Neuroinformatics Toolbox Documentation

Release 0.1

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CONTENTS

The NI Toolbox contains python versions of commonly used functions to deal with spike data. Get the pdf version here

CHAPTER

ONE

FRAGEN

- **splines** - was für constraints müssen erfüllt sein?
- Welche Modelle sind sinnvoll zu vergleichen für generieren und fitten?

Contents:

1.1 Tutorial

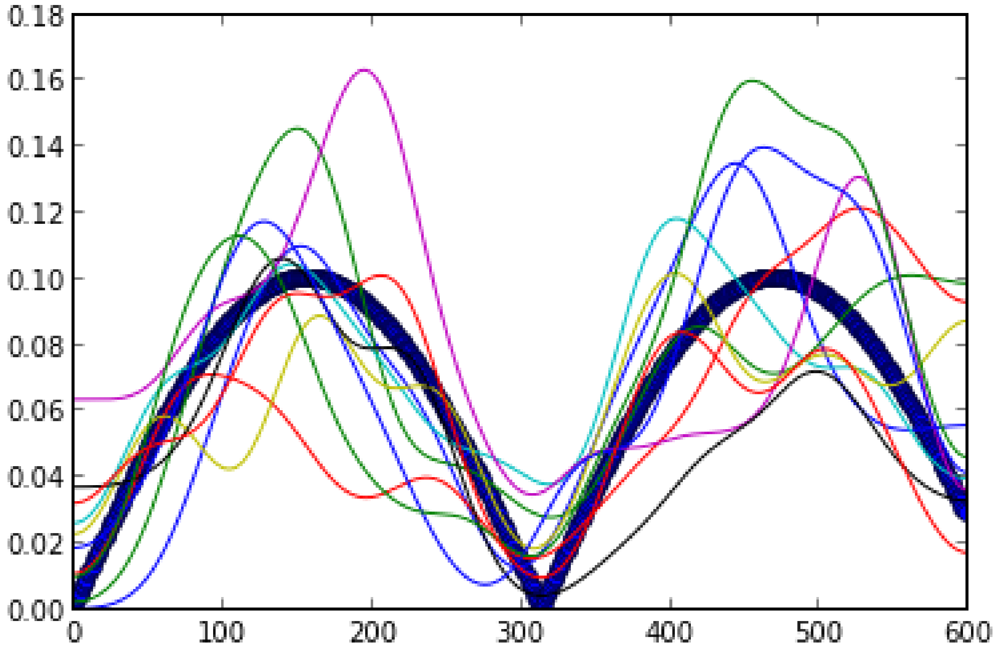
Something here

1.2 Some Examples

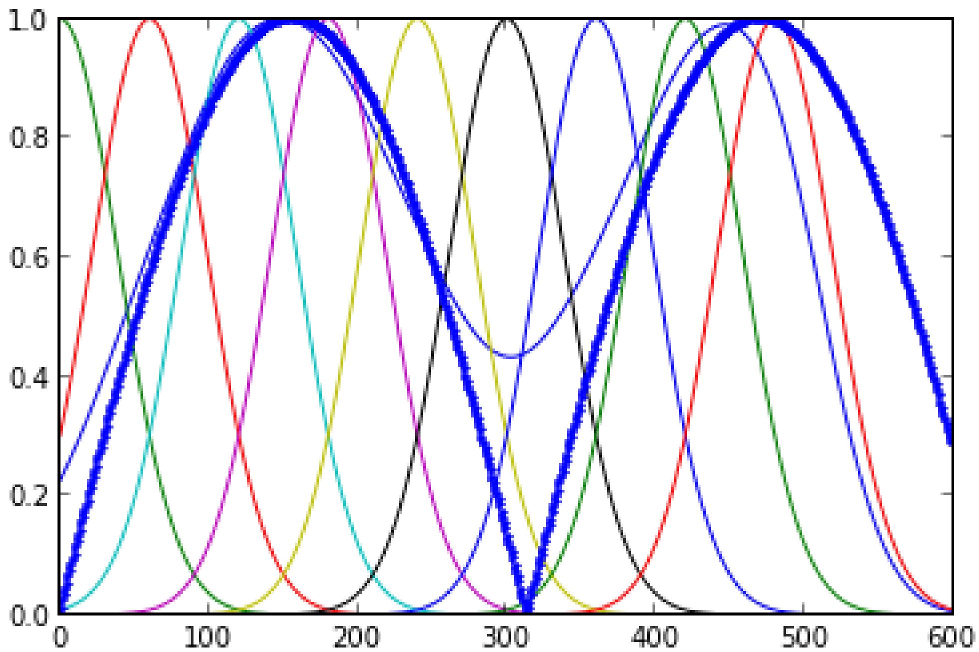
This code can be executed in an **ipython notebook –pylab inline** in browser maltlab like environment.

```
cd uni/MT/EIC/py

import pandas as pd
import ni.model.pointprocess
reload(ni.model.pointprocess)
p1 = ni.model.pointprocess.createPoisson(0.1,1000)

p2 = ni.model.pointprocess.createPoisson(sin(numpy.array(range(0,200))*0.01)*0.5- 0.2,1000)

import matplotlib
matplotlib.rcParams['savefig.dpi'] = 72

from scikits.statsmodels.genmod import generalized_linear_model
from scikits.statsmodels.genmod.families.family import Binomial

spikes = np.array(ni.model.pointprocess.createPoisson(sin(numpy.array(range(0,200))*0.01)*0.5- 0.2,1

design_matrix = [[exp(-1*(((i-j*100))**2)/1000) for j in range(0,9)] for i in linspace(0,999,1000)]
glm = generalized_linear_model.GLM(spikes,design_matrix, family = Binomial())
res = glm.fit()

import ni.model.glm as glm
import ni.tools.bootstrap as bs
reload(glm)
reload(bs)
```

```
length = 600

target = abs(sin(numpy.array(range(0,length))*0.01)*0.1)
spikes = np.array([ni.model.pointprocess.createPoisson(target,length).getCounts() for i in range(0,1
#design_matrix = [[exp(-1*(((i-j*60))**2)/10000) for j in range(0,9)] for i in linspace(0,length-1,le
design_matrix = [[exp(-1*(((i-j*60))**2)/3000) for j in range(0,9)] for i in linspace(0,length-1,leng
design_matrix2 = []
for i in range(0,10):
    design_matrix2.append(design_matrix)
design_matrix = vstack(design_matrix2)
plot(target,'bo')
for i in range(0,10):
    ni.model.pointprocess.plotGaussed(spikes[i],30)
#bs.evaluate(glm.GLM(spikes,design_matrix),spikes,10)
```




```
from scikits.statsmodels.genmod import generalized_linear_model
from scikits.statsmodels.genmod.families.family import Binomial

Data = reshape(spikes,(length * 10,1))
#plot(Data,'bo')
#plot(design_matrix[:,3])

dev = np.array([abs((design_matrix[find(Data.transpose()),i])) for i in range(0,9)])
prediction = sum(design_matrix * mean(dev,1),1)
plot(prediction[0:length]/max(prediction))
plot(design_matrix[0:length,:])
plot(target/max(target),'b.')
#g = generalized_linear_model.GLM(Data,design_matrix[:,1:5], family = Binomial())
#res = g.fit()

#model = glm.GLM(Data,design_matrix)
#m = model.fit(Data)
```




```
g = generalized_linear_model.GLM(Data,design_matrix, family = Binomial())
res = g.fit()
```

Note: Generates an ERROR

ValueError Traceback (most recent call last) /home/plogic/uni/MT/EIC/py/<ipython-input-298-79fc06ff0302> in <module>()

1 g = generalized_linear_model.GLM(Data,design_matrix, family = Binomial())

—-> 2 res = g.fit()

/usr/lib/pymodules/python2.7/scikits/statsmodels/genmod/generalized_linear_model.pyc in fit(self, maxiter, method, tol, scale)
404 wlsendog = eta + self.family.link.deriv(mu) * (self.endog-mu) 405 - offset

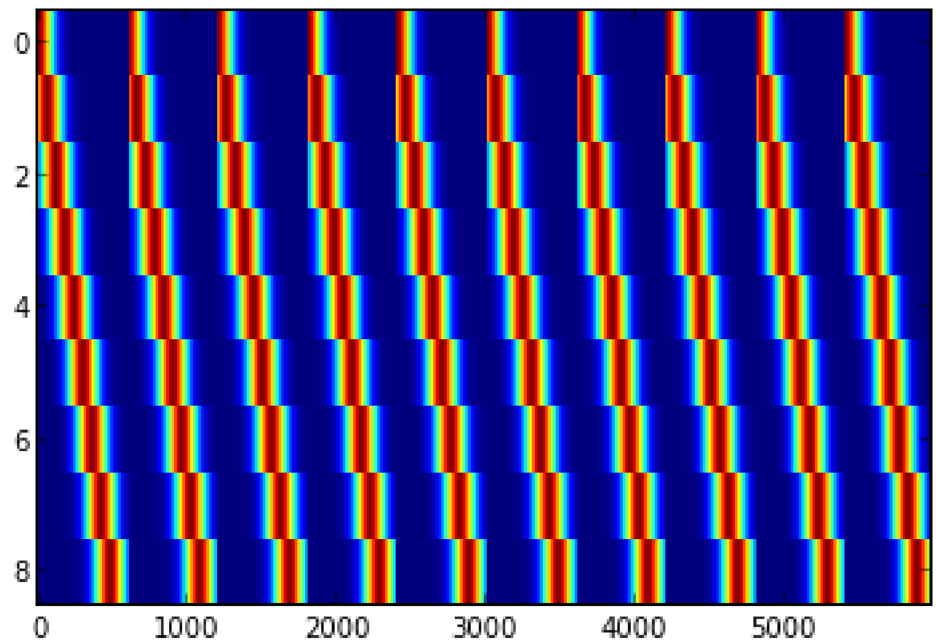
–> 406 wls_results = WLS(wlsendog, wlsexog, self.weights).fit() 407 eta = np.dot(self.exog, wls_results.params) + offset 408 mu = self.family.fitted(eta)

/usr/lib/pymodules/python2.7/scikits/statsmodels/regression/linear_model.pyc in __init__(self, endog, exog, weights)
383 weights.size == design_rows) : 384 raise ValueError(

–> 385 'Weights must be scalar or same length as design') 386 self.weights = weights.reshape(design_rows) 387 super(WLS, self).__init__(endog, exog)

ValueError: Weights must be scalar or same length as design

```
design_matrix = [[exp(-1*(((i-j*30))**2)/10000) for j in range(0,9)] for i in linspace(0,299,300)]
design_matrix2 = []
for i in range(0,10):
    design_matrix2.append(design_matrix)
#design_matrix2
design_matrix = vstack(design_matrix2)

img = imshow(np.array(design_matrix).transpose(), aspect='auto')
img.set_interpolation('nearest')
```




```
res.summary()
```

Note:

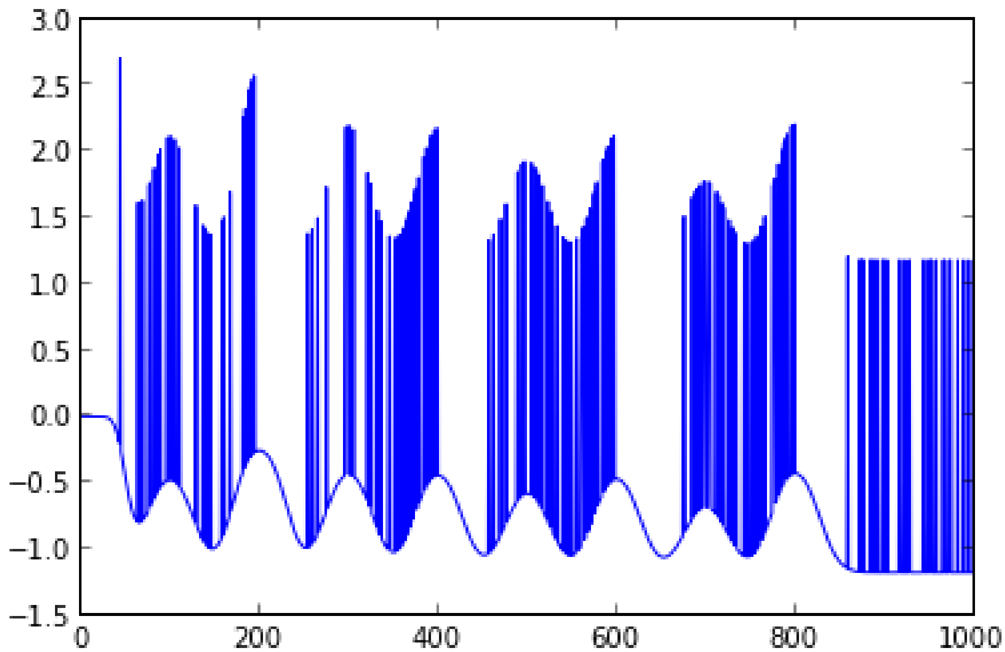
Generalized linear model

Model Family: Binomial # of obs: 1000 Method: IRLS Df residuals: 991 Dependent Variable: Y Df model: 8 Date: Thu, 30 May 2013 Scale: 1.0000 Time: 17:29:30 Log likelihood: -521.6848

