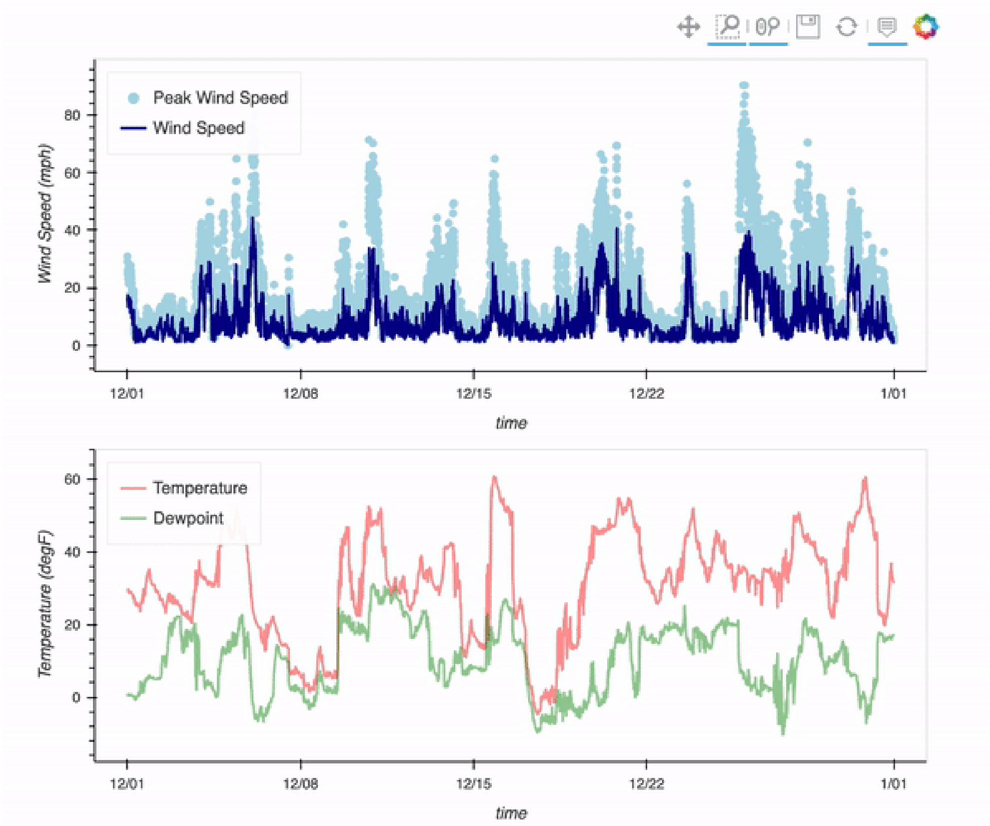
Processing Data from the NCAR Mesa Lab Weather Station

There is a weather station located at the Mesa Lab, situated along the Foothills of the Rockies in Boulder, Colorado!

By the end of this post, you will be able to plot an interactive visualization of the weather data collected at the Mesa Lab, as shown below!



Here is a picture of the lab!

The Data

This station collects data every 10 minutes, is publicly available from this site, with live plots viewable here

For this example, we downloaded a month's worth of daily data from December 2016. You can access the FTP server using this this link, pulling data from the `/mesa` directory. You will also need to unzip the files.

Imports

In this example, we utilize `xarray` and `pandas` for data cleaning, and `hvplot`/`holoviews` for visualization!

```
import holoviews as hv
import hvplot
import hvplot.xarray
import pandas as pd
import xarray as xr
from metpy.units import units

hv.extension('bokeh')
```

The Problem

When first accessing the data, you'll notice that are file extenstions - `.cdf` and `.nc`

The data are all stored in `netcdf` format, which is a binary data format. If you are interested in learning more about `netcdf`, check out the Pythia Foundations material on "NetCDF and CF: The Basics"!

