(columns = {'event_type':'rolling mean'})
 .plot(ax=ax)
)

rs.expanding(6).mean().rename(columns = {'event_type':'expanding mean'}).plot(ax=ax)
rs.ewm(6).mean().rename(columns = {'event_type':'ewm mean'}).plot(ax=ax)
plt.show()
```



With Apply

Intuitively, windows are like GroupBy, so you can apply anything you want after the grouping, e.g.: geometric mean.

```
fig, ax = plt.subplots()
rs.plot(ax=ax,linestyle='--')
(rs
 .rolling(6)
 .apply(lambda x: np.power(np.product(x),1/len(x)), raw=True )
 .rename(columns = {'event_type':'Rolling Geometric Mean'})
 .plot(ax=ax)
)
plt.show()
```



Combine with GroupBy

Pandas has no problem with groupby and resample together. It's as simple as `groupby[col1,col2]`. In our specific case, we want to cound events in an interval per event type.

```
per_event = (df
            .groupby('event_type')
            .resample('15T')
            .apply('count')
            .rename(columns={'event_type':'amount'})
          )
per_event.head()
```

		amount
event_type	**date_**	
A	**2018-10-09 17:00:00**	8
	2018-10-09 17:15:00	6
	2018-10-09 17:30:00	6
	2018-10-09 17:45:00	9

	2018-10-09 18:00:00	3 amount
event_type	date_	

Stack, Unstack

Unstack

In this case, working with a wide format indexed on intervals, with event types as columns, will make a lot more sense.

The Old way

Pivot table in modern pandas is more robust than it used to be. Still, it requires you to specify everything.

```
pt = pd.pivot_table(per_event,values = 'amount',columns='event_type',index='date_')
pt.head()
```

event_type	A	B	C
date_			
2018-10-09 17:00:00	8	4	2
2018-10-09 17:15:00	6	11	4
2018-10-09 17:30:00	6	9	4
2018-10-09 17:45:00	9	10	10
2018-10-09 18:00:00	3	18	7

A better way

When you have just one column of values, unstack does the same easily

```
pt = per_event.unstack('event_type')
pt.columns = pt.columns.droplevel() # Unstack creates a multiindex on columns
pt.head()
```

event_type	A	B	C
date_			
2018-10-09 17:00:00	8	4	2
2018-10-09 17:15:00	6	11	4
2018-10-09 17:30:00	6	9	4
2018-10-09 17:45:00	9	10	10
2018-10-09 18:00:00	3	18	7

Unstack

And some extra tricks

```
pt.stack().head()
```

```
date_                event_type
2018-10-09 17:00:00  A             8
                     B             4
                     C             2
2018-10-09 17:15:00  A             6
                     B            11
dtype: int64
```

This looks kind of what we had expected but:

- It's a series, not a DataFrame
- The levels of the index are reversed
- The main sort is on the date, yet it used to be on the event type

```
stack_back = (pt
             .stack()
             .to_frame('amount') # Turn Series to DF without calling the DF constructor
             .swaplevel() # Swaps the levels of the index
             .sort_index() # Sort by index, makes so much sense yet I used to do .reset_index().sort_values()
            )
stack_back.head()
```

		amount
event_type	**date_**	
A	**2018-10-09 17:00:00**	8
	2018-10-09 17:15:00	6
	2018-10-09 17:30:00	6
	2018-10-09 17:45:00	9
	2018-10-09 18:00:00	3

```
stack_back.equals(per_event)
```

```
True
```

Sorting

By Values

```
per_event.sort_values(by=['amount']).head(10)
```

		amount
event_type	**date_**	
B	**2018-10-09 19:45:00**	0
	2018-10-09 19:00:00	0
	2018-10-09 19:15:00	0
	2018-10-09 19:30:00	0
C	**2018-10-09 19:00:00**	0

A	2018-10-09 19:30:00	0 amount
event_type	2018-10-09 19:15:00 date_	0
	2018-10-09 19:00:00	0
	2018-10-09 19:45:00	0
C	2018-10-09 19:30:00	0

By Index

