# Community Detection on NIPS12

January 22, 2019

## 1 Community Detection on NIPS12 dataset

In [1]: %matplotlib inline

1.1 We will visualize and detect the overlapping communities from the latent structure learned by our framework

```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as mpl
from IPython.display import Markdown, display
from utils import plota_fn

def printmd(string):
    display(Markdown(string))

import scipy.io as sio

from input_data import load_data

/usr/local/lib/python2.7/dist-packages/h5py/__init__.py:34: FutureWarning: Conversion of the sec
from ._conv import register_converters as _register_converters
```

1.1.1 Embedding learned using the following command! The embedding learned is also attached for quick reference. For ease of visualization, we have taken K=10 and alpha=2.

```
python train.py --dataset nips12 --hidden 64_10 --alpha0 2 --split_idx 0
--reconstruct_x 0 --early_stopping 0 --deep_decoder 0 --split_idx 0 --model dglfrm
--epochs 1000 --weighted_ce 1 --dropout 0
   The above command trains the DGLFRM model on 85% of the adjacency matrix.

In [2]: nips12 = np.load('data/qual_nips12_dglfrm.npz')
        # nips12_vae = np.load('data/qual_nips12_gcn_vae.npz')
        print nips12.keys()

        nips_author = sio.loadmat('data/nips12authors.mat')
        nips_author_names = nips_author['anames']
```

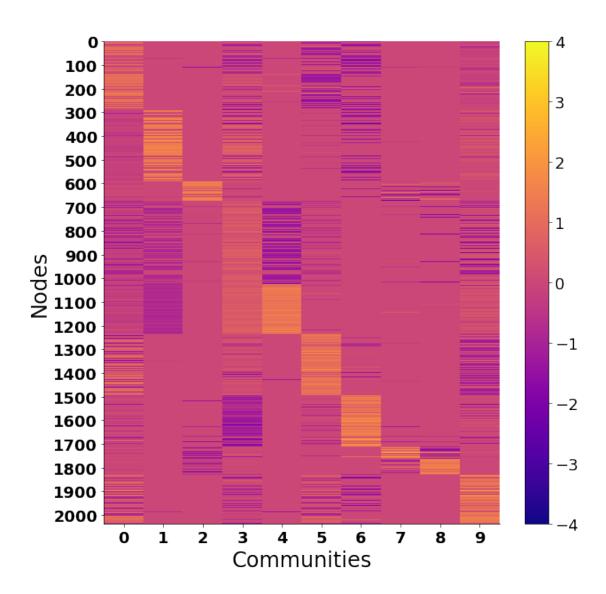
```
['z_out', 'z_real', 'z_discrete', 'adj_rec']
```

## 1.2 Creating the node embedding $z_n = b_n * r_n$

where "\*" is the element wise product.

```
In [3]: size = (10, 10)
       b = np.round(nips12['z_discrete'])
       r = nips12['z_real']
        avg_activated_communities = np.sum(b) / b.shape[0]
        z = np.multiply(r, b)
        # Reordering the communities (Columns of Z) for visualization.
        total_community_strength = np.sum(z, axis=0)
        new_community_idx = np.argsort(-total_community_strength)
        z = z[:, new_community_idx]
        # Reordering the nodes (Rows of Z) such that nodes having
        # high strength for communities with lower indices are on top.
        max_node_community_idx = np.argmax(z, axis=1)
        new_node_idx = np.argsort(max_node_community_idx)
        z = z[new_node_idx, :]
        # Since we re-ordered the nodes, we should re-arrange the author_names as well
        author_names = nips_author_names[new_node_idx, :]
        printmd ("**Average activated communities: {}**".format(avg_activated_communities))
        plota_fn(z, size, 'plasma', f_name="", x_step=1, y_step=100, vmin=-4, vmax=4, x_label='C
```

Average activated communities: 4.16200294551



#### 1.3 Print authors in communities

```
for arr_name in author_names:
        author_list += arr_name[0][0] + ', '
    return author_list

print ('Ordering is based on strength of the membership in a community. We are printing

K = 10 # Number of communities to print.

for i in np.arange(K):
    printmd ('**Community {}**'.format(2*i))
    print (flat(np.flip(author_names[author_negative[:,i]], 0)))
    printmd ('**Community {}**'.format(2*i+1))
    print (flat(author_names[author_positive[:,i]]))
```

Ordering is based on strength of the membership in a community. We are printing top 50 authors.

