TSNE analysis

April 7, 2020

Navigate to folder containing .mat files. used in this notebook: NPR-075.b11.mat

```
[1]: cd ../_data/matlabData
```

/home/gustav/Documents/DD142X/code/_data/matlabData

Imports and function definitions

```
[2]: import numpy as np
     import matplotlib.pyplot as plt
     from h5py import File
     def getMatlabValues(fileName):
         with File(fileName, "r") as data:
             return {
                 key: np.array(data[key]["values"]).flatten() for key in data.keys()
             }
     # Fourier Feature Vector
     def ffv(xs, Fs = 16000., epoch_size = 2 ** 11, fft_n = 2 ** 14):
         # Pad with zeroes for more frequency outputs
         # Compare np.fft.fftfreq(n, 1/16000) for n = 2**11, 2**14
         fft_in = np.zeros((xs.shape[0], fft_n))
         fft_in[ : , 0:epoch_size] = xs
         frqs = np.fft.fftfreq(fft_n, 1./Fs)
         lo = np.where(frqs > 12)[0][0]
         hi = np.where(frqs > 30)[0][0]
         fftxs = np.abs(np.fft.fft(fft_in)[:,lo:hi])
         return fftxs, frqs[lo:hi]
```

```
[3]: mldict = getMatlabValues("NPR-075.b11.mat")
```

Read all str, gp channels

```
[4]: str_lfp = np.array([ v for k, v in mldict.items() if "str_lfp" in k ])
gp_lfp = np.array([ v for k, v in mldict.items() if "gp_lfp" in k ])
all_lfp = np.concatenate((str_lfp, gp_lfp), axis = 0)
```

Trim to size - channel lengths should be epoch size * epochs

```
[5]: epoch_n = 2 ** 11
Fs = 16000
epochs_n = int(str_lfp.shape[1] / epoch_n)

# epoch_n and epochs_n, admittedly, somewhat confusing
# epoch_n : n points in an epoch
# epochs_n : amount of epochs

str_lfp = str_lfp[:, 0 : epoch_n * epochs_n]
gp_lfp = gp_lfp [:, 0 : epoch_n * epochs_n]
all_lfp = all_lfp[:, 0 : epoch_n * epochs_n]
```

Reshape to epoch-rows

```
[6]: str_lfp = str_lfp.reshape((-1, epoch_n))
gp_lfp = gp_lfp.reshape((-1, epoch_n))
all_lfp = all_lfp.reshape((-1, epoch_n))
```

If curious, amount of samples in total

```
[7]: print(str_lfp.shape)
print(gp_lfp.shape)
print(all_lfp.shape)
```

```
(8525, 2048)
(11625, 2048)
(20150, 2048)
```

[8]: from sklearn.manifold import TSNE

Generate feature vectors

```
[10]: ffv_str, _ = ffv(str_lfp)
    ffv_gp , _ = ffv(gp_lfp )
    ffv_all, _ = ffv(all_lfp)
    n_features = ffv_str.shape[1]
```

Generate TSNE embeddings

```
[11]: tsne_str = TSNE().fit_transform(ffv_str.copy())
    print(ffv_str.shape)
    print(tsne_str.shape)

    tsne_gp = TSNE().fit_transform( ffv_gp.copy())
    print(ffv_gp.shape)
    print(tsne_gp.shape)

    tsne_all = TSNE().fit_transform(ffv_all.copy())
    print(ffv_all.shape)
    print(tsne_all.shape)

(8525, 18)
    (8525, 2)
    (11625, 18)
    (11625, 2)
    (20150, 18)
    (20150, 2)
```

Convert to 3-dim tensors channels n x epochs n * 2 (2-component TSNE)

(26, 775, 2)

```
[12]: tsne_str = tsne_str.reshape((-1, epochs_n, 2))
    tsne_gp = tsne_gp.reshape((-1, epochs_n, 2))
    tsne_all = tsne_all.reshape((-1, epochs_n, 2))

print(tsne_str.shape)
    print(tsne_gp.shape)
    print(tsne_all.shape)

(11, 775, 2)
    (15, 775, 2)
```

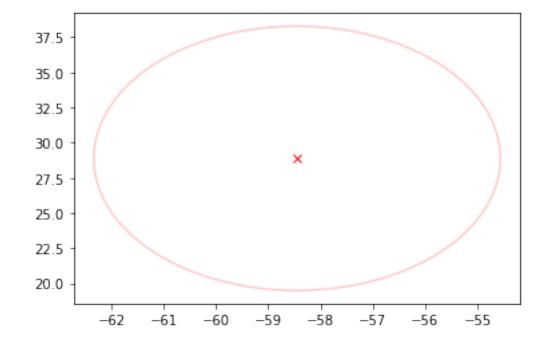
Mean, standard deviation over channels Results in mean and standard deviation for feature vectors for each epoch