```
per_event.sort_index().head(7)
```

		amount
event_type	date_	
A	2018-10-09 17:00:00	8
	2018-10-09 17:15:00	6
	2018-10-09 17:30:00	6
	2018-10-09 17:45:00	9
	2018-10-09 18:00:00	3
	2018-10-09 18:15:00	2
	2018-10-09 18:30:00	1

```
per_event.sort_index(level=1).head(7)
```

		amount
event_type	date_	
A	2018-10-09 17:00:00	8
B	2018-10-09 17:00:00	4
C	2018-10-09 17:00:00	2
A	2018-10-09 17:15:00	6
B	2018-10-09 17:15:00	11
C	2018-10-09 17:15:00	4
A	2018-10-09 17:30:00	6

By Both (New in 0.23)

If the index has a name, just treat it has a column.

```
per_event.sort_values(['amount','event_type'], ascending=(False, True)).head(10)
```

		amount
event_type	date_	

event_type	date_	amount
B	2018-10-09 18:00:00	18
	2018-10-09 20:30:00	17
	2018-10-09 18:30:00	16
	2018-10-09 22:45:00	14
A	2018-10-09 18:45:00	12
	2018-10-09 20:45:00	12
B	2018-10-09 22:00:00	12
	2018-10-09 22:30:00	12
C	2018-10-09 20:30:00	12
A	2018-10-09 22:15:00	11

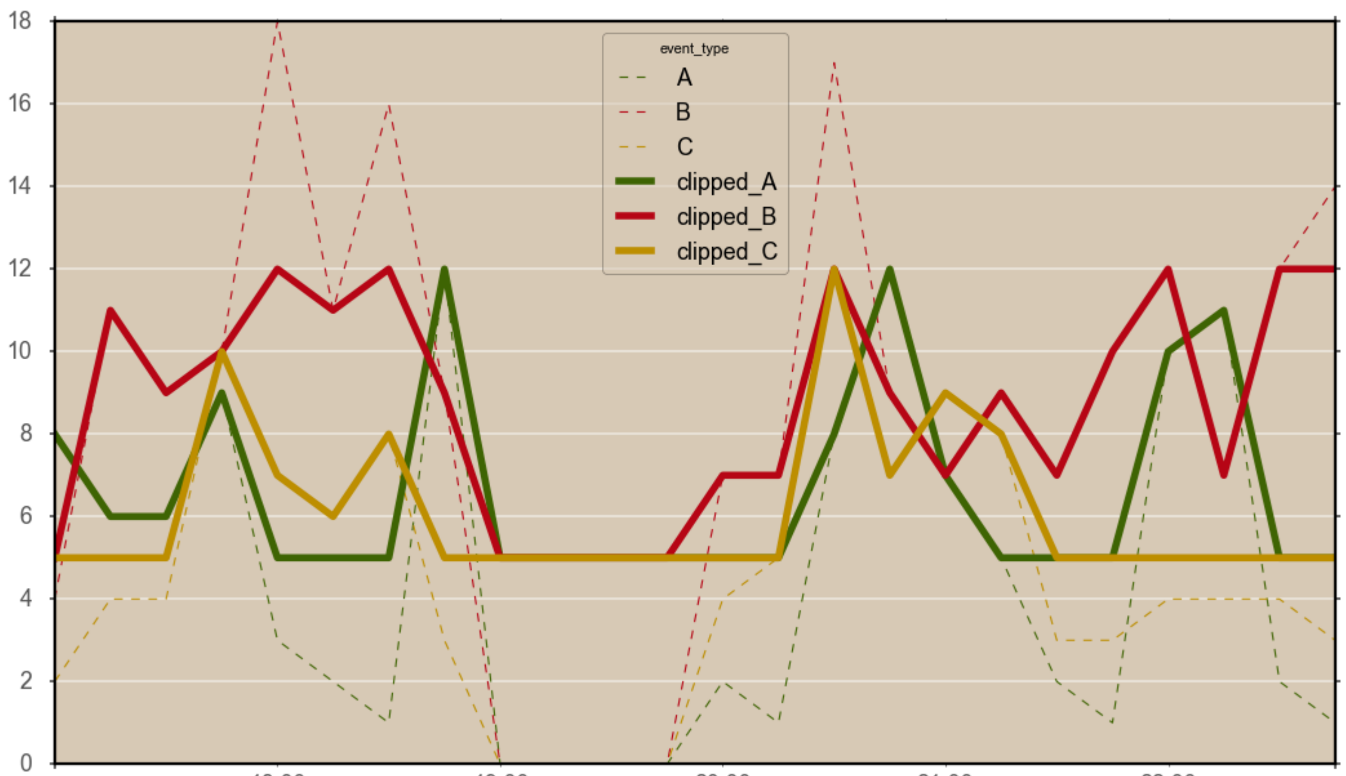
Clip

Let's say, we know from domain knowledge the that an event takes place a minimum of 5 and maximum of 12 at each timestamp. We would like to fix that. In a real world example, we many time want to turn negative numbers to zeroes or some truly big numbers to sum known max.

The Old Way

Iterate over columns and change values that meet condition.

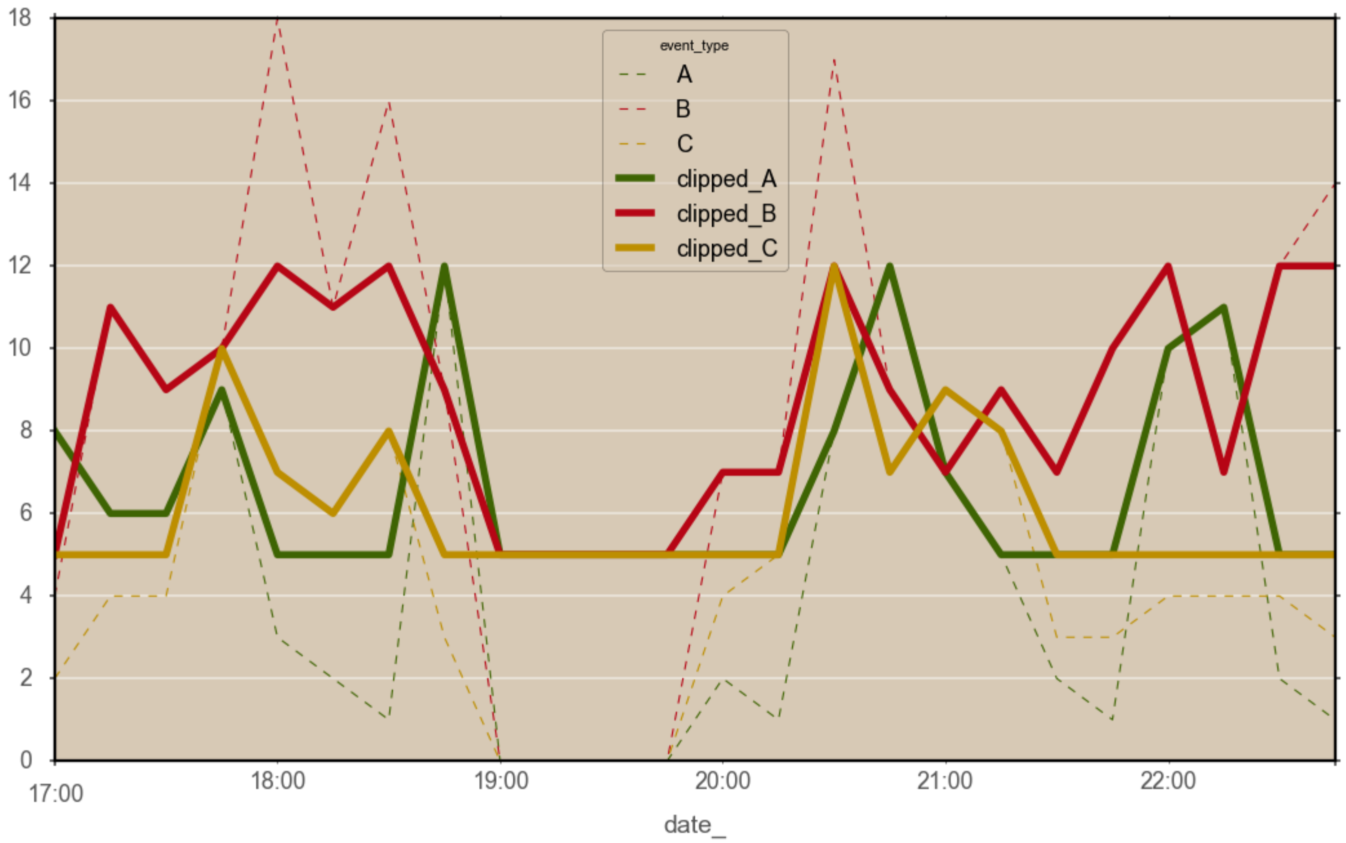
```
cl = pt.copy()
lb = 5
ub = 12
# Needed A loop of 3 lines
for col in ['A','B','C']:
    cl['clipped_{}'.format(col)] = cl[col]
    cl.loc[cl[col] < lb,'clipped_{}'.format(col)] = lb
    cl.loc[cl[col] > ub,'clipped_{}'.format(col)] = ub
my_utils.plot_clipped(cl) # my_utils can be found in the github repo
```



A better way

`.clip(lb,ub)`