coefficient stand errors t-statistic Conf. Interval

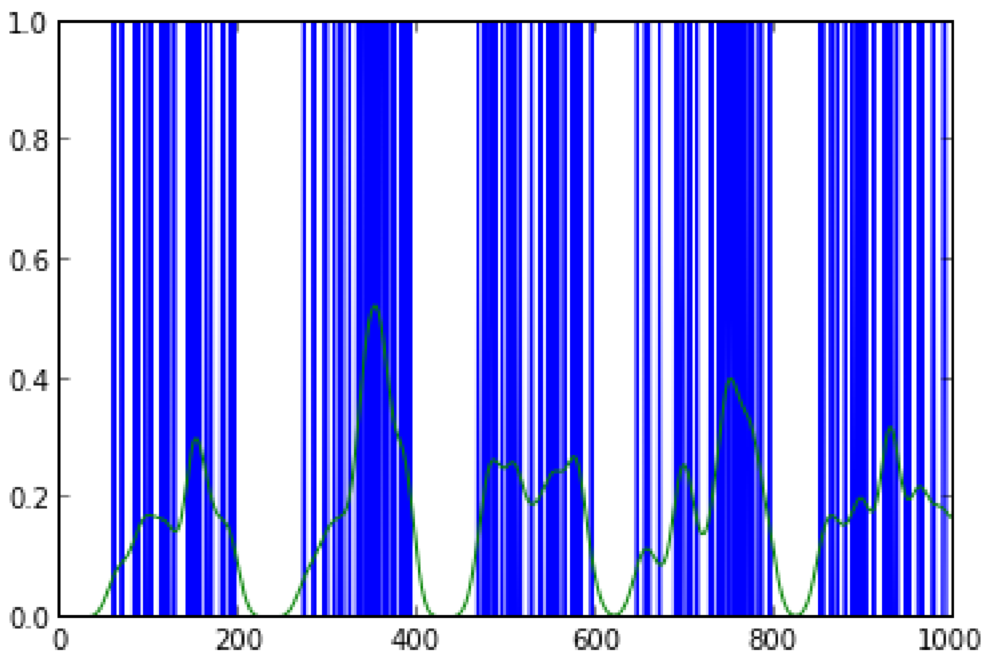
x0 -24.4281 -2.4888 [-43.666, -5.190] x1 -2.1134 -4.7164 [-2.992, -1.235] x2 -3.3877 -5.3690 [-4.624, -2.151] x3 -2.2992 -4.9481 [-3.210, -1.388] x4 -2.2641 -4.9220 [-3.166, -1.362] x5 -1.6907 -4.2519 [-2.470, -0.911] x6 -2.1377 -4.8080 [-3.009, -1.266] x7 -1.3351 -3.6306 [-2.056, -0.614] x8 -2.3364 -4.9854 [-3.255, -1.418]

```
plot(res.resid_deviance)
```

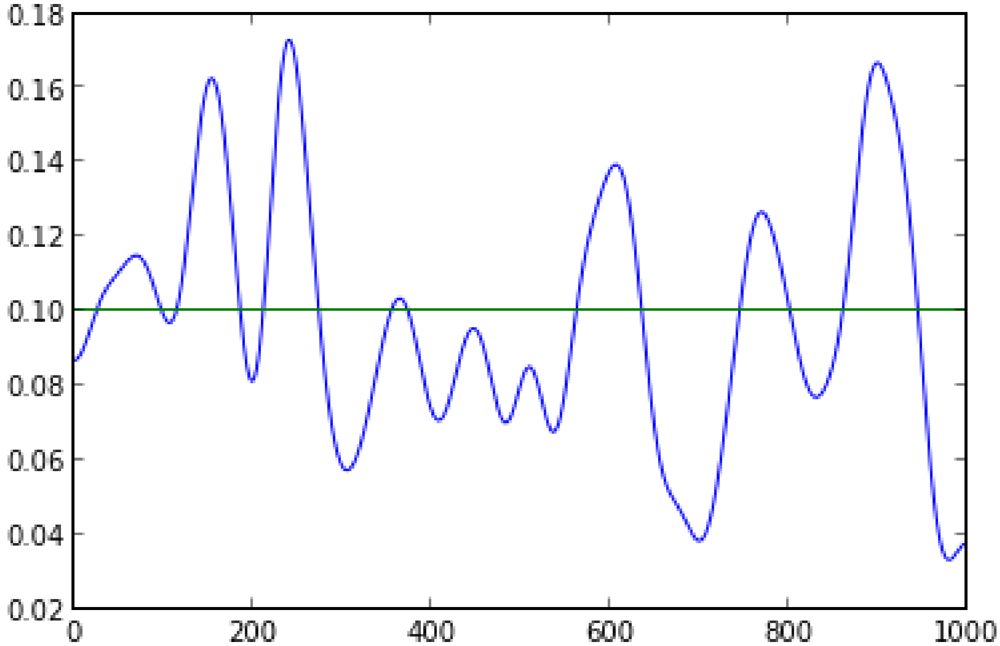



```
p2.plot()
```

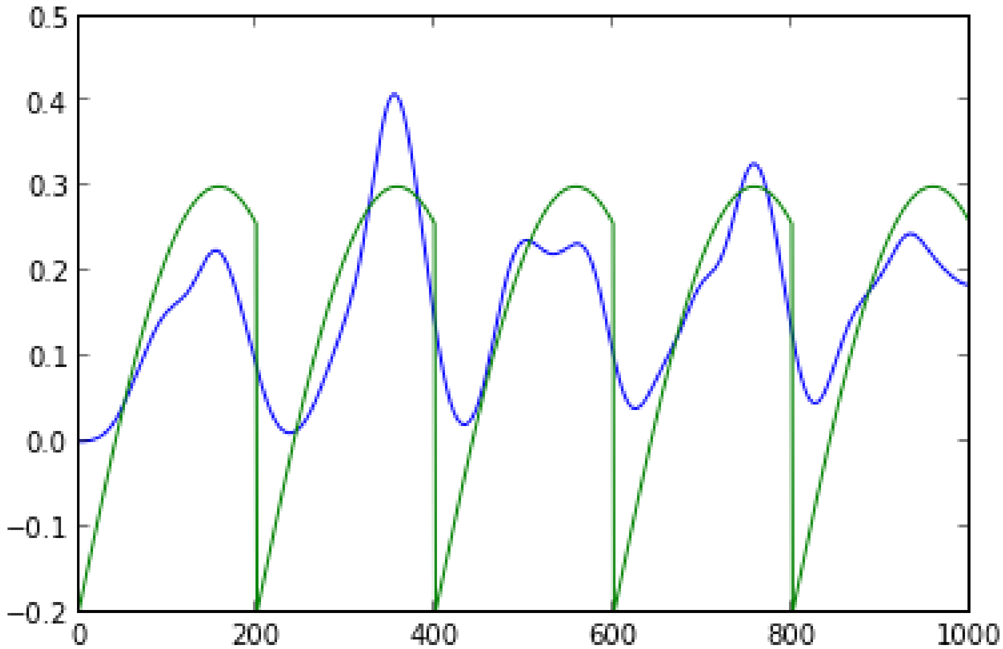
```
p2.plotGaussed(10)
```




```
p1.plotGaussed(20)
plot(p1.frate)
```

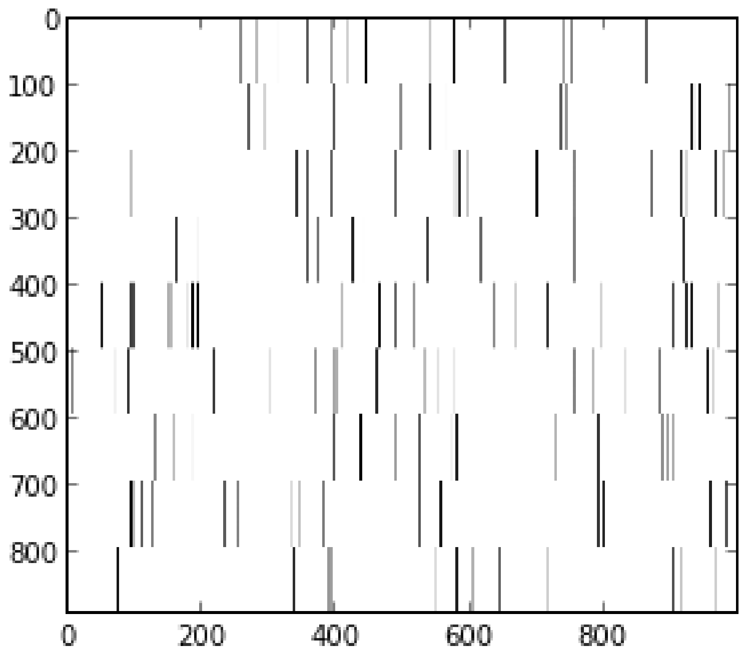



```
p2.plotGaussed(20)
plot(p2.frate)
```

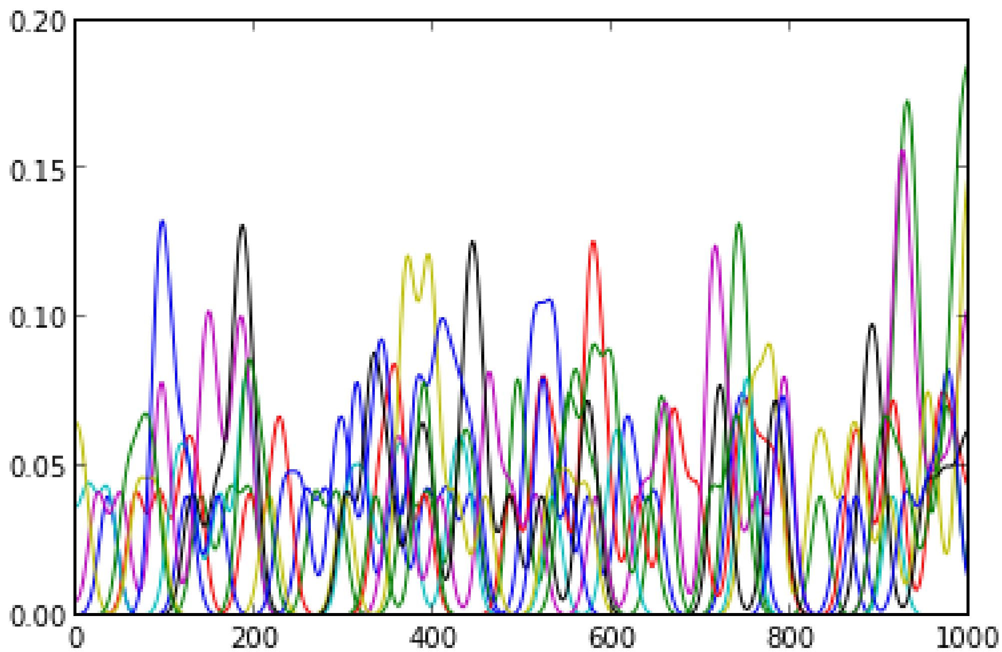



```
frate = (numpy.array(range(0,200))*0.001)*0.2+0.01
channels = 9

dists = [ni.model.pointprocess.createPoisson(frate,1000) for i in range(0,channels)]
#for i in range(0,9): dists[i].plotGaussed(10)
import itertools
spks = np.array([dists[i].getCounts() for i in range(0,channels) for j in range(0,99) ])
imshow(-1*spks)
```

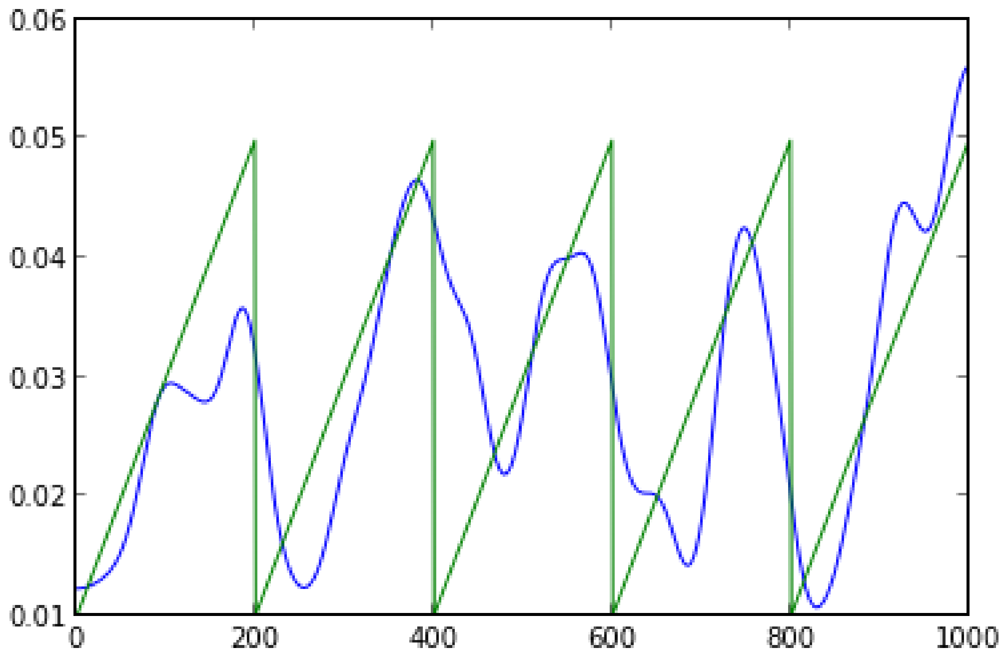
```
set_cmap('gray')
```



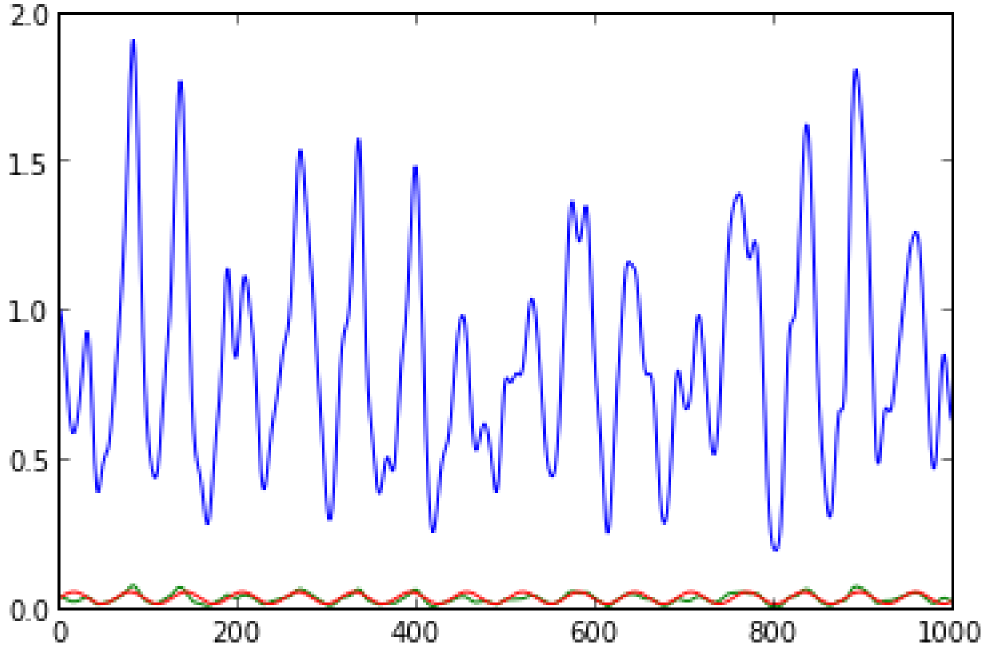
```
for i in range(0,channels): dists[i].plotGaussed(10)
```



```
ni.model.pointprocess.plotGaussed(np.array([dists[i].getCounts() for i in range(0,channels)]).mean(a
plot(dists[0].frate)
```

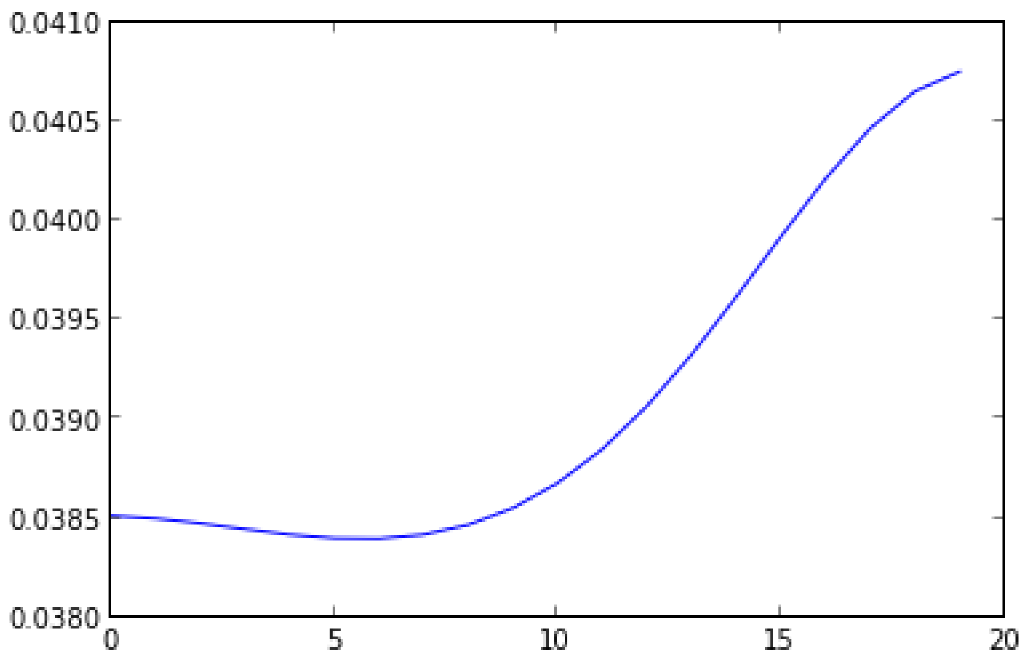



```
reload(ni.model.pointprocess)

frate = sin(numpy.array(range(0,1000))*0.1)*0.02+0.04
mc = ni.model.pointprocess.MultiChannelPointProcess(20)
mc.set(lambda x: ni.model.pointprocess.createPoisson(frate,1000))
#m = ni.model.pointprocess.createPoisson(0.1,1000)
#mc.set(lambda x: m)

ni.model.pointprocess.plotGaussed(mc.getMeanCounts(),5)
c = np.array(mc.get(lambda x: x.getCounts())).var(axis=0)

ni.model.pointprocess.plotGaussed(c,5)
plot(frate)
```



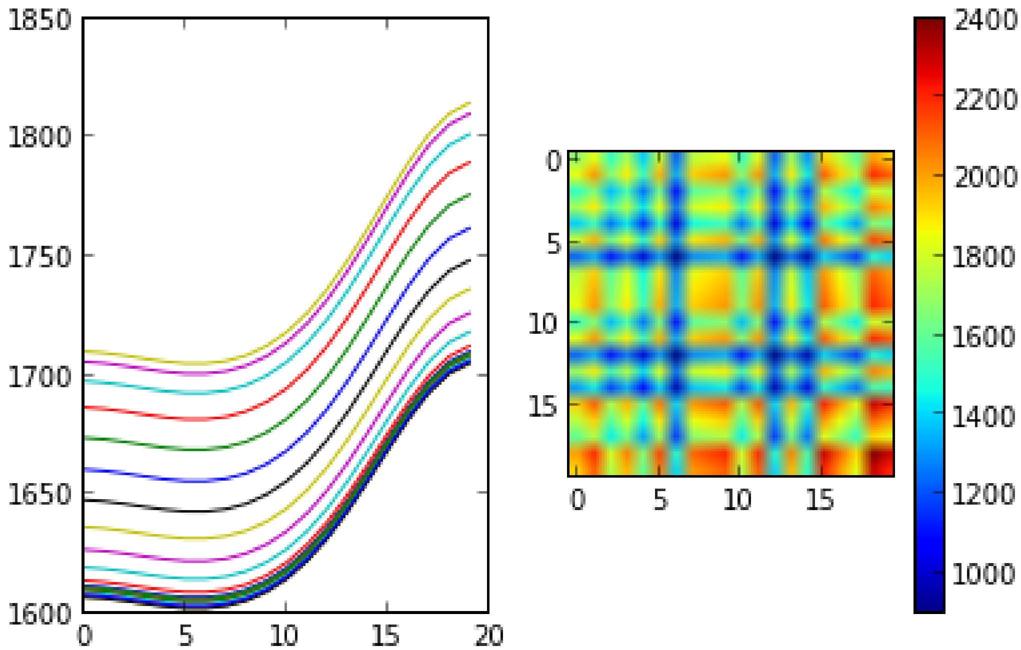

```
c = np.array(mc.get(lambda x: x.getCounts())).var(axis=1)
```

```
ni.model.pointprocess.plotGaussed(c,5)
```



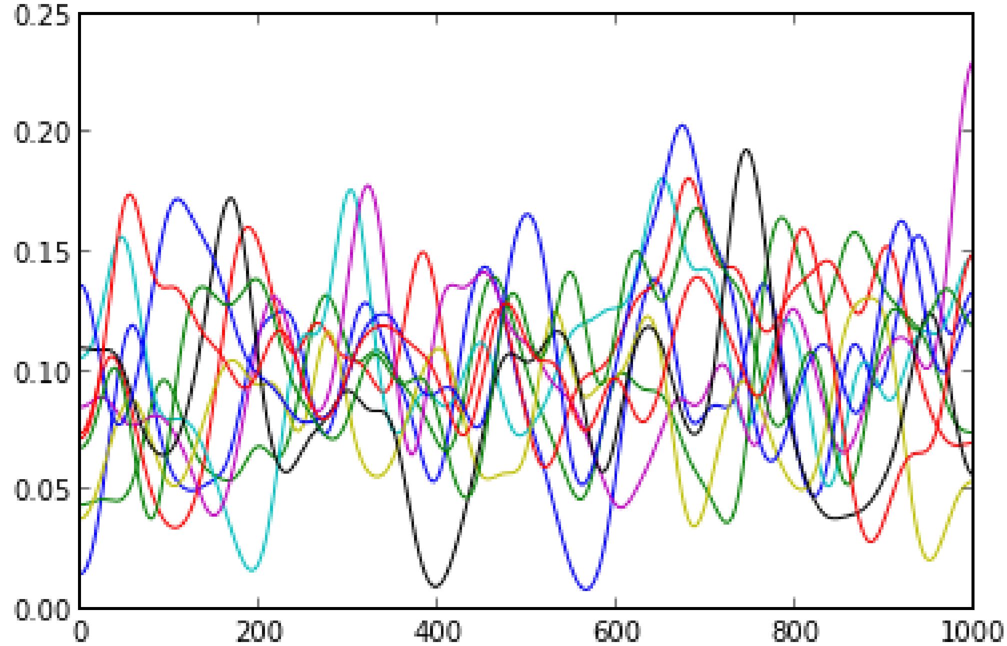

```
c2 = np.array(mc.get2(lambda x,y: np.convolve(x.getCounts(),y.getCounts()).sum()))
subplot(1,2,1)
ni.model.pointprocess.plotGaussed(c2,5)
subplot(1,2,2)

imshow(c2)
colorbar()
```

```
set_cmap('jet')
```

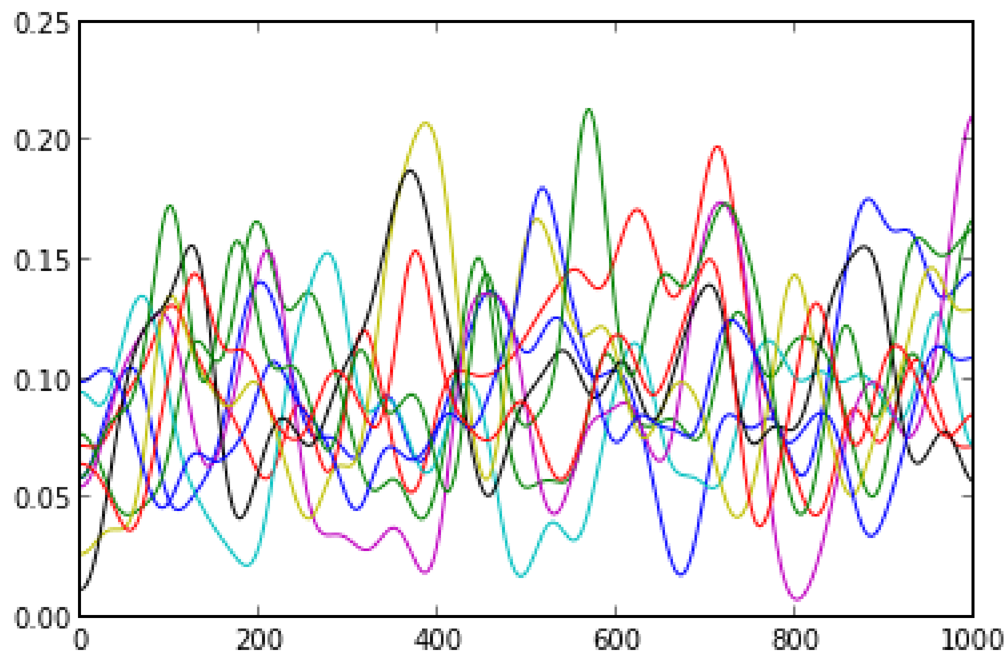



```
reload(ni.model.pointprocess)

ppc = ni.model.pointprocess.PPContainer()
ppc.setData([ni.model.pointprocess.createPoisson(0.1,1000).getCounts() for i in range(0,10)])
ppc.data.columns
[ni.model.pointprocess.plotGaussed(ppc.data[i],20) for i in range(0,10)]
```

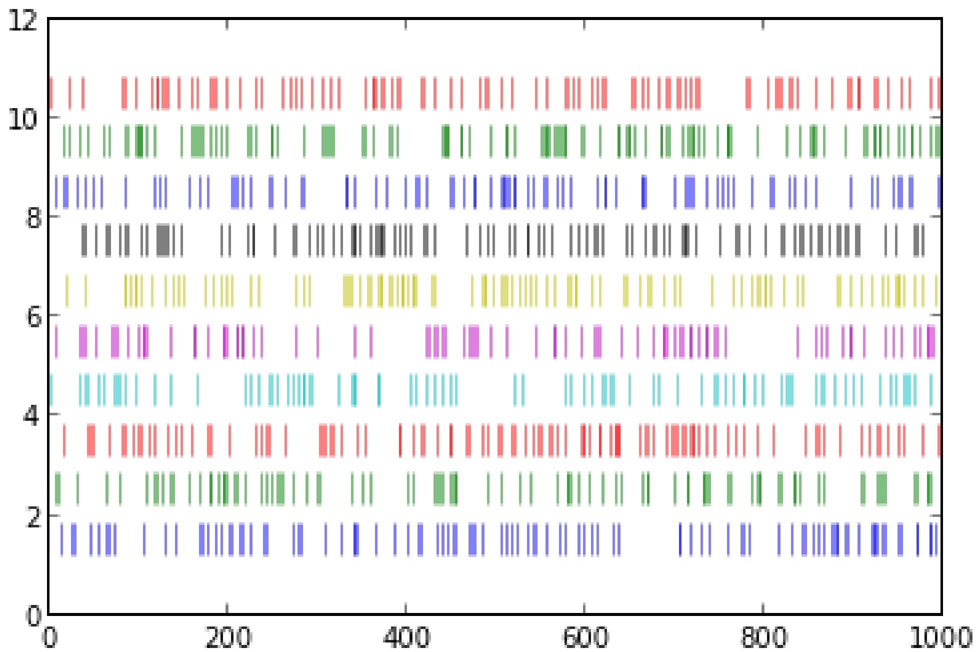
Note: [None, None, None, None, None, None, None, None, None, None]




```
cont = pd.DataFrame([ni.model.pointprocess.createPoisson(0.1,1000).getCounts() for i in range(0,10)])
[ni.model.pointprocess.plotGaussed(cont.T[i],20) for i in cont.T.columns]
```




```
ni.model.pointprocess.plotMultiSpikes(cont.T)
```

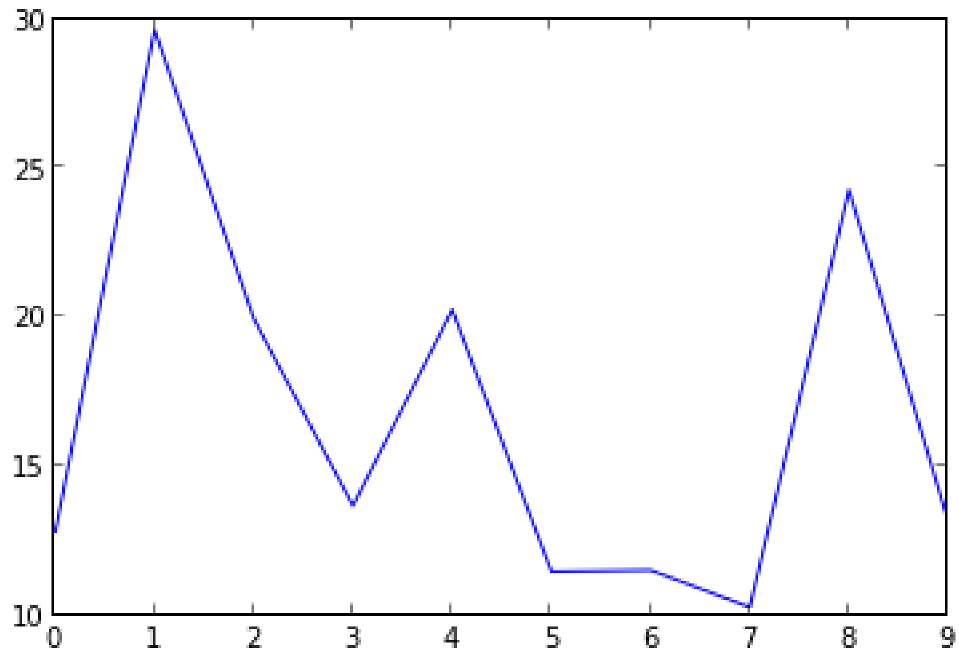



```
import ni.model.net_sim
reload(ni.model.net_sim)
c = ni.model.net_sim.SimulationConfiguration()
c.Nneur = 10
net = ni.model.net_sim.Net(c)
print net
net.plot_firing_rates()
```

Note: 'ni.model.net_sim' Simulation Setup Timerange: (250, 10250)

10 channels with firing rates: [12.815928361, 29.6328550796, 19.9415819867, 13.6710936491, 20.242131795, 11.4661487294, 11.5071338947, 10.2727521514, 24.2587596858, 13.1497981307]

Firing Rates plot




```
connections = [[abs(net.Jall[i,j,:].sum()) < 0.001 for i in range(0,10)] for j in range(0,10)]
#imgplot = imshow(connections)
#imgplot.set_interpolation('nearest')
import pydot
d = pydot.graph_from_edges(np.argwhere(connections), directed=True)
#d.create_png()
d.set_layout('neato')
d.set_mindist(10)
d.write_png("test2.png")

d2 = pydot.graph_from_edges(connections, directed=True)
#d.create_png()
d2.set_layout('neato')
d2.write_png("test1.png")

for i in range(1,11):
    print i
    res1 = net.simulate() #ni.model.net_sim.simulate(c)
    res1.plot_firing_rates()
    print res1
```

Note: 0 Firing Rates plot 'ni.model.net_sim' Simulation Result Took 5.07s to compute. Timerange: (0, 10250) 2359 Spikes in 10 channels:

[242, 277, 131, 336, 326, 199, 260, 141, 233, 214]

1 Firing Rates plot 'ni.model.net_sim' Simulation Result Took 5.32s to compute. Timerange: (0, 10250) 2305 Spikes in 10 channels:

[246, 329, 134, 299, 303, 199, 273, 123, 201, 198]

2 Firing Rates plot 'ni.model.net_sim' Simulation Result Took 5.17s to compute. Timerange: (0, 10250) 2449 Spikes in 10 channels:

[251, 334, 125, 326, 324, 235, 261, 162, 214, 217]

3 Firing Rates plot 'ni.model.net_sim' Simulation Result Took 9.69s to compute. Timerange: (0, 10250) 2436 Spikes in 10 channels:

[241, 343, 131, 310, 324, 210, 277, 131, 235, 234]

4 Firing Rates plot 'ni.model.net_sim' Simulation Result Took 6.74s to compute. Timerange: (0, 10250) 2352 Spikes in 10 channels:

[251, 334, 121, 332, 306, 206, 278, 113, 225, 186]

5 Firing Rates plot 'ni.model.net_sim' Simulation Result Took 5.3s to compute. Timerange: (0, 10250) 2342 Spikes in 10 channels:

[253, 332, 126, 325, 321, 216, 240, 114, 198, 217]

6 Firing Rates plot 'ni.model.net_sim' Simulation Result Took 5.39s to compute. Timerange: (0, 10250) 2395 Spikes in 10 channels:

[263, 340, 121, 328, 305, 207, 268, 135, 216, 212]

7 Firing Rates plot 'ni.model.net_sim' Simulation Result Took 5.72s to compute. Timerange: (0, 10250) 2340 Spikes in 10 channels:

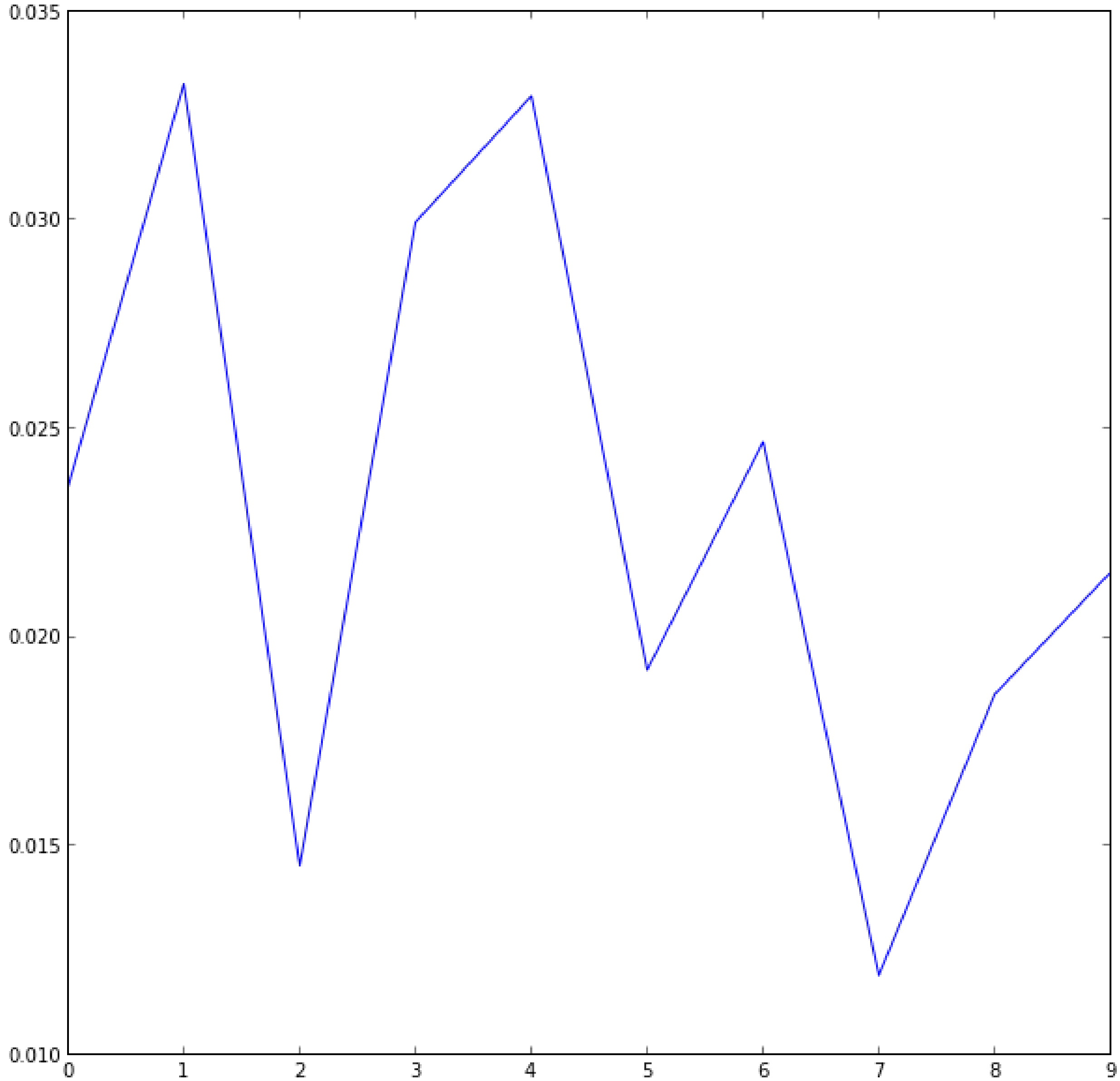
[248, 308, 137, 317, 317, 189, 277, 116, 225, 206]

8 Firing Rates plot 'ni.model.net_sim' Simulation Result Took 5.64s to compute. Timerange: (0, 10250) 2357 Spikes in 10 channels:

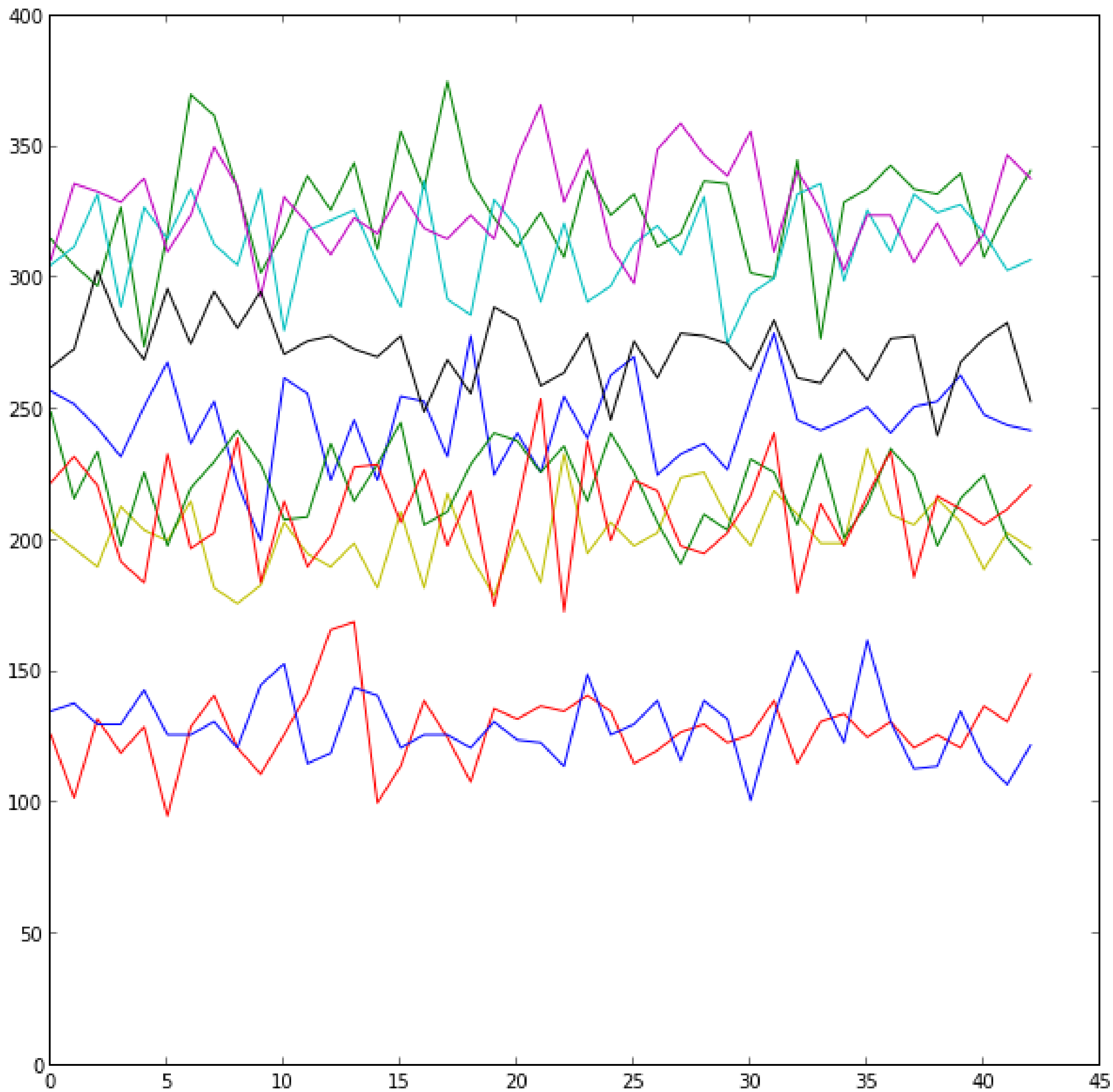
[244, 326, 131, 303, 347, 203, 283, 107, 201, 212]

9 Firing Rates plot 'ni.model.net_sim' Simulation Result Took 5.71s to compute. Timerange: (0, 10250) 2361 Spikes in 10 channels:

[242, 341, 149, 307, 338, 197, 253, 122, 191, 221]



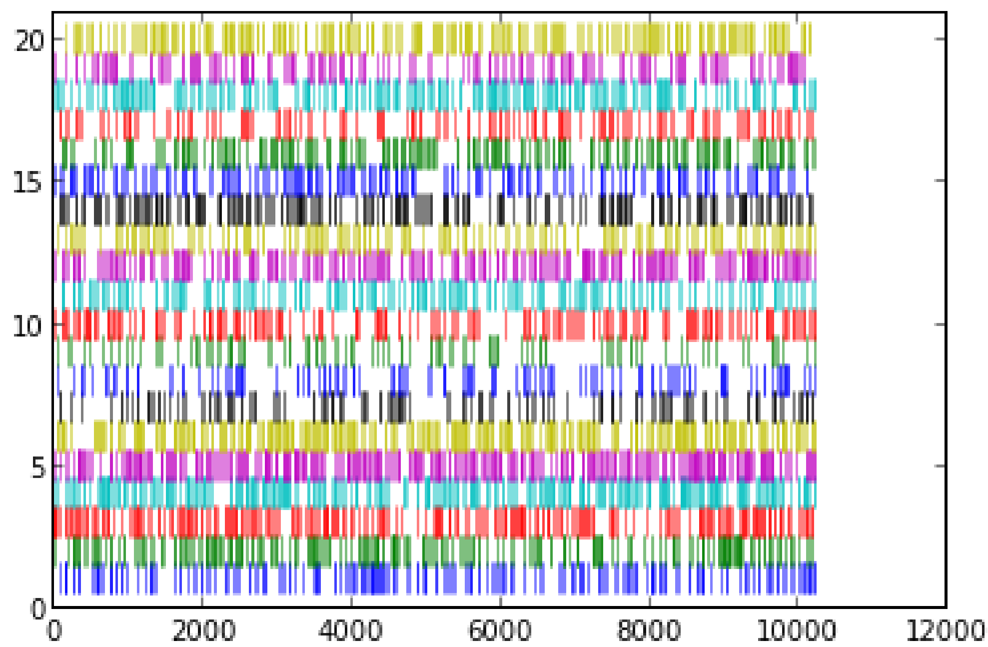

```
#[r.plot_firing_rates() for r in net.results]
plot(numpy.array([r.num_spikes_per_channel for r in net.results]))
#plot([r.spikes.T.mean() for r in net.results].T)
plot([0]*len(net.results))
```




```
res2 = net.simulate()
res2.plot()
print res2
```

Note: 'ni.model.net_sim' Simulation Result Took 11.85s to compute. Timerange: (0, 10250) 4883 Spikes in 20 channels:

[219, 258, 299, 343, 379, 346, 153, 139, 106, 220, 223, 310, 193, 274, 212, 252, 163, 291, 202, 301]

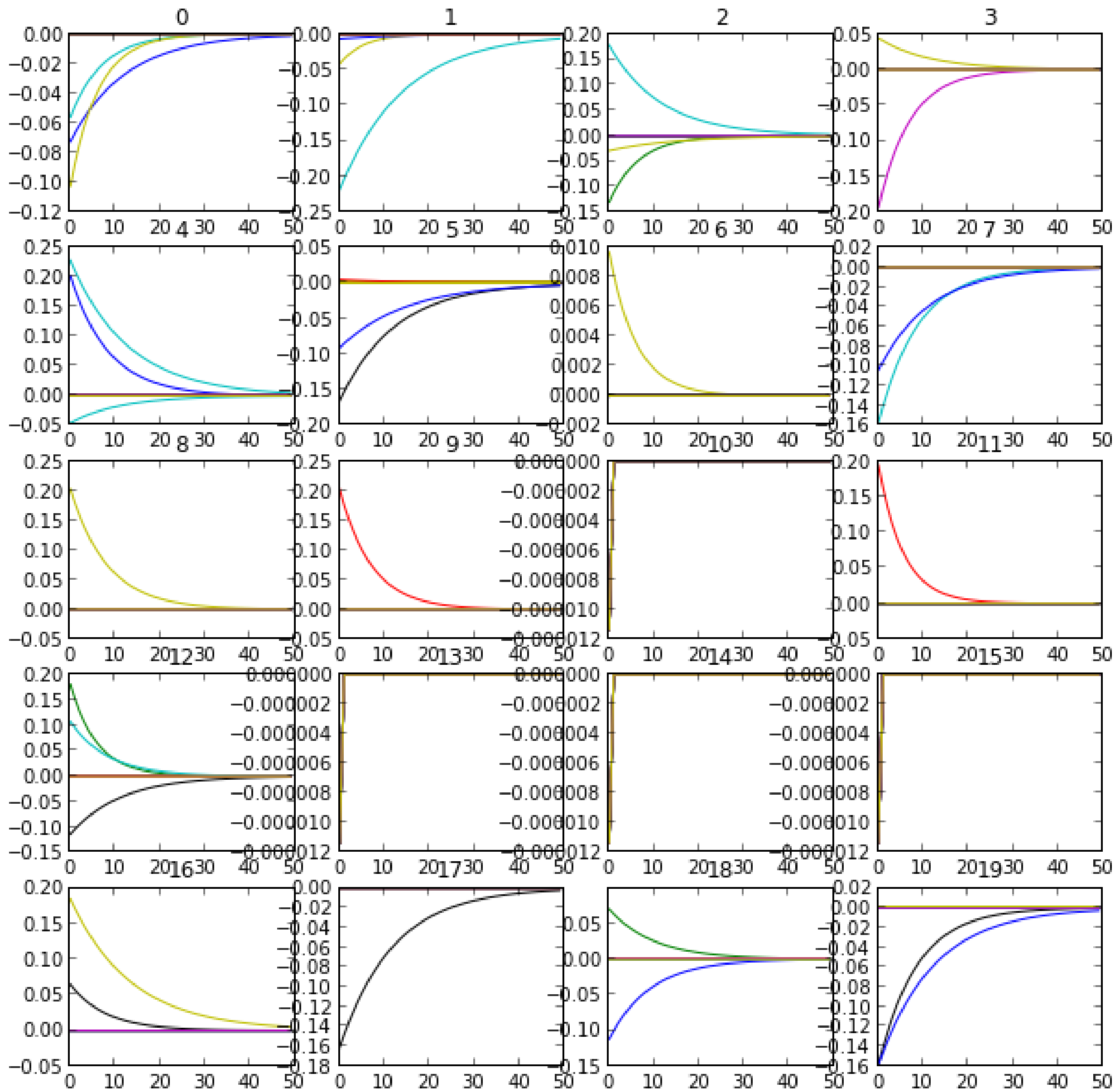



```
print res1
len(net.Jall.nonzero()[0])
print "Interaction plot"
pyplot.figsize(10,10)
for i in range(0,net.config.Nneur):
  subplot(5,net.config.Nneur/5,i+1)
  p = plot(net.Jall[i,:,:].T)
  print i, net.Jall[i,:,:].sum()
  #p.set_cmap('hot')
  title(str(i))
```

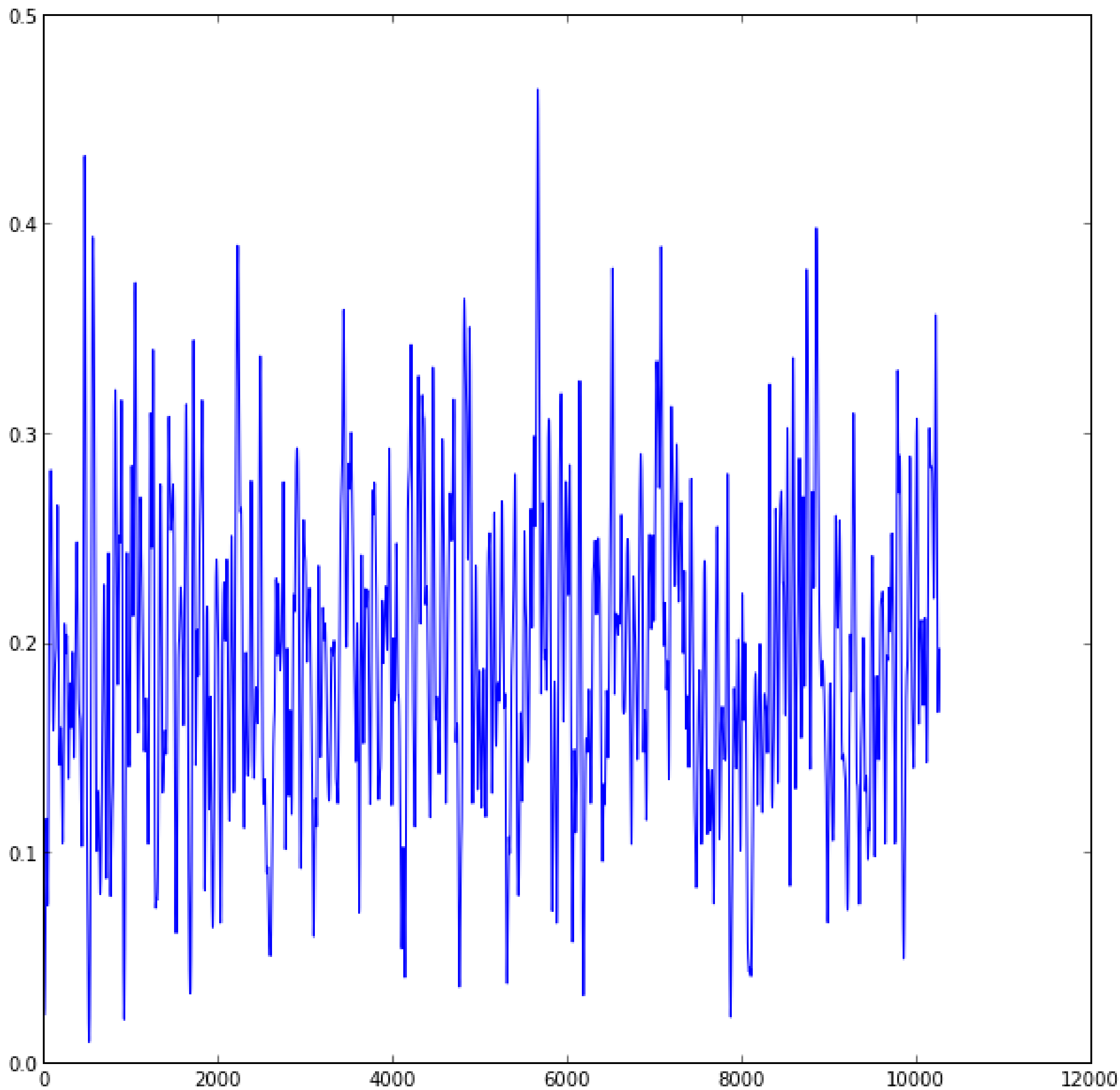
Note: 'ni.model.net_sim' Simulation Result Took 18.46s to compute. Timerange: (0, 10250) 4801 Spikes in 20 channels:

[202, 280, 241, 307, 347, 358, 140, 149, 110, 210, 206, 323, 185, 281, 239, 255, 174, 262, 248, 284]

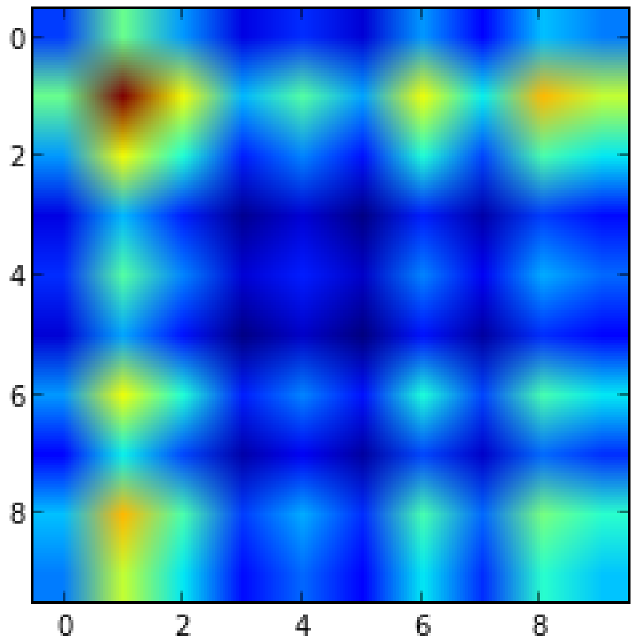
Interaction plot 0 -2.03759911202 1 -3.44761233133 2 0.723006313412 3 -0.952023565109 4 4.25574511824 5 -3.3453963685 6 0.0627568073968 7 -2.69221647701 8 1.76568144941 9 1.52325958899 10 -0.000215659457296 11 1.16132044427 12 0.784372891918 13 -0.000215659457296 14 -0.000215659457296 15 -0.000215659457296 16 3.06368154242 17 -1.95556680782 18 -0.349520835524 19 -3.41784456774



```
ni.model.pointprocess.plotGaussed(res.spikes.T.sum(),10)
```



```
#conv = [[np.convolve(p1,p2) for p1 in res.spikes] for p2 in res.spikes]
imshow([[np.convolve(res.spikes[j],res.spikes[i]).sum() for i in range(0,10)] for j in range(0,10)])
```




```
res.spikes.info
```

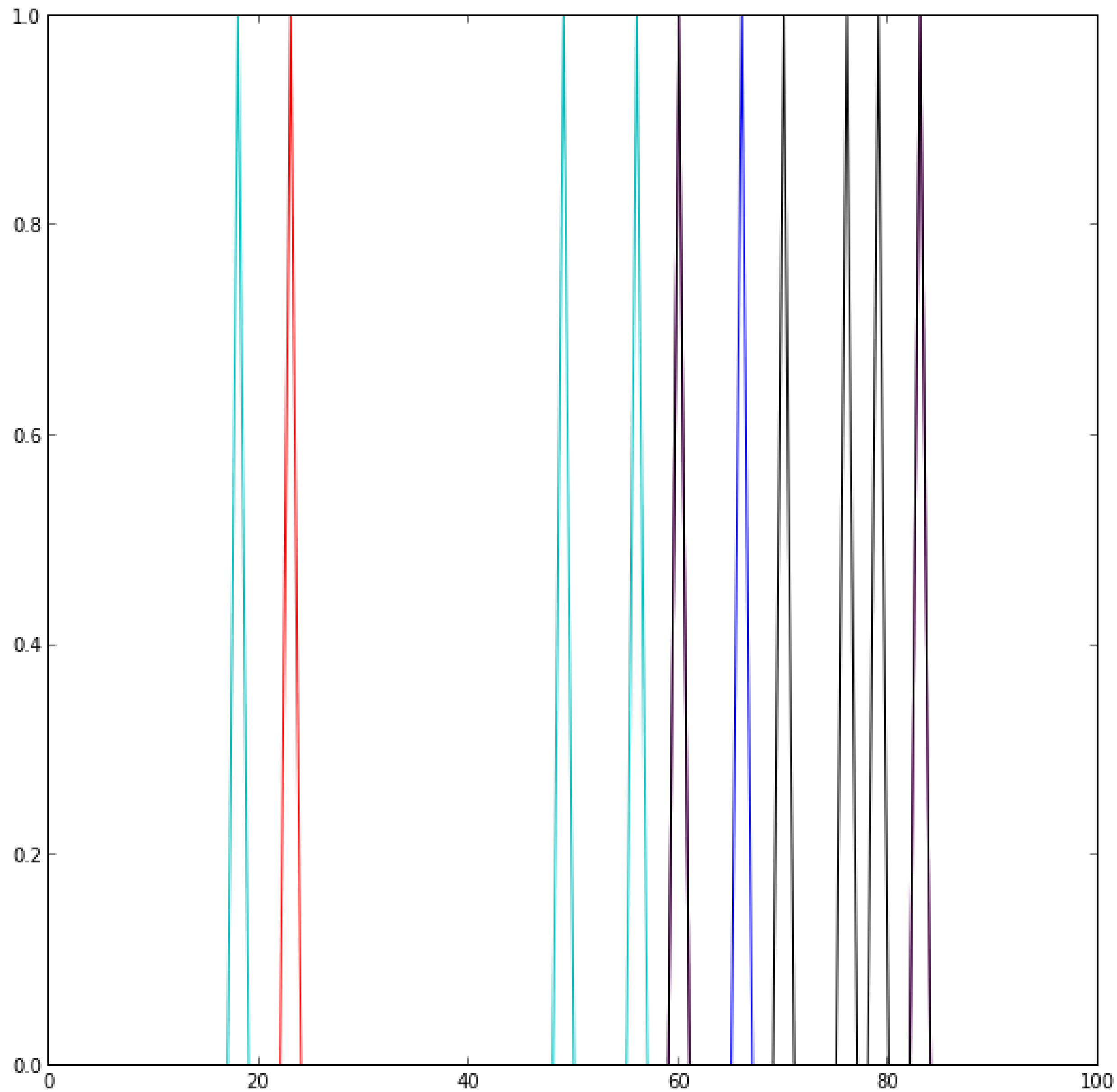
Note: <bound method DataFrame.info of <class 'pandas.core.frame.DataFrame'> Int64Index: 10250 entries, 0 to 10249 Data columns: 0 10250 non-null values 1 10250 non-null values 2 10250 non-null values 3 10250 non-null values 4 10250 non-null values 5 10250 non-null values 6 10250 non-null values 7 10250 non-null values 8 10250 non-null values 9 10250 non-null values dtypes: float64(10)>

```
import sklearn

enet = sklearn.linear_model.ElasticNet()
X = np.array(res.spikes)[0:100,0:8]
y = np.array(res.spikes)[0:100,9]
enet.fit(X,y)
enet.predict([4,5,6])
```

Note:

ElasticNet(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1000, normalize=False, precompute='auto', rho=0.5, tol=0.0001)

```
plot(np.array(res.spikes)[0:100,0:8])
```



1.3 model Package

1.3.1 `glm` Module

Not yet functional, instead the statmodels glm can be used directly:

```
from scikits.statsmodels.genmod import generalized_linear_model
from scikits.statsmodels.genmod.families.family import Binomial

spikes = np.array(ni.model.pointprocess.createPoisson(sin(numpy.array(range(0,200))*0.01)*0.5- 0.2,1

design_matrix = [[exp(-1*(((i-j*100))**2)/1000) for j in range(0,9)] for i in linspace(0,999,1000)]
glm = generalized_linear_model.GLM(spikes,design_matrix, family = Binomial())
```

```
res = glm.fit()
```

Todo

Talk with Robert about his code

Todo

create different models that use glm in various ways / designs

class `ni.model.glm.`**`GLM`**`(`*X*, *Y*`)`
Undocumented

`fit``(`*X*`)`
Undocumented

class `ni.model.glm.`**`GLM_model`**`(`*m*, *coef*`)`
Undocumented

`predict``(`*X*`)`
Undocumented

1.3.2 `net_sim` Module

The Net Simulator is divided into a Configuration, Net and a Result object.

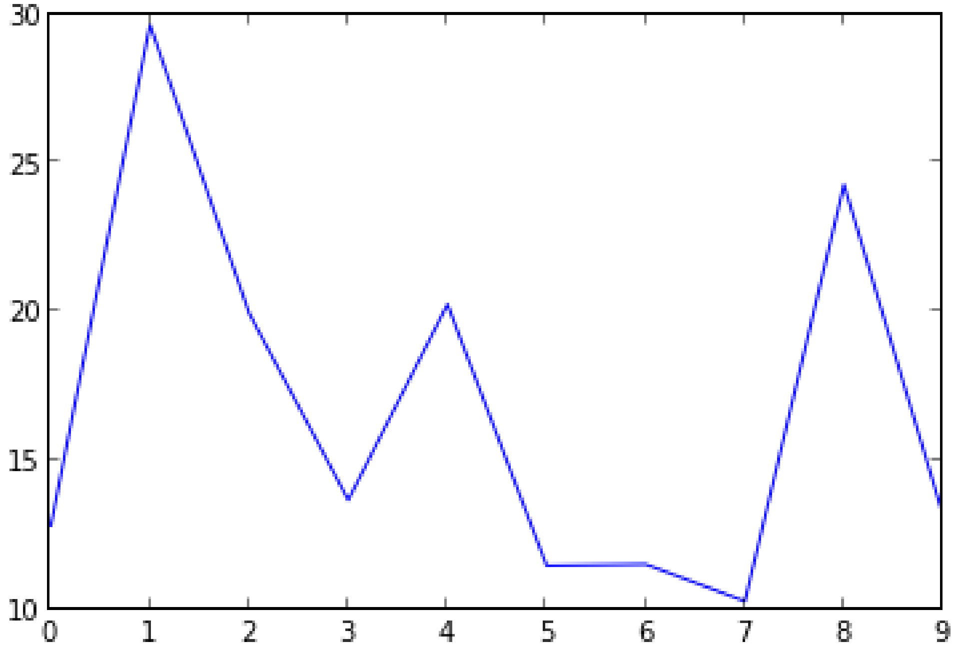
After configuration of the network it can be instantiated by calling *Net(conf)* with a valid configuration *conf*. This creates eg. random connectivity so that the simulation with the same network can be repeated multiple times.

Todo

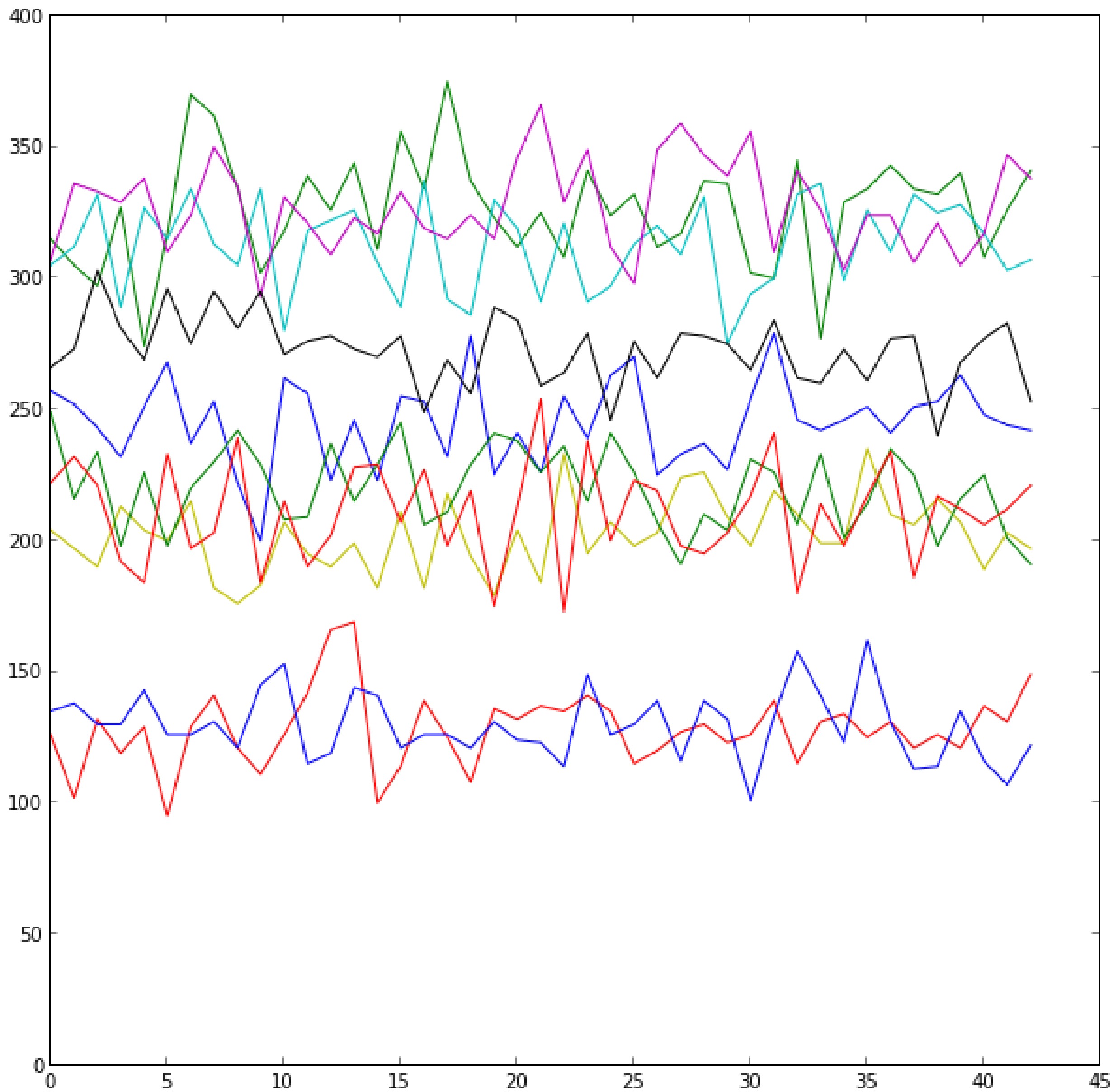
Add options for random number generator seeds, so that the *exact* same trial can be run over and over again.

```
c = ni.model.net_sim.SimulationConfiguration()
c.Nneur = 10
net = ni.model.net_sim.Net(c)
print net
net.plot_firing_rates()
```

```
'ni.model.net_sim' Simulation Setup
Timerange: (250, 10250)
 10 channels with firing rates:
        [12.815928361, 29.6328550796, 19.9415819867, 13.6710936491, 20.242131795, 11.4661487294, 11.5
Firing Rates plot
```




```
for i in range(1,11):
    print i
    res1 = net.simulate()
    res1.plot_firing_rates()

plot(numpy.array([r.num_spikes_per_channel for r in net.results]))
plot([0]*len(net.results))
```



class `ni.model.net_sim.`**`Net`**(*config*)

Undocumented

`load`(*filename*)

Undocumented

`plot_firing_rates`()

Undocumented

`plot_interaction`()

Undocumented

`save`(*filename*)

Undocumented

`simulate`()

Undocumented

class `ni.model.net_sim.`**`SimulationConfiguration`**
Undocumented

class `ni.model.net_sim.`**`SimulationResult`**
Undocumented

`plot`()
Undocumented

`plot_firing_rates`()
Undocumented

`stopTimer`()
Undocumented

`store`(*data*)
Undocumented

`ni.model.net_sim.`**`simulate`**(*config*)
Undocumented

1.3.3 `pointprocess` Module

Todo

Use different internal representations, depending on use. Ie. Spike times vs. binary array

---

class `ni.model.pointprocess.`**`MultiChannelPointProcess`**(*channels*)

`get`(*fun*)

`get2`(*fun*)

`getMeanCounts`()

`set`(*fun*)

`set2`(*fun*)

class `ni.model.pointprocess.`**`PPContainer`**

`setData`(*d*)

class `ni.model.pointprocess.`**`PointProcess`**(*dimensionality*)
A Point Process container.

Usually generated by loading from a file or via `ni.model.pointprocess.createPoisson()`

`addSpike`(*t*)
Undocumented

`getCounts`()
Undocumented

`getProbability`(*t_from*, *t_to*)
Undocumented

`plot`()
Undocumented

plotGaussed (*width*)
Undocumented

class ni.model.pointprocess.**SimpleFiringRateModel**
Uses just the firing rate as a predictor

fit (*Data*)

loglikelihood (*Data*, *Prediction*)

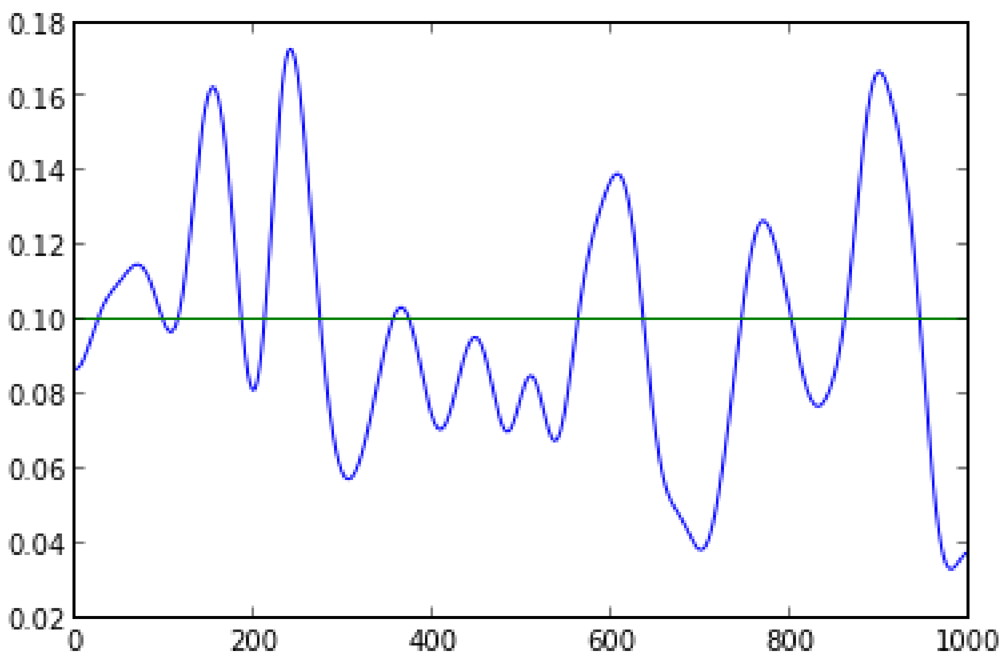
predict (*Data*)

ni.model.pointprocess.**createPoisson** (*p*, *l*)
This generates a spike sequence of length *l* according to either a fixed firing rate *p*, or a repeated sequence of firing rates if *type(p) == np.ndarray*.

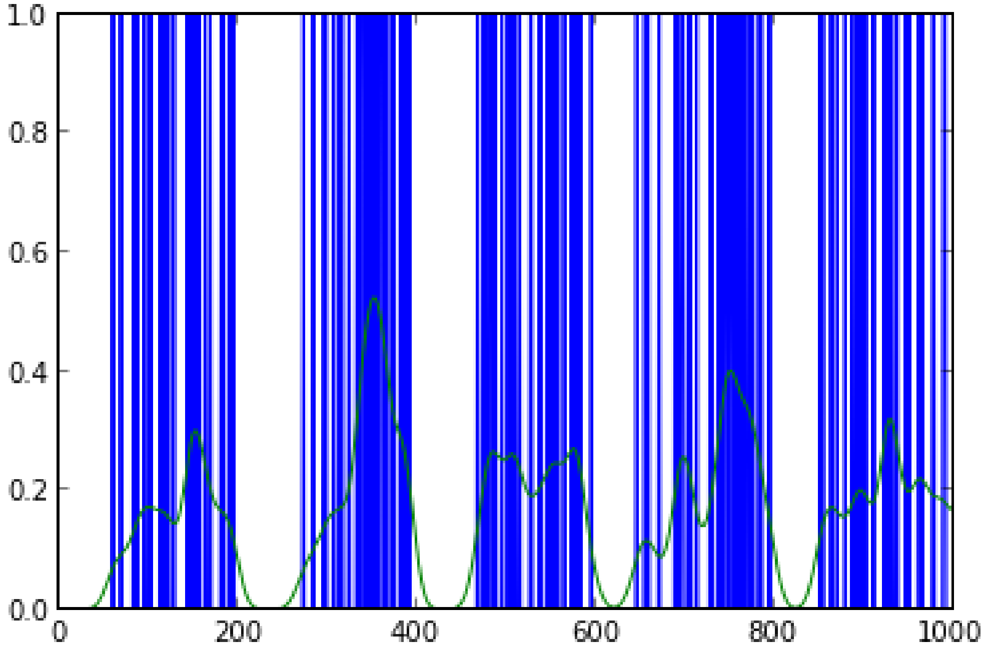
It creates a ni.model.pointprocess.PointProcess

Example 1:

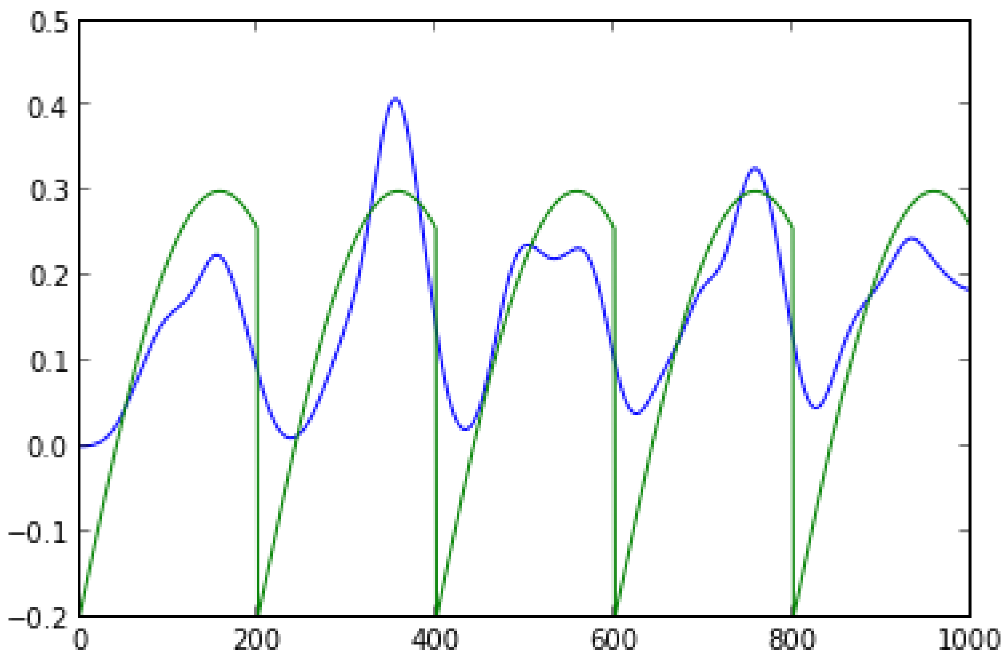
```
p1 = ni.model.pointprocess.createPoisson(0.1,1000)
p1.plotGaussed(20)
plot(p1.frate)
```




```
p2 = ni.model.pointprocess.createPoisson(sin(numpy.array(range(0,200))*0.01)*0.5- 0.2,1000)
p2.plot()
p2.plotGaussed(10)
```




```
p2.plotGaussed(20)
plot(p2.frate)
```



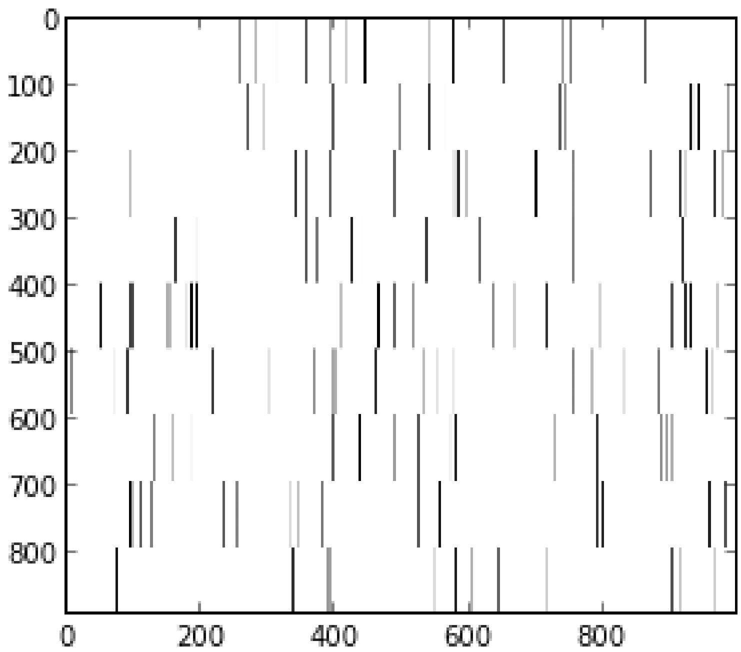
Example with multiple channels:

```
frate = (numpy.array(range(0,200))*0.001)*0.2+0.01
channels = 9

dists = [ni.model.pointprocess.createPoisson(frate,1000) for i in range(0,channels)]
#for i in range(0,9): dists[i].plotGaussed(10)
import itertools
```