One issue here though is within the `.cdf` data... we can read in the data, but we do not have helpful time information...

We can load it in using `xarray`, as shown below!

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Max Grover

xarray time preprocess

```
cdf_ds = xr.open_dataset('mlab.20161201.cdf')
cdf_ds
```

xarray.Dataset

▸ Dimensions: (time: 288)

▸ Coordinates: (0)

▸ Data variables: (20)

▸ Attributes: (0)

Dealing with the time

We do have a few time related variables:

- `base_time` - number of seconds since 1970-01-01
- `samp_secs` - sample interval in seconds
- `time_offset` - number of seconds from `base_time` for a given observation

```
cdf_ds[['base_time', 'samp_secs', 'time_offset']]
```

xarray.Dataset

▸ Dimensions: (time: 288)

▸ Coordinates: (0)

▾ Data variables:

base_time	()	int32	1480550400
samp_secs	()	int32	300
time_offset	(time)	float32	0.0 300.0 ... 8.58e+04 8.61e+04

▸ Attributes: (0)

The Solution

Fortunately, we can use the `time_offset` variable, in conjunction with the `base_time` to determine a human-readable time dimension!

`pandas.to_datetime` has a helpful tool for this! If you are interested in learning more about this functionality, check out the [official **pandas.to_datetime** documentation]

Calculating the New Time Axis

We start first by calculating the time in units `seconds since 1970-01-01`, by adding the `time_offset` to `base_time`

```
new_time = cdf_ds.base_time + cdf_ds.time_offset
new_time
```

xarray.DataArray (time: 288)

```
array([1.4805504e+09, 1.4805507e+09, 1.4805510e+09, 1.4805513e+09,
       1.4805516e+09, 1.4805519e+09, 1.4805522e+09, 1.4805525e+09,
       1.4805528e+09, 1.4805531e+09, 1.4805534e+09, 1.4805537e+09,
       1.4805540e+09, 1.4805543e+09, 1.4805546e+09, 1.4805549e+09,
       1.4805552e+09, 1.4805555e+09, 1.4805558e+09, 1.4805561e+09,
       1.4805564e+09, 1.4805567e+09, 1.4805570e+09, 1.4805573e+09,
       1.4805576e+09, 1.4805579e+09, 1.4805582e+09, 1.4805585e+09,
       1.4805588e+09, 1.4805591e+09, 1.4805594e+09, 1.4805597e+09,
       1.4805600e+09, 1.4805603e+09, 1.4805606e+09, 1.4805609e+09,
       1.4805612e+09, 1.4805615e+09, 1.4805618e+09, 1.4805621e+09,
       1.4805624e+09, 1.4805627e+09, 1.4805630e+09, 1.4805633e+09,
       1.4805636e+09, 1.4805639e+09, 1.4805642e+09, 1.4805645e+09,
       1.4805648e+09, 1.4805651e+09, 1.4805654e+09, 1.4805657e+09,
       1.4805660e+09, 1.4805663e+09, 1.4805666e+09, 1.4805669e+09,
       1.4805672e+09, 1.4805675e+09, 1.4805678e+09, 1.4805681e+09,
       1.4805684e+09, 1.4805687e+09, 1.4805690e+09, 1.4805693e+09,
       1.4805696e+09, 1.4805699e+09, 1.4805702e+09, 1.4805705e+09,
       1.4805708e+09, 1.4805711e+09, 1.4805714e+09, 1.4805717e+09,
       1.4805720e+09, 1.4805723e+09, 1.4805726e+09, 1.4805729e+09,
       1.4805732e+09, 1.4805735e+09, 1.4805738e+09, 1.4805741e+09,
...
       1.4806128e+09, 1.4806131e+09, 1.4806134e+09, 1.4806137e+09,
       1.4806140e+09, 1.4806143e+09, 1.4806146e+09, 1.4806149e+09,
       1.4806152e+09, 1.4806155e+09, 1.4806158e+09, 1.4806161e+09,
       1.4806164e+09, 1.4806167e+09, 1.4806170e+09, 1.4806173e+09,
       1.4806176e+09, 1.4806179e+09, 1.4806182e+09, 1.4806185e+09,
       1.4806188e+09, 1.4806191e+09, 1.4806194e+09, 1.4806197e+09,
       1.4806200e+09, 1.4806203e+09, 1.4806206e+09, 1.4806209e+09,
       1.4806212e+09, 1.4806215e+09, 1.4806218e+09, 1.4806221e+09,
       1.4806224e+09, 1.4806227e+09, 1.4806230e+09, 1.4806233e+09,
       1.4806236e+09, 1.4806239e+09, 1.4806242e+09, 1.4806245e+09,
       1.4806248e+09, 1.4806251e+09, 1.4806254e+09, 1.4806257e+09,
       1.4806260e+09, 1.4806263e+09, 1.4806266e+09, 1.4806269e+09,
```

```
        1.4806272e+09, 1.4806275e+09, 1.4806278e+09, 1.4806281e+09,
        1.4806284e+09, 1.4806287e+09, 1.4806290e+09, 1.4806293e+09,
        1.4806296e+09, 1.4806299e+09, 1.4806302e+09, 1.4806305e+09,
        1.4806308e+09, 1.4806311e+09, 1.4806314e+09, 1.4806317e+09,
        1.4806320e+09, 1.4806323e+09, 1.4806326e+09, 1.4806329e+09,
        1.4806332e+09, 1.4806335e+09, 1.4806338e+09, 1.4806341e+09,
        1.4806344e+09, 1.4806347e+09, 1.4806350e+09, 1.4806353e+09,
        1.4806356e+09, 1.4806359e+09, 1.4806362e+09, 1.4806365e+09])
```

