demo

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1 A demonstration of some basic computations using `infotopo` package

- Link: http://github.com/leihuang/infotopo
- Reference: https://github.com/leihuang/infotopo/blob/master/docs/PhDThesisLeiHuang.pdf (Section 2.7)
- About `SloppyCell`, around which much of the computation on reaction networks in `rxnnet` is wrapped: http://sloppycell.sourceforge.net/user.pdf

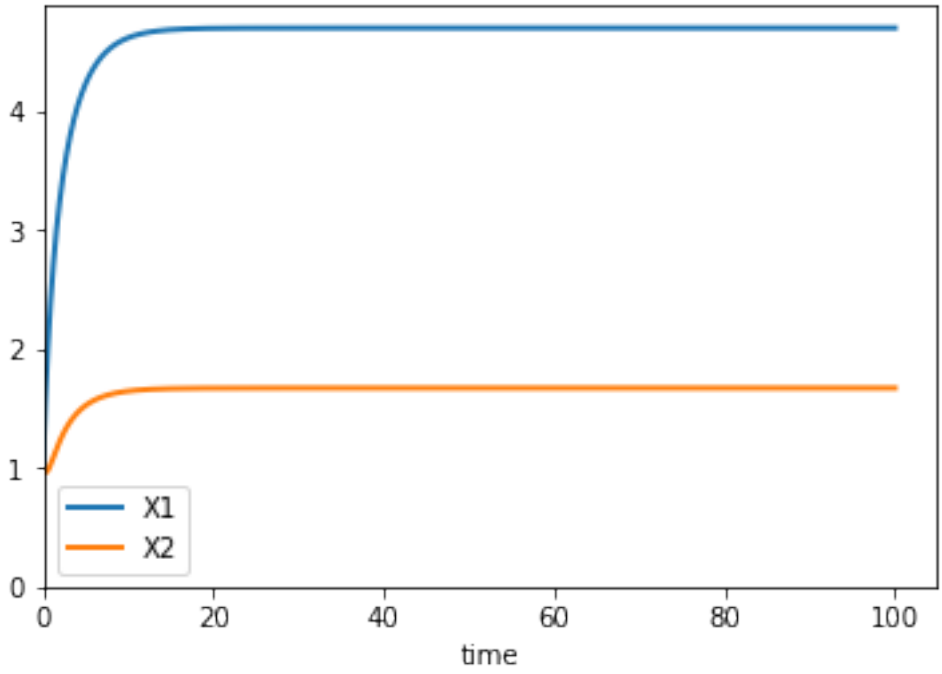
```
In [1]: from __future__ import division, print_function, absolute_import
        from collections import OrderedDict as OD

        from rxnnet import network, mca, experiments, util
        from infotopo import residual, fitting, sampling
```

```
In [2]: net = network.Network('path3mmh')
        net.add_compartment(id='env')
        net.add_compartment(id='cell')
        net.add_species(id='C1', compartment='env', initial_value=2, is_constant=True)
        net.add_species(id='C2', compartment='env', initial_value=0.5, is_constant=True)
        net.add_species(id='X1', compartment='cell', initial_value=1)
        net.add_species(id='X2', compartment='cell', initial_value=1)
        net.add_reaction(id='R1', eqn='C1<->X1', ratelaw='V1f/K1C1*(C1-X1/KE1)/(1+C1/K1C1+X1/K
                         p=OD([('V1f',1),('K1C1',1),('K1X1',1),('KE1',5)]))
        net.add_reaction(id='R2', eqn='X1<->X2', ratelaw='V2f/K2X1*(X1-X2/KE2)/(1+X1/K2X1+X2/K
                         p=OD([('V2f',1),('K2X1',1),('K2X2',1),('KE2',4)]))
        net.add_reaction(id='R3', eqn='X2<->C2', ratelaw='V3f/K3X2*(X2-C2/KE3)/(1+X2/K3X2+C2/K
                         p=OD([('V3f',1),('K3X2',1),('K3C2',1),('KE3',1)]))
        for KEid in ['KE1', 'KE2', 'KE3']:
            net.set_var_optimizable(KEid, False)
```

```
In [3]: p = net.p.randomize(seed=0, sigma=1)
```

```
In [17]: traj = net.get_traj((0,100), p=p)
         traj.plot()
```




```
In [5]: # get steady-state concentrations
        s = net.get_s(p=p)
        print(s)
```

```
X1    4.704357
X2    1.673599
dtype: float64
```

```
In [6]: # Structural calculation: get stoichiometry matrix and steady-state flux vectors
        print(net.N, '\n\n', net.K)
```

```
    R1  R2  R3
X1   1  -1   0
X2   0   1  -1


     J1
R1   1
R2   1
R3   1
```

```
In [7]: # MCA calculation: get flux control matrix (rows should sum up to one by the Summation
        nCJ = mca.get_flux_control_matrix(net, p=p, normed=True)
        print(nCJ, '\n')
        print(nCJ.sum(axis=1))
```

```
          R1        R2        R3
R1  0.276937  0.372677  0.350386
R2  0.276937  0.372677  0.350386
R3  0.276937  0.372677  0.350386

R1    1.0
R2    1.0
R3    1.0
dtype: float64
```

At the core of **information geometry** and **information topology** is the abstraction of mathematical models as functions (f) that map from parameters (p) to predictions (y):

$$f : p \mapsto y, \text{ or } y = f(p)$$

.

With an f specified, one can do a number of standard modeling tasks: * **Parameter estimation**: $p^* = f^{-1}(y)$ with uncertainty estimated as $\delta p = \left(Df^{-1}\right) \delta y$ * **Ensemble sampling**: eg, sampling posterior distribution $f(p|y) \propto f(p)f(y|p)$ * **Model comparison** (which includes **model selection** and **model reduction**): given f_1 and f_2 that both predict y, how does one compare them and which one is better?

```
In [8]: # get experiments objects that specify the model predictions (that is, y)
        expts_xc = experiments.get_experiments(net.xids, ['C1','C2'],
                                               us=util.get_product(*[[1,2,3]]*2))
        expts_jc = experiments.get_experiments(net.Jids[0], ['C1','C2'],
                                               us=util.get_product(*[[1,2,3]]*2))
```

```
In [18]: expts_xc
```

```
Out[18]:                              condition    varids  times
         experiment
         1           ((C1, =, 1), (C2, =, 1))  [X1, X2]  [inf]
         2           ((C1, =, 1), (C2, =, 2))  [X1, X2]  [inf]
         3           ((C1, =, 1), (C2, =, 3))  [X1, X2]  [inf]
         4           ((C1, =, 2), (C2, =, 1))  [X1, X2]  [inf]
         5           ((C1, =, 2), (C2, =, 2))  [X1, X2]  [inf]
         6           ((C1, =, 2), (C2, =, 3))  [X1, X2]  [inf]
         7           ((C1, =, 3), (C2, =, 1))  [X1, X2]  [inf]
         8           ((C1, =, 3), (C2, =, 2))  [X1, X2]  [inf]
         9           ((C1, =, 3), (C2, =, 3))  [X1, X2]  [inf]
```

```
In [9]: # combine model objects and experiments objects to get predict objects (that is, f)
        pred_xc = net.