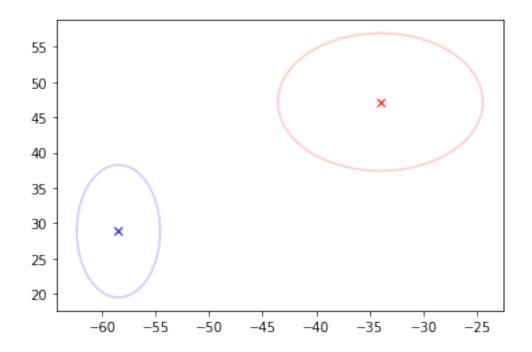
```
[13]: mean_str = tsne_str.mean(axis = 0)
std_str = tsne_str.std(axis = 0)
mean_gp = tsne_gp.mean(axis = 0)
std_gp = tsne_gp.std(axis = 0)
mean_all = tsne_all.mean(axis = 0)
std_all = tsne_all.std(axis = 0)
```

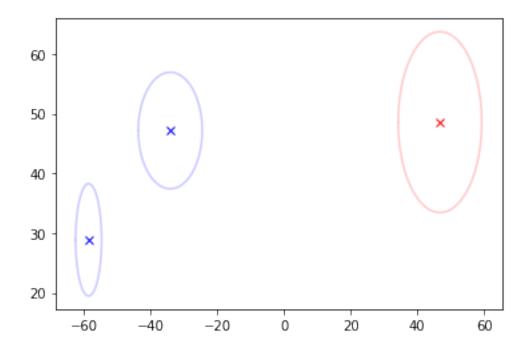
Example plot usage: Generates A LOT of plots Generates mean (with ellipse showing st. dev.) for each epoch, per epoch

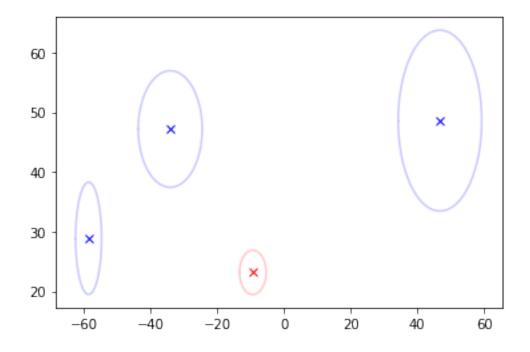
```
[14]: angles = np.linspace(-np.pi, np.pi, 100)
      # Amount of epochs to iterate through
      # Start low
      EPOCH_MAX = 10
      # These are for str
      plt.clf()
      for hi in range(0, EPOCH_MAX):
          for ep in range(0, hi):
              col = 'b'
              if ep == hi - 1:
                  col = 'r'
              plt.plot(mean_str[ep][0], mean_str[ep][1], 'x'+col)
              plt.plot(
                  mean_str[ep][0] + std_str[ep][0] * np.cos(angles),
                  mean_str[ep][1] + std_str[ep][1] * np.sin(angles),
                  col,
                  alpha = 0.2
              )
          plt.show()
```