▸ Coordinates: (0)

▸ Attributes: (0)

That array is hard to read though… we can pass this into `pandas.to_datetime` to handle the conversion!

```
times = pd.to_datetime(new_time.values, unit='s')
times
```

```
DatetimeIndex(['2016-12-01 00:00:00', '2016-12-01 00:05:00',
               '2016-12-01 00:10:00', '2016-12-01 00:15:00',
               '2016-12-01 00:20:00', '2016-12-01 00:25:00',
               '2016-12-01 00:30:00', '2016-12-01 00:35:00',
               '2016-12-01 00:40:00', '2016-12-01 00:45:00',
               ...
               '2016-12-01 23:10:00', '2016-12-01 23:15:00',
               '2016-12-01 23:20:00', '2016-12-01 23:25:00',
               '2016-12-01 23:30:00', '2016-12-01 23:35:00',
               '2016-12-01 23:40:00', '2016-12-01 23:45:00',
               '2016-12-01 23:50:00', '2016-12-01 23:55:00'],
              dtype='datetime64[ns]', length=288, freq=None)
```

That looks better! We can now add this to our dimensions for the dataset.

```
cdf_ds['time'] = times
cdf_ds
```

xarray.Dataset

▸ Dimensions: (**time**: 288)

▾ Coordinates:

time (time) datetime64[ns] 2016-12-01 ... 2016-12-01T23:55:00

▸ Data variables:

(20)

▸ Attributes: (0)

Wrapping into a Function and Using as a Preprocessor

We can wrap this into a function, then pass this into `xr.open_mfdataset` to process multiple files at the same time!