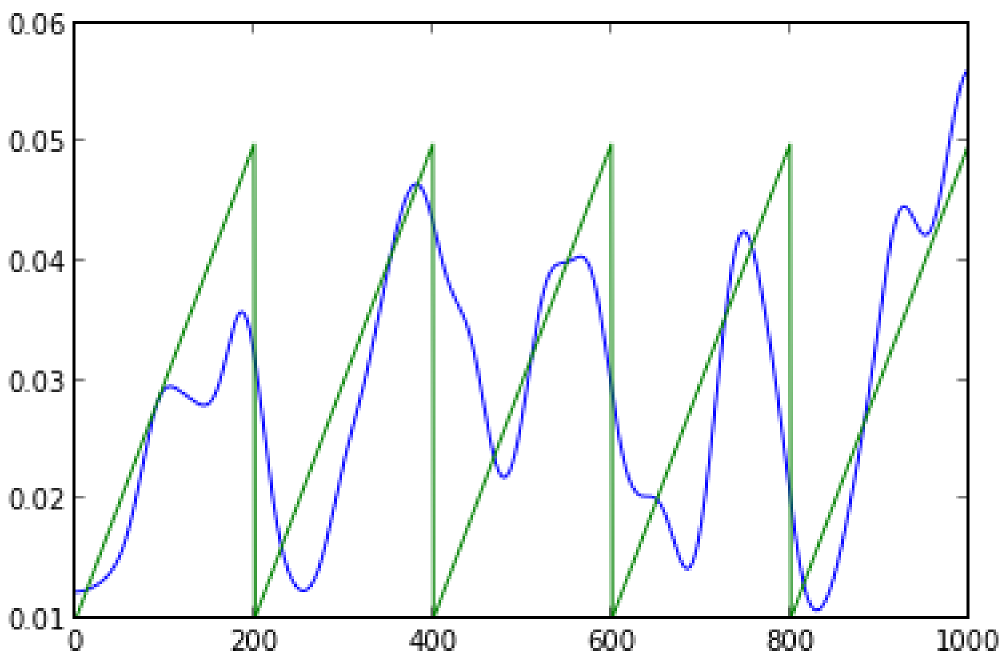
```
spks = np.array([dists[i].getCounts() for i in range(0,channels) for j in range(0,99) ])
imshow(-1*spks)
set_cmap('gray')
```

Will generate:

```
(A plot of spikes)
```

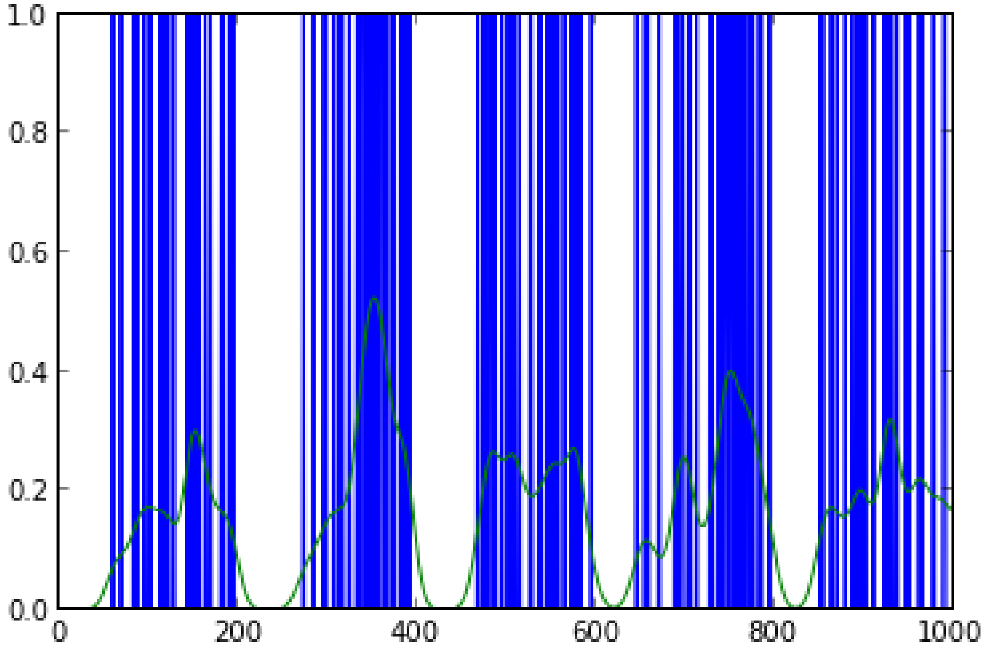



```
ni.model.pointprocess.plotGaussed(np.array([dists[i].getCounts() for i in range(0,channels)]).me
plot(dists[0].frate)
```



ni.model.pointprocess.**plotGaussed**(*data*, *width*)

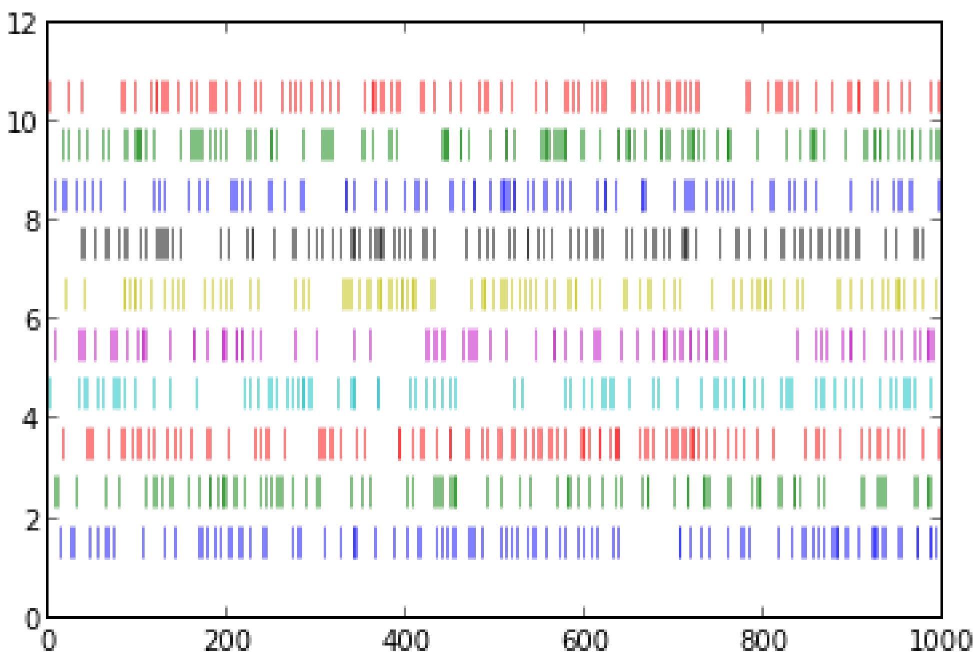
```
p2 = ni.model.pointprocess.createPoisson(sin(numpy.array(range(0,200))*0.01)*0.5- 0.2,1000)
p2.plot()
p2.plotGaussed(10)
```



ni.model.pointprocess.**plotMultiSpikes**(*spikes*)

- *spikes* is a binary 2d matrix

Generates something like:



1.4 tools Package

1.4.1 bootstrap Module

ni.tools.bootstrap.**evaluate**(*Model*, *Data*, *bootstrap_repetitions*, *return_all=False*)

Executes a certain number of bootstrap repetitions to calculate the bias of the likelihood he model computes

Model

A model object that is capable of loglikelihood estimation

Data

Data that is to be reshuffled. A bootstrap sample is drawn from this Data of the same length with each Element of Data being equally probable of being included.

bootstrap_repetitions

Number of repetitions

return_all

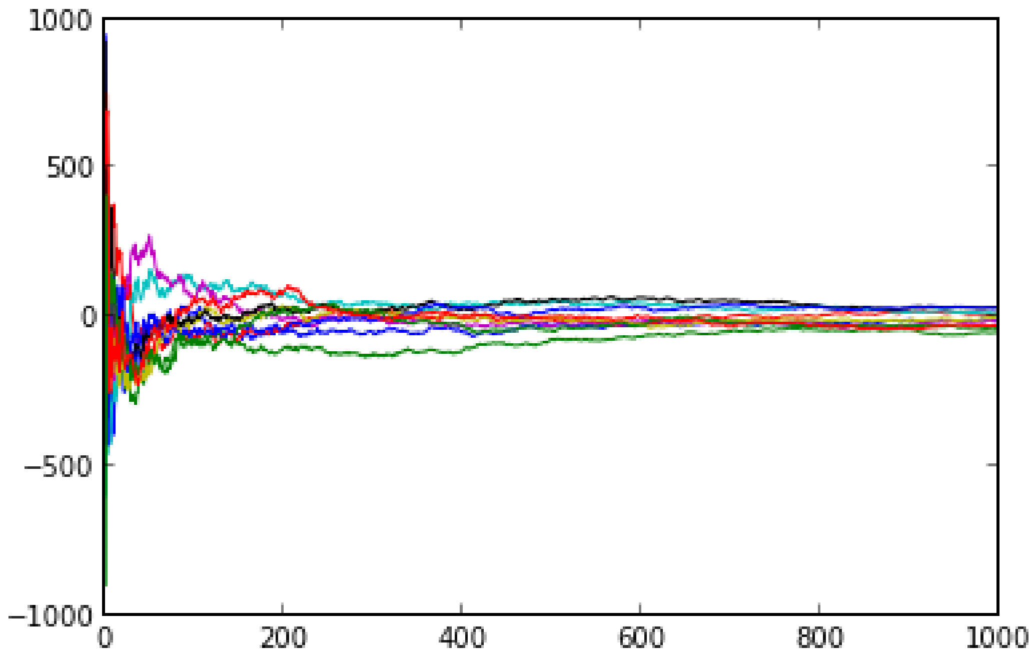
Default: False. Whether an array of all bootstrap biases should be returned or just the mean.

Example:

```
import ni.tools.bootstrap
reload(ni.tools.bootstrap)
import ni.model.pointprocess
reload(ni.model.pointprocess)
p1 = np.array([ni.model.pointprocess.createPoisson(0.1,1000).getCounts() for i in range(0,10)])
p2 = np.array([ni.model.pointprocess.createPoisson(sin(numpy.array(range(0,200))*0.01)*0.5- 0.2,

m1 = ni.model.pointprocess.SimpleFiringRateModel()

ni.tools.bootstrap.evaluate(m1,p1,10000)
```

Or to see the effect of increasing bootstrap size:

```
[plot(np.cumsum(ni.tools.bootstrap.evaluate(m1,p1,1000,return_all=True))/range(1,1001)) for i in
```



`ni.tools.bootstrap.`**`likelihood_Fun`**(*y*, *x*, *mu*)
Calculates the likelihood for a binary vector and a predicted firing rate

$$-(size(y)/2) \cdot log(2 \cdot \pi \cdot x^2) - (1/x^2 \cdot (y - mu)^2)$$

1.4.2 `progressbar` Module

`ni.tools.progressbar.`**`progress`**(*a*, *b*)
Undocumented

`ni.tools.progressbar.`**`progress_end`**()
Undocumented

`ni.tools.progressbar.`**`progress_init`**()
Undocumented

1.4.3 `project` Module

NI Project Management

- All steps in a configuration / simulation process will be logged to some folder structure
- after the simulation and even after changing the original code, the results should still be viewable / interpretable with a project viewer
- batches of runs should be easy to batch interpret (characteristic plots etc.)
- **metadata should contain among others:** date software versions configuration options manual comments
- saving of plots/data should be done by the project manager

class `ni.tools.project.`**`Project`**(*name*, *folder*)
Undocumented

CHAPTER

TWO

LIST OF TODO ITEMS

Todo

Talk with Robert about his code

(The *original entry* is located in /home/plogic/uni/MT/EIC/py/ni/model/glm.py:docstring of ni.model.glm, line 19.)

Todo

create different models that use glm in various ways / designs

---

(The *original entry* is located in /home/plogic/uni/MT/EIC/py/ni/model/glm.py:docstring of ni.model.glm, line 23.)

Todo

Add options for random number generator seeds, so that the *exact* same trial can be run over and over again.

(The *original entry* is located in /home/plogic/uni/MT/EIC/py/ni/model/net_sim.py:docstring of ni.model.net_sim, line 11.)

Todo

Use different internal representations, depending on use. Ie. Spike times vs. binary array

---

(The *original entry* is located in /home/plogic/uni/MT/EIC/py/ni/model/pointprocess.py:docstring of ni.model.pointprocess, line 7.)

CHAPTER

THREE

INDICES AND TABLES

- *genindex*
- *modindex*
- *search*

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