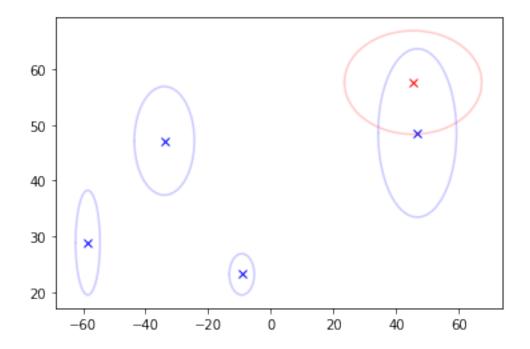
<Figure size 432x288 with 0 Axes>

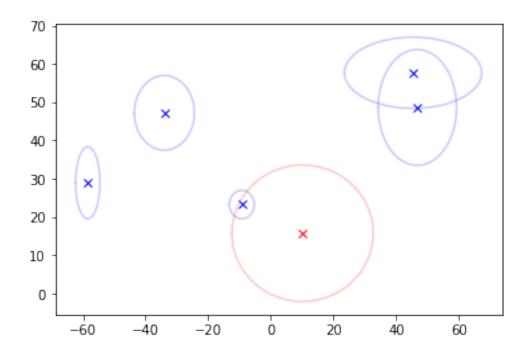


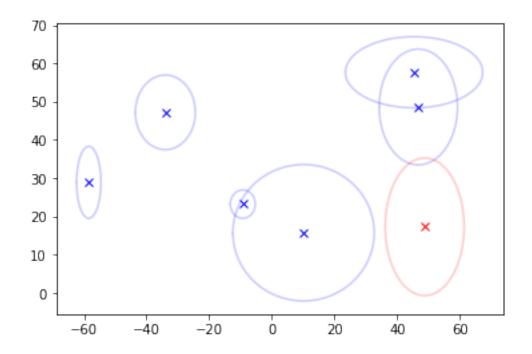


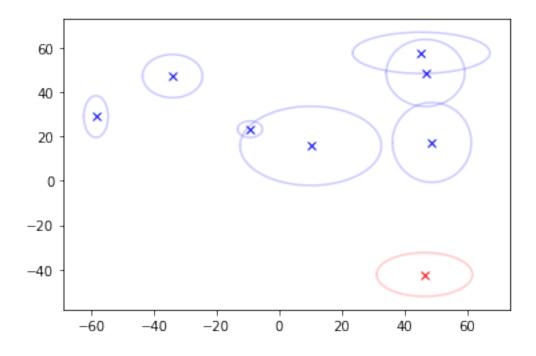


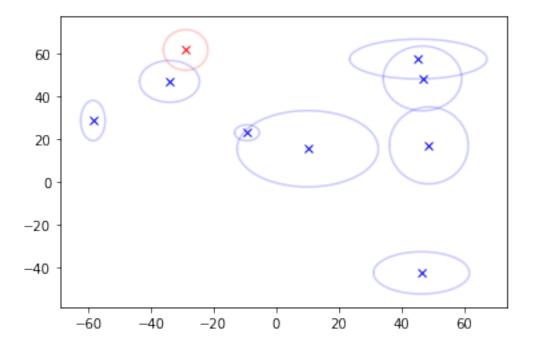






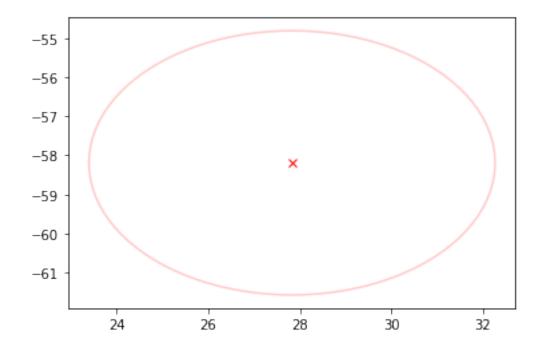


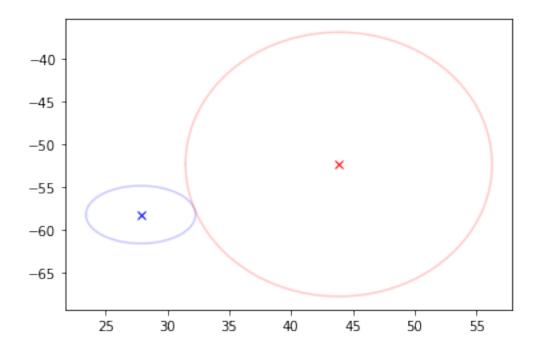


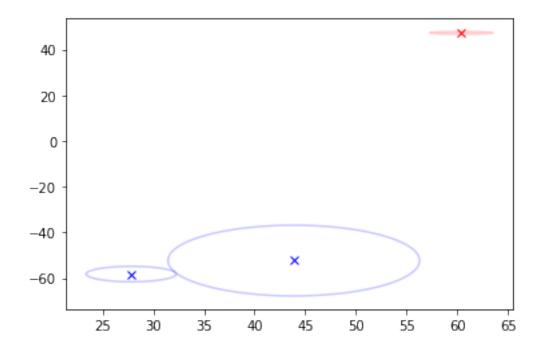


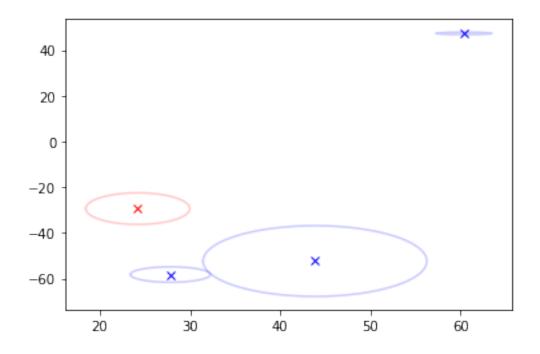
```
for hi in range(0, EPOCH_MAX):
    for ep in range(0, hi):
        col = 'b'
        if ep == hi - 1:
            col = 'r'
        plt.plot(mean_gp[ep][0], mean_gp[ep][1], 'x'+col)
        plt.plot(
            mean_gp[ep][0] + std_gp[ep][0] * np.cos(angles),
            mean_gp[ep][1] + std_gp[ep][1] * np.sin(angles),
        col,
            alpha = 0.2
        )
    plt.show()
```

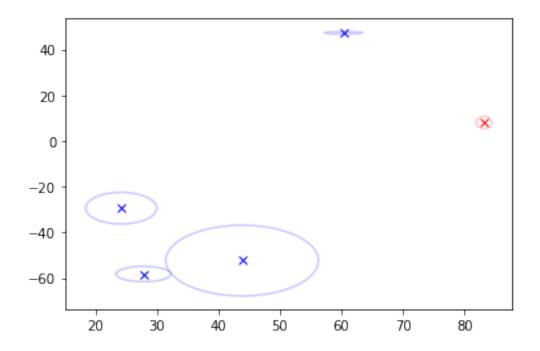
<Figure size 432x288 with 0 Axes>

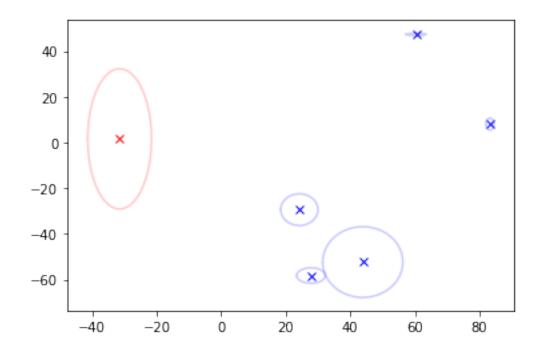


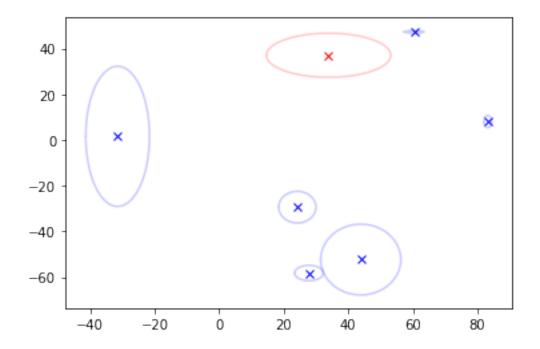


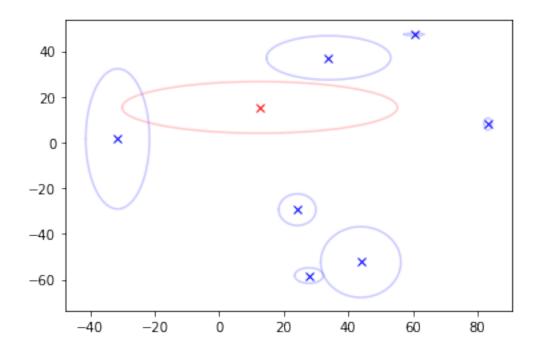


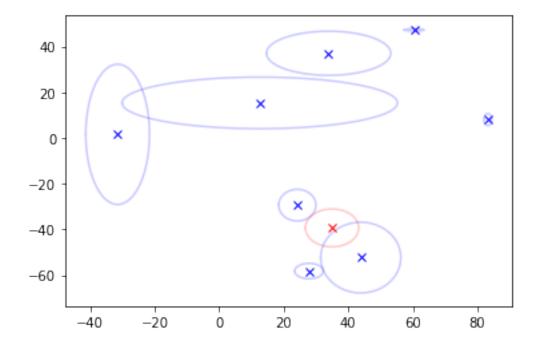










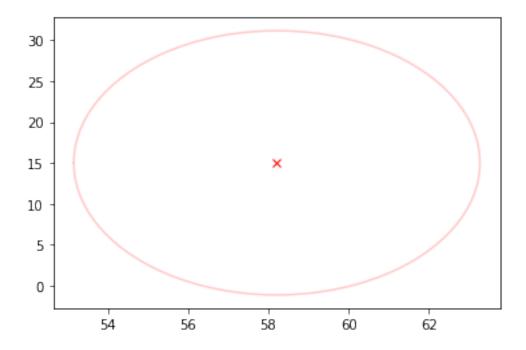


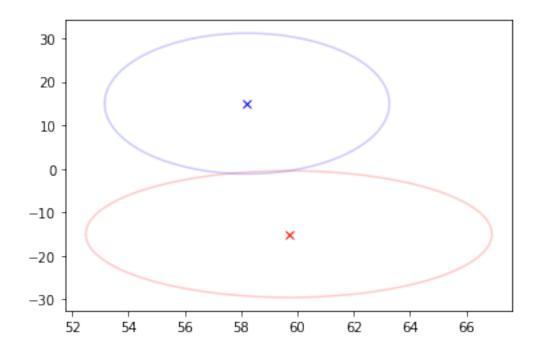
```
[17]: EPOCH_MAX = 10

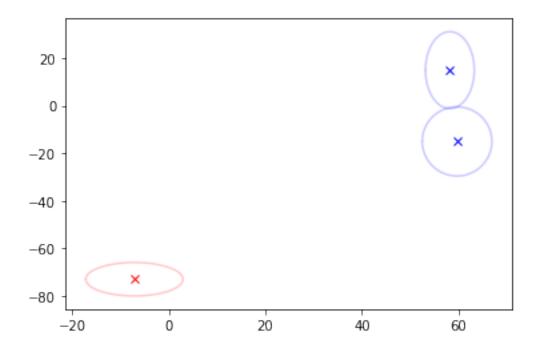
# For all
plt.clf()
```

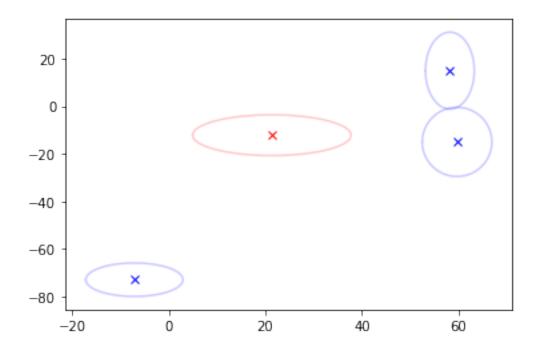
```
for hi in range(0, EPOCH_MAX):
    for ep in range(0, hi):
        col = 'b'
        if ep == hi - 1:
            col = 'r'
        plt.plot(mean_all[ep][0], mean_all[ep][1], 'x'+col)
        plt.plot(
            mean_all[ep][0] + std_all[ep][0] * np.cos(angles),
            mean_all[ep][1] + std_all[ep][1] * np.sin(angles),
            col,
            alpha = 0.2
        )
    plt.show()
```