#### Community 0

Koch\_C, Bower\_J, Moore\_A, Coolen\_A, Moody\_J, Horiuchi\_T, DeWeerth\_S, Bair\_W, Tishby\_N, Saad\_D, F

## **Community 1**

Sejnowski\_T, Spence\_C, Barto\_A, Muller\_K, Dayan\_P, Platt\_J, Scholkopf\_B, Mozer\_M, Smola\_A, Gelfa

#### Community 2

Cowan\_J, Chiang\_Y, Hanson\_S, Shavlik\_J, Wang\_D, Munro\_P, Schreiner\_C, Roychowdhury\_V, Potter\_D,

#### Community 3

Edelman\_S, Ruppin\_E, Horn\_D, Cooper\_L, Weinshall\_D, Intrator\_N, Meilijson\_I, Eeckman\_F, Bert\_J,

## **Community 4**

Anderson\_C, Yuan\_J, Latham\_P, Malik\_J, Schuster\_M, Vu\_V, Phillips\_P, Malkoff\_D, Lang\_K, Annaswan

## **Community 5**

Walter\_J, Leong\_H, Berthold\_M, Waskiewicz\_J, Lewis\_M, Caprile\_B, Siegel\_R, Santos\_E, Grove\_A, We

#### Community 6

Hinton\_G, Guyon\_I, Jordan\_M, LeCun\_Y, Giles\_C, Simard\_P, Schapire\_R, Opper\_M, Bengio\_Y, Personna

## **Community 7**

Shavlik\_J, Blair\_A, Roychowdhury\_V, Cowan\_J, Peper\_F, Maass\_W, Horn\_D, Toomarian\_N, Hanson\_S, Co

## **Community 8**

Cowan\_J, Shavlik\_J, Munro\_P, Tsitsiklis\_J, Hancock\_E, Hanson\_S, Thakoor\_A, Paugam-Moisy\_H, Ullma

## Community 9

Roychowdhury\_V, Baluja\_S, van-Schaik\_A, Poggio\_T, Kailath\_T, Linden\_A, Xiang\_D, Maass\_W, Thrun\_S

## **Community 10**

Barto\_A, Smola\_A, Bartlett\_P, Scholkopf\_B, Meir\_R, Sutton\_R, Shawe-Taylor\_J, Andreou\_A, Alspecto

### **Community 11**

Sejnowski\_T, Goodman\_R, Moody\_J, Yang\_H, Chauvin\_Y, Coolen\_A, Krogh\_A, Henkle\_V, Obermayer\_K, Ba

### **Community 12**

Jordan\_M, Kawato\_M, Murray\_A, Bishop\_C, Atlas\_L, Wolpert\_D, Opper\_M, Abbott\_L, Ghahramani\_Z, Col

#### **Community 13**

Giles\_C, Cottrell\_G, Bengio\_Y, Graf\_H, Morgan\_N, Lippmann\_R, Jabri\_M, Mjolsness\_E, Waibel\_A, Plu

#### **Community 14**

Sundararajan\_S, Bengio\_Y, Monaco\_J, Metcalfe\_J, Margaritis\_D, Fukumizu\_K, Metz\_C, Kamimura\_R, Gh

#### **Community 15**

Kremer\_S, Wejchert\_J, Haffner\_P, Page\_E, Brand\_M, Murphy\_K, Lambert\_R, Simmons\_J, Smith\_L, Tanak

#### **Community 16**

Marts\_A, Sereno\_M, Burgess\_A, Stolorz\_P, Asogawa\_M, Levemon\_M, Freeman\_D, Pareigis\_S, Ring\_M, Gl

## **Community 17**

Zeitouni\_O, Carley\_L, Duda\_R, Hormel\_M, Kremer\_S, Lemmon\_M, Slaney\_M, Tam\_D, Cole\_C, Hartstein\_A

## **Community 18**

Koch\_C, Sejnowski\_T, Ruderman\_D, Bower\_J, Dayan\_P, Mel\_B, Obermayer\_K, Touretzky\_D, Harris\_J, Ba

## **Community 19**

Mozer\_M, Stork\_D, Tishby\_N, Tresp\_V, Wolff\_G, Ohmi\_T, McNaughton\_B, Yamashita\_T, Nakashima\_M, Bu

## 1.4 Example of communities inferred on a random split:

Community 6: Hinton\_G, Jordan\_M, LeCun\_Y, Bengio\_Y, Bishop\_C, Williams\_C ...

Community 10: Barto\_A, Sutton\_R, Singh\_S ...

Community 12: Jordan\_M, Bishop\_C, ...

Community 18: Sejnowski\_T, Pearlmutter\_B, Abu-Mostafa\_Y, Tang\_A

In []: