cross_correlate_noise

November 19, 2018

1 Cross-correlation coefficient distributions from pure noise

In this notebook I explore the distributions of cross-correlation coeffiecients from cross-correlating pure noise. This test is necessary to determine if the AC6 cross-correlation coefficients are high enough to avoid falling into this pitfall.

```
In [27]: import numpy as np
         import matplotlib.pyplot as plt
         import matplotlib.image as mpimg
         %matplotlib inline
         np.random.seed(0) # For reproducibility
```

Define background baselines and cross-correlation width in data points

```
In [2]: CC_widths = [5, 10, 15, 20]
        n_trials = 1000
        baseline = 100
```

Make a time series array with dimensions (CC_width x nBaslines x n_trials) where CC_width is the number of points to cross correlate, nBaseline is the number of baselines to study, and n_trials is how many random trails to cross-correlate. The noise-model used here Poisson at various count baselines

```
In [3]: timeseries = {width:np.zeros((width, n_trials), dtype=float) for width in CC_widths}
        for key in timeseries:
            timeseries[key] = np.random.poisson(lam=baseline, size=(key, n_trials))
```

Now here we define the cross-correlation function

```
In [5]: def cross_correlate(x, y):
            cc = np.correlate(x-x.mean(), y-y.mean(), mode='valid')
            norm = np.sqrt(len(y)*len(y)*np.var(x)*np.var(y))
            return cc/norm
```

Now for each baseline, cross-correlate random pairs of noise from timeseries array

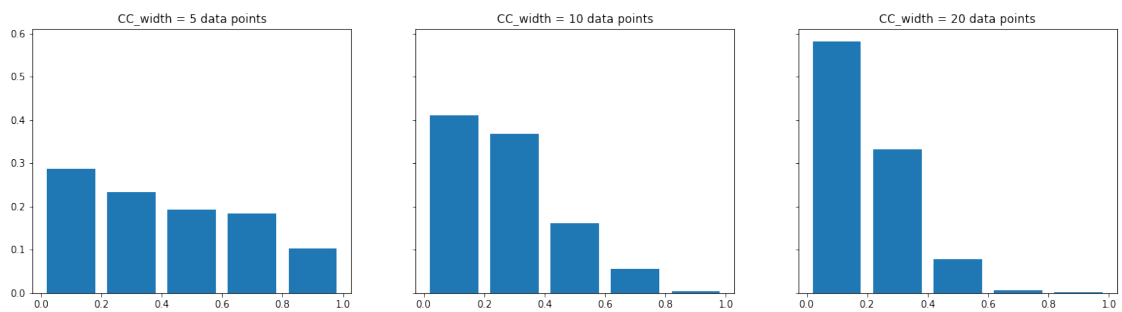
```
In [40]: cc_bins = np.arange(0, 1.1, 0.2)
         # number of baselines x number of histrogram bins.
         cc_hist = {width:np.zeros(len(cc_bins)-1, dtype=float) for width in CC_widths}
```

```
    for key in timeseries:
        for _ in range(n_trials):
            # Pick two trials at random.
            idxA, idxB = np.random.choice(np.arange(n_trials), size=2)
            # Cross-correlate the two random time series.
            cc = cross_correlate(timeseries[key][:, idxA], timeseries[key][:, idxB])
            # Now histogram it.
            cc_hist[key] += np.histogram(cc, bins=cc_bins)[0]
```

Normalize each histogram

```
In [41]: for i in cc_hist:
             cc_hist[i] /= np.sum(cc_hist[i])
```

```
In [49]: fig, ax = plt.subplots(1, 3, figsize=(20, 5), sharey=True, sharex=True)
         plt_keys = [5, 10, 20]
         bin_width = cc_bins[1] - cc_bins[0]
         for i, key in enumerate(plt_keys):
             ax[i].bar(cc_bins[1:]-bin_width/2, cc_hist[key], width=0.8*bin_width)
             ax[i].set_title('CC_width = {} data points'.format(key))
```



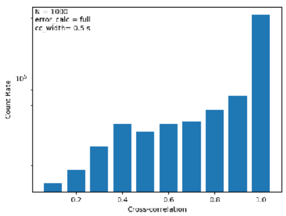
Lesson learned: cross-correlating more data points of noise results in a more peaked distribution around CC = 0.

1.0.1 Comparison to the autocorrelation study

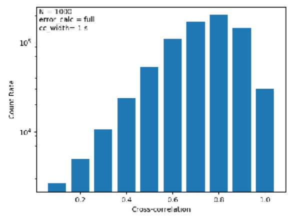
From the auto-correlation Monte Carlo study,

```
In [52]: fnames = ['auto_corr_noise_all_events_0dot5s_width.png',
                   'auto_corr_noise_all_events_1s_width.png',
                   'auto_corr_noise_all_events_2s_width.png']
         fig, ax = plt.subplots(1, 3, figsize=(25, 20))
         for i, fname in enumerate(fnames):
             img = mpimg.imread(fname)
             ax[i].imshow(img)
             ax[i].set_title(fname)
             ax[i].axis('off')
```

auto_corr_noise_all_events_0dot5s_width.png



auto_corr_noise_all_events_1s_width.png



auto_corr_noise_all_events_2s_width.png