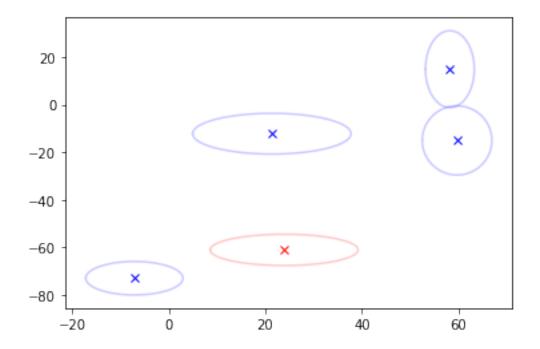
<Figure size 432x288 with 0 Axes>

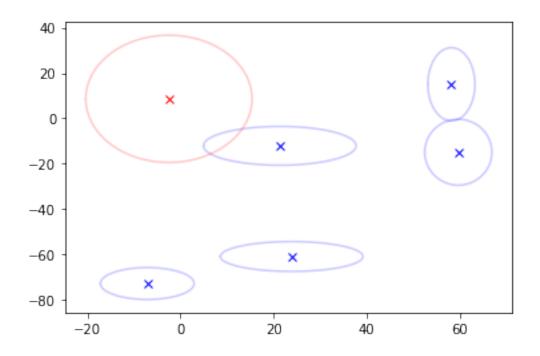


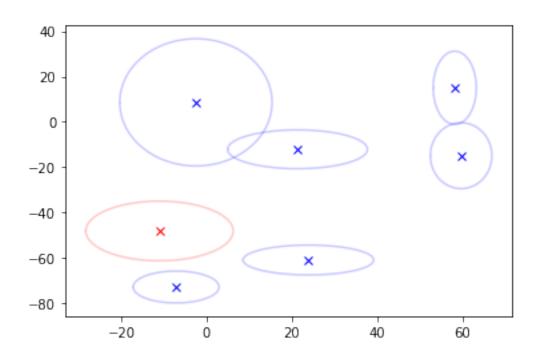


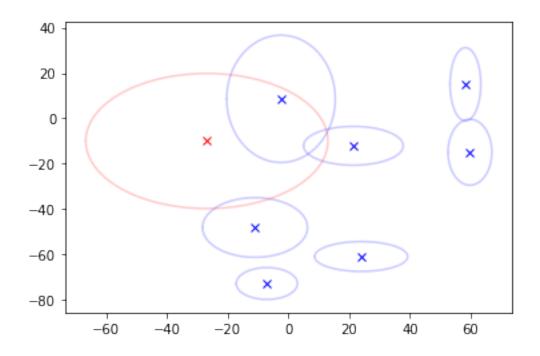


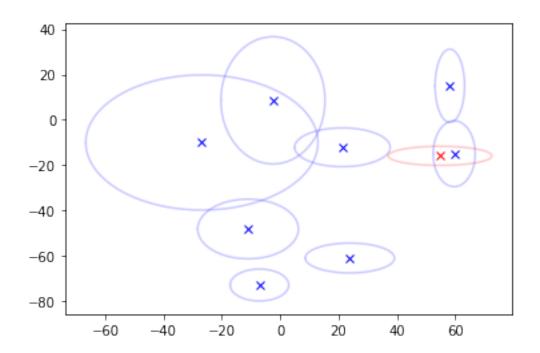








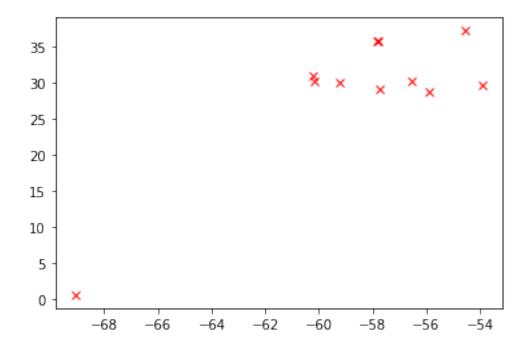


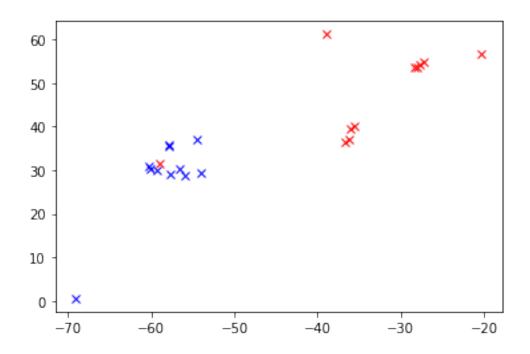


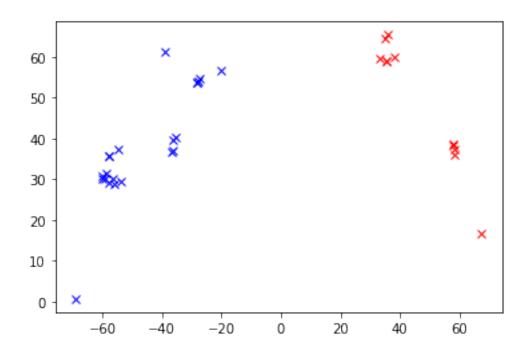
```
[18]: EPOCH_MAX = 10

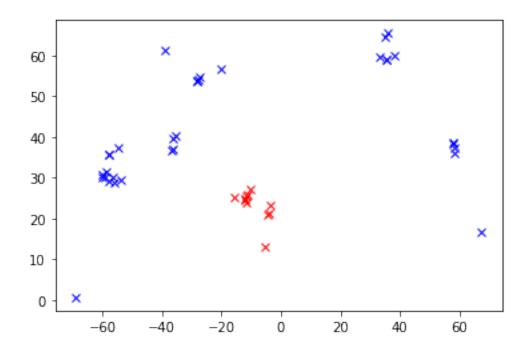
# In this example, plot all TSNE-embedded feature vectors
# Per epoch ("over time") as before
```

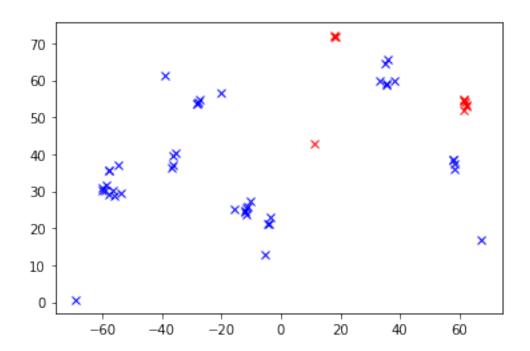
<Figure size 432x288 with 0 Axes>

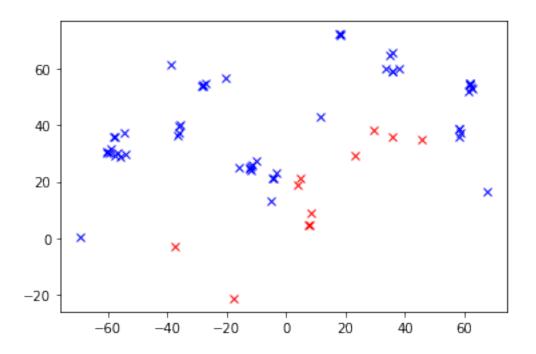


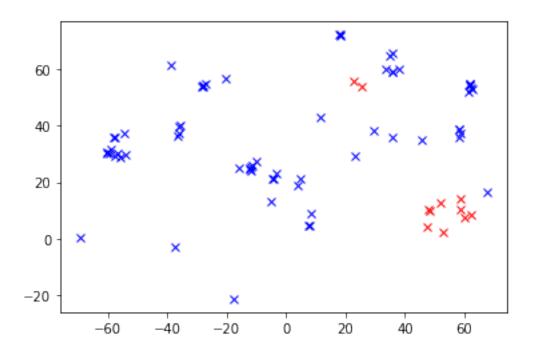


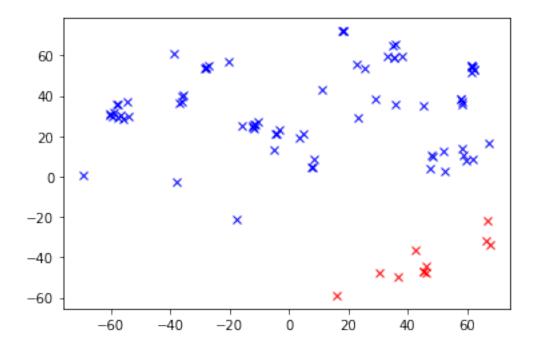


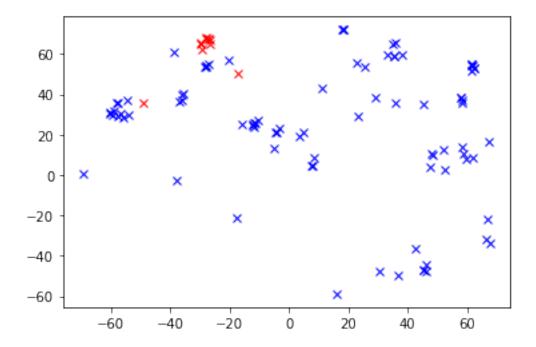












Per channel type Ordering (should) remain same in such a way that the following makes sense:

```
[19]: str_tmp = tsne_all[0:11]
gp_tmp = tsne_all[11:26]
```

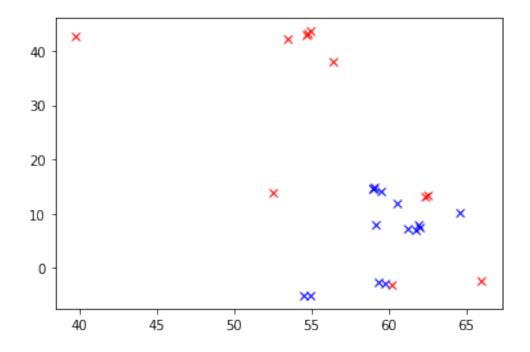
Above is not tested particularily extensively 11 channels str, 16 channels gp

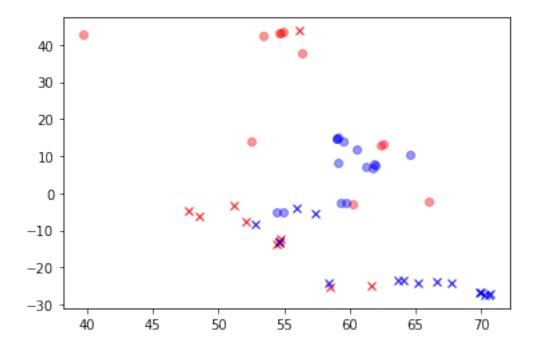
Now plot simultaneously

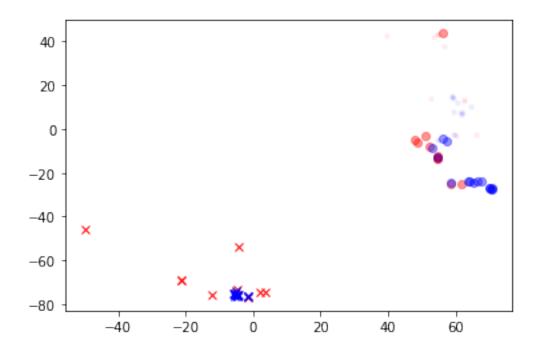
What's different from before is that we're plotting TSNE embeddings generated from ALL feature vectors. If synchronization is high, then str embeddings and gp embeddings should be close. Old samples are shown with low alpha. Red for str, blue for gp.