```
cl = pt.copy()
# Beutiful One Liner
cl[['clipped_A','clipped_B','clipped_C']] = cl.clip(5,12)
my_utils.plot_clipped(cl) # my_utils can be found in the github repo
```



Reindex

Now I have 3 event types from 17:00 to 23:00. Let's imagine, I know that actually I have 5 event types. I also know that the period was from 16:00 to 00:00.

```
etypes = list('ABCDZ') # New columns

# Define a date range - Pandas will automatically make this into an index
idx = pd.date_range(start='2018-10-09 16:00:00',end='2018-10-09 23:59:00',freq='15T')
type(idx)
```

```
pandas.core.indexes.datetimes.DatetimeIndex
```

```
pt.reindex(idx, columns=etypes, fill_value=0).head()
```

event_type	A	B	C	D	Z
2018-10-09 16:00:00	0	0	0	0	0
2018-10-09 16:15:00	0	0	0	0	0

event_type	A	B	C	D	Z
2018-10-09 16:30:00	0	0	0	0	0
2018-10-09 16:45:00	0	0	0	0	0
2018-10-09 17:00:00	8	4	2	0	0

```python
### Let's put this in a function - This will help us later.
def get_all_types_and_timestamps(df, min_date='2018-10-09 16:00:00',
                                 max_date='2018-10-09 23:59:00', etypes=list('ABCDZ')):
    ret = df.copy()
    time_idx = pd.date_range(start=min_date,end=max_date,freq='15T')
    # Indices work like set. This is a good practive so we don't override our intended index
    idx = ret.index.union(time_idx)
    etypes = df.columns.union(set(etypes))
    ret = ret.reindex(idx, columns=etypes, fill_value=0)
    return ret
```

Method Chaining

Assign

Assign is for creating new columns on the dataframes. This is instead of `df[new_col] = function(df[old_col])` . They are both one lines, but `.assign` doesn't break the flow.

```python
pt.assign(mean_all = pt.mean(axis=1)).head()
```

event_type	A	B	C	mean_all
date_				
2018-10-09 17:00:00	8	4	2	4.666667
2018-10-09 17:15:00	6	11	4	7.000000
2018-10-09 17:30:00	6	9	4	6.333333
2018-10-09 17:45:00	9	10	10	9.666667
2018-10-09 18:00:00	3	18	7	9.333333

Pipe

Think R's %>% (Or rather, avoid thinking about R), `.pipe` is a method that accepts a function. `pipe` , by default, assumes the first argument of this function is a dataframe and passes the current dataframe down the pipeline. The function should return a dataframe also, if you want to continue with the pipe. Yet, it can also return any other value if you put it in the last step.
This is incredibly valueable because it takes you one step further from "sql" where you do things "in reverse".
$f(g(h(df)))$ = `df.pipe(h).pipe(g).pipe(f)`