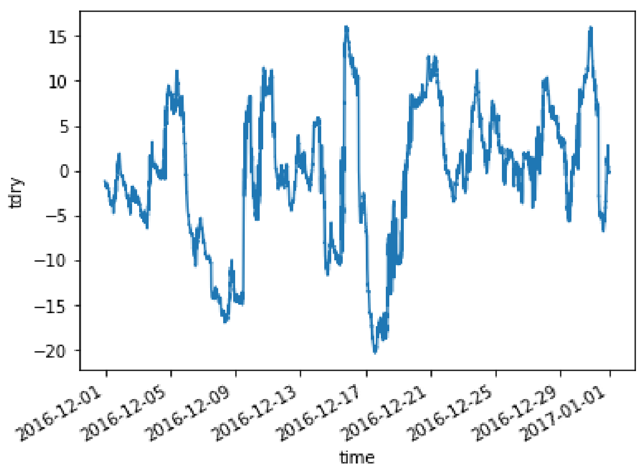
```
def fix_times(ds):
    ds['time'] = pd.to_datetime((ds.base_time + ds.time_offset).values, unit='s')
    return ds.drop(['base_time', 'samp_secs', 'time_offset'])
```

We can then pass our `fix_time` function into `xr.open_mfdataset` using the `preprocess` argument

```
ds = xr.open_mfdataset('*.cdf', engine='netcdf4', concat_dim='time', preprocess=fix_times).load()
```

We can plot a basic plot using the `.plot()` method in `xarray`

```
ds.tdry.plot();
```



Plotting an Interactive Meteogram

We can also plot a “meteogram” which is a collection of different surface observations.

We know from the `.nc` files that variables have the following units:

- Temperature (`tdry`) - `degrees Celsius`

- Dewpoint (`dp`) - `degrees Celsius`
- Wind (`wspd`)- `meter/second`
- Max Wind Speed (`wmax`) - `meter/second`

We start by defining our plots, as shown below:

Converting to Standard Units

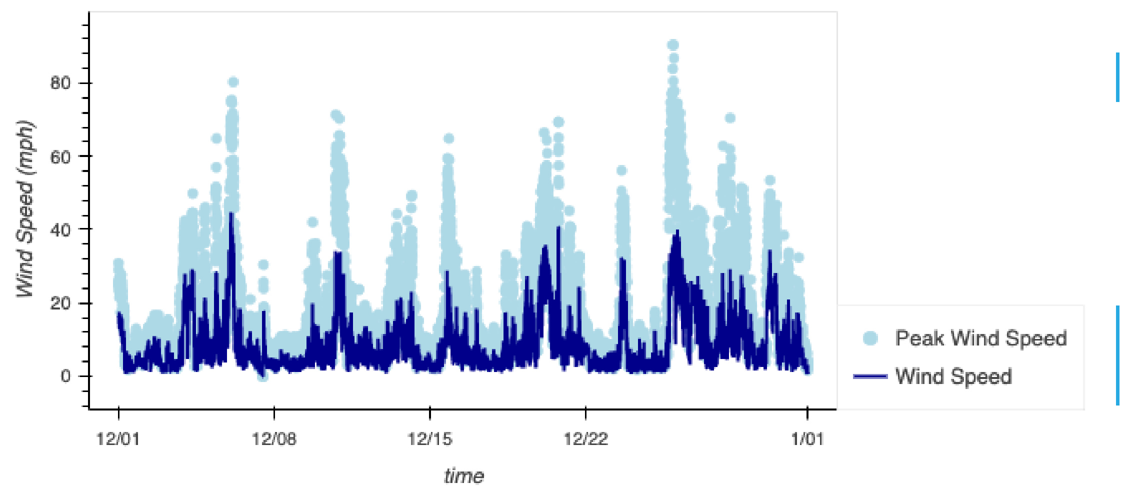
We can use `metpy.units` here to convert to US customary units!

```
ds_standard_units = ds.copy()

# Convert windspeed
ds_standard_units['wspd'] = ('time', (ds.wspd.values * units('m/s')).to('mph'))
ds_standard_units.wspd.attrs['units'] = 'mph'

# Convert max windspeed
ds_standard_units['wmax'] = ('time', (ds.wmax.values * units('m/s')).to('mph'))
ds_standard_units.wmax.attrs['units'] = 'mph'

# Convert windspeed
ds_standard_units['tdry'] = ('time', (ds.tdry.values * units('degC')).to('degF'))
ds_standard_units.tdry.attrs['units'] = 'degF'

# Convert max windspeed
ds_standard_units['dp'] = ('time', (ds.dp.values * units('degC')).to('degF'))
ds_standard_units.dp.attrs['units'] = 'degF'
```

Setup our Wind Plots

We now can setup our plots - starting with wind speed. We add a few labels, and merge them within the same subplot using the `*` syntax in `holoviews`!