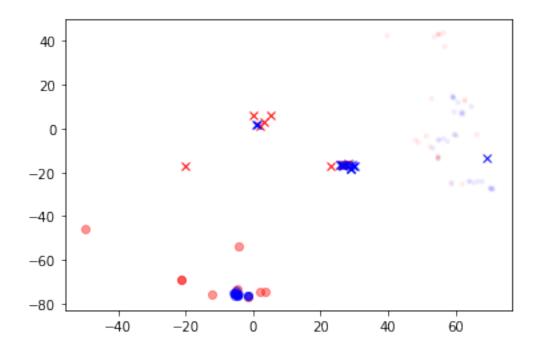
```
[21]: EPOCH MAX = 10
      plt.clf()
      for hi in range(0, EPOCH_MAX):
          for ep in range(0, hi):
              alpha = 0.05
              shape = '.'
              if ep == hi - 1:
                  alpha = 1
                  shape = 'x'
              elif ep == hi - 2:
                  shape = 'o'
                  alpha = 0.4
              plt.plot(
                   [x for x,_ in str_tmp[ : , ep]],
                   [y for _,y in str_tmp[ : , ep]],
                   'r' + shape,
                  alpha=alpha
              )
              plt.plot(
                   [x for x,_ in gp_tmp[ : , ep]],
                   [y for _,y in gp_tmp[ : , ep]],
                   'b' + shape,
                  alpha=alpha
              )
          plt.show()
```

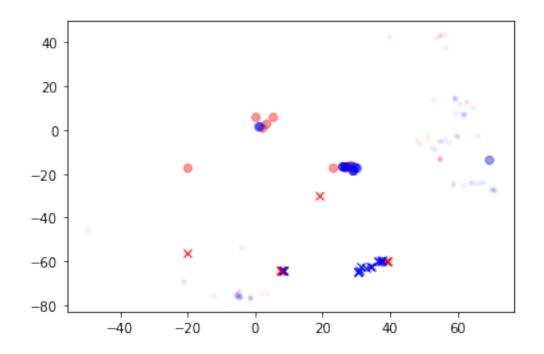
<Figure size 432x288 with 0 Axes>

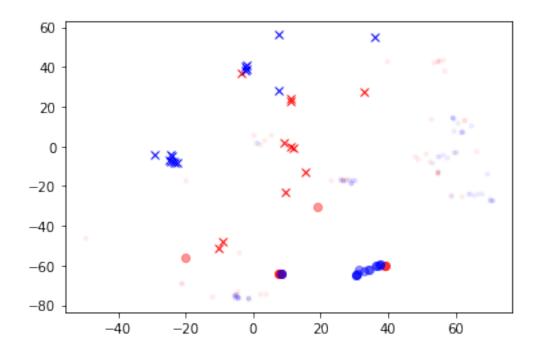


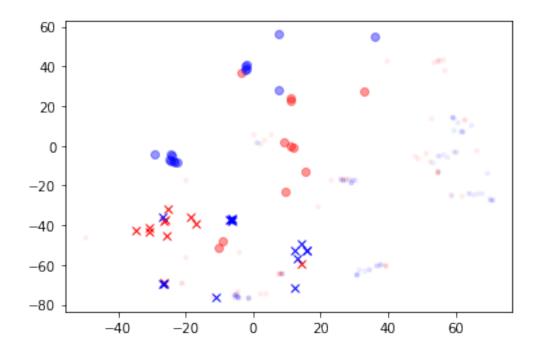


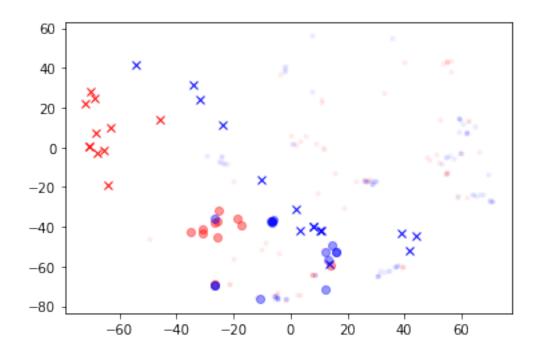


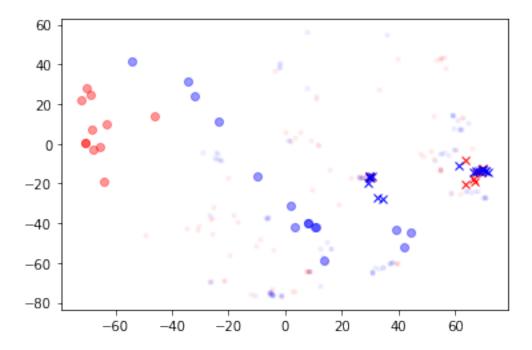












Results (my results, at least): Very strong synchronization happens very rarely, but does happen. Identifying these particular epochs and researching more thoroughly with other methods could be beneficial.

Some quite weak synchronization over str/gp seems to be implied. All embeddings are generally in the same part of the plot. However, str and gp embeddings generally closer same class than other class.