```python
def do_something(df, col='A', n = 200):
    ret = df.copy()
    # A dataframe is mutable, if you don't copy it first, this is prone to many errors.
    # I always copy when I enter a function, even if I'm sure it shouldn't change anything.
    ret[col] = ret[col] + n
    return ret
```

```python
do_something(do_something(do_something(pt), 'B', 100), 'C',500).head()
```

event_type	A	B	C
date_			
2018-10-09 17:00:00	208	104	502
2018-10-09 17:15:00	206	111	504
2018-10-09 17:30:00	206	109	504
2018-10-09 17:45:00	209	110	510
2018-10-09 18:00:00	203	118	507

```
(pt
  .pipe(do_something)
  .pipe(do_something, col='B', n=100)
  .pipe(do_something, col='C', n=500)
  .head(5))
```

event_type	A	B	C
date_			
2018-10-09 17:00:00	208	104	502
2018-10-09 17:15:00	206	111	504
2018-10-09 17:30:00	206	109	504
2018-10-09 17:45:00	209	110	510
2018-10-09 18:00:00	203	118	507

You can always do this with multiple lines of `df = do_something(df)` but I think this method is more elegant.

Beautiful Code Tells a Story

Your code is not just about making the computer do things. It's about telling a story of what you wish to happen. Sometimes other people will want to read you code. Most time, it is you 3 months in the future who will read it. Some say good code documents itself; I'm not that extreme. Yet, storytelling with code may save you from many lines of unnecessary comments. The next and final block tells the story in one block, or rather one pipe. It's elegant, it tells a story. If you build utility functions and `pipe` them while following meaningful naming, they help tell a story. if you `assign` columns with meaningful names, they tell a story. you `drop` , you `apply` , you `read` , you `groupby` and you `resample` - they all tell a story.

(Well... Maybe they could have gone with better naming for `resample`)

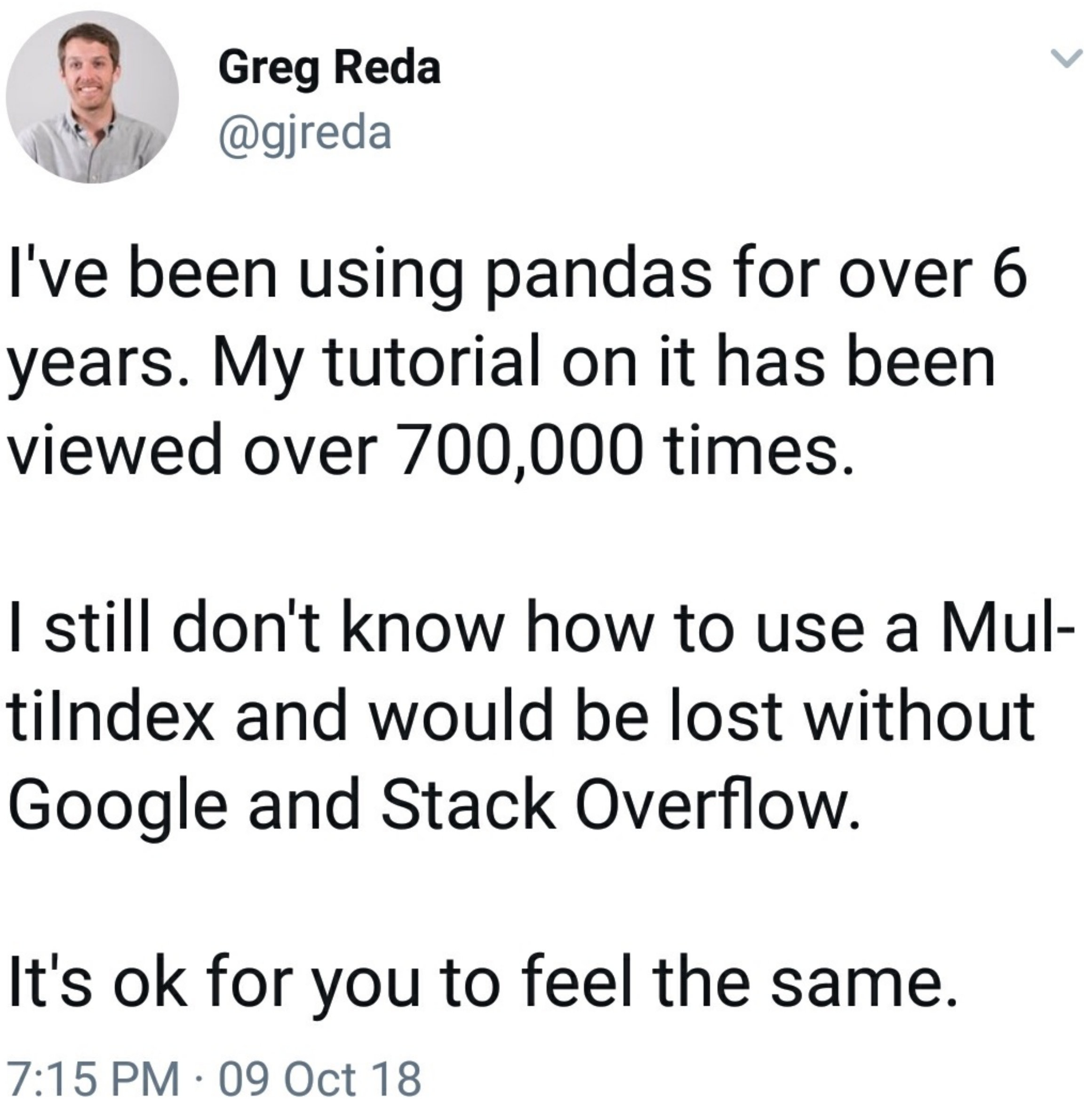