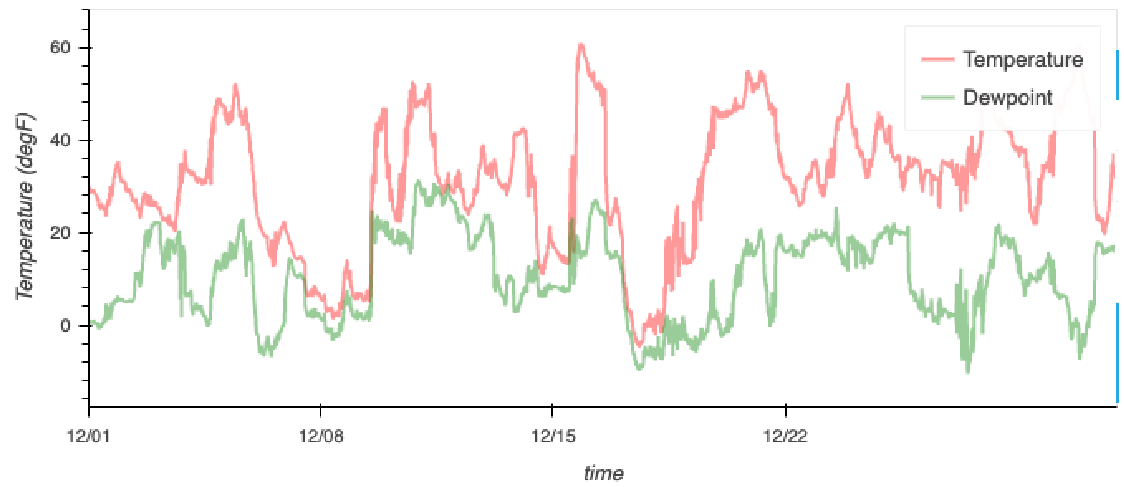
```
wind_speed_plot = ds_standard_units.wspd.hvplot.line(
    ylabel='Wind Speed (mph)', color='darkblue', label='Wind Speed'
)
wind_speed_max_plot = ds_standard_units.wmax.hvplot.scatter(
    color='lightblue', label='Peak Wind Speed'
)
wind_speed_max_plot * wind_speed_plot
```



Setup our Temperature Plots

We follow the same process for our temperature/dewpoint plots, adding an `alpha` argument to lighten the colors a bit.