```
df = (pd
     .read_csv    ('./data.csv', index_col=0, parse_dates=['date_'])
     .assign      (event_type=lambda df: df.event_type.map({1: 'A', 5: 'B', 7: 'C'}))
     .sort_values ('date_')
     .set_index   ('date_')
     .drop        (columns='val_updated')
     .groupby     ('event_type')
     .resample    ('15T')
     .apply       ('count')
     .rename      (columns={'event_type': 'amount'})
     .unstack     ('event_type')
     .pipe        (my_utils.remove_multi_index)
     .pipe        (get_all_types_and_timestamps) # Remember this from before?
     .assign      (mean_event=lambda df: df.mean(axis=1))
     .loc         [:, ['mean_event']]
     .pipe        (my_utils.make_sliding_time_windows, steps_back=6)
     # Imagine last pipe is an api. Not sure how it's implemented, but the name is meaningful
     .dropna      ()
     )
```

```
df.head()
```

	mean_event	mean_event_1	mean_event_2	mean_event_3	mean_event_4	mean_event_5	mean_event_6
2018-10-09 17:30:00	3.8	4.2	2.8	0.0	0.0	0.0	0.0
2018-10-09 17:45:00	5.8	3.8	4.2	2.8	0.0	0.0	0.0
2018-10-09 18:00:00	5.6	5.8	3.8	4.2	2.8	0.0	0.0
2018-10-09 18:15:00	3.8	5.6	5.8	3.8	4.2	2.8	0.0
2018-10-09 18:30:00	5.0	3.8	5.6	5.8	3.8	4.2	2.8

You don't have to memorize this

Just put this in the back of your mind and remember that modern Pandas has so many superpowers. Just remember they exist, and google them when you actually need them. Always, when I feel I'm insecure about Pandas, I go back to Greg Reda's tweet:



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Resources

- Modern Pandas by Tom Augspurger
- Basic Time Series Manipulation with Pandas by Laura Fedoruk
- Pandas Docs. You don't have to thoroughly go over everything, just randomly open a page in the docs and you're sure to learn a new thing.

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