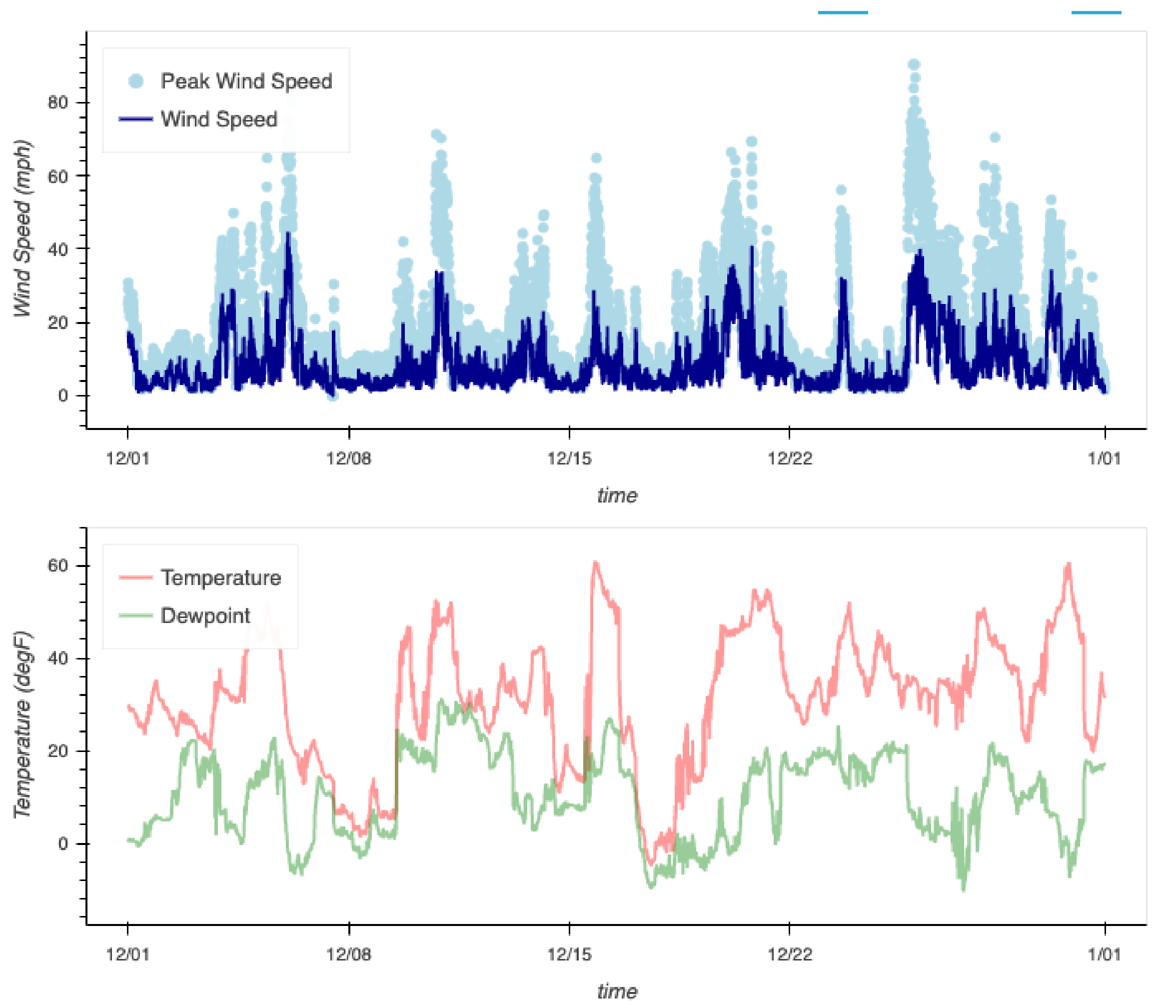
```
temperature_plot = ds_standard_units.tdry.hvplot.line(
    ylabel='Temperature (degF)', color='red', label='Temperature', alpha=0.4
)
dewpoint_plot = ds_standard_units.dp.hvplot.line(color='green', label='Dewpoint', alpha=0.4)
temperature_plot * dewpoint_plot
```



Bringing it All Together

Now that our plots are all setup, we can merge them into the same figure using the following syntax, specifying a single column and a legend located in the top left of each subplot:

```
hv.Layout(
    (wind_speed_max_plot * wind_speed_plot).opts(legend_position='top_left')
    + (temperature_plot * dewpoint_plot).opts(legend_position='top_left')
).cols(1)
```



Conclusion

Both `Xarray` and `Pandas` have helpful tools to deal with data cleaning, especially when working with time! Within this example, we showed how to apply this time cleaning step to data collected from the NCAR Mesa Lab Weather Station, passing this cleaning step into the `preprocess` argument in `open_mfdataset`!

Object Oriented Programming Tutorial

Correctly Calculating Annual Averages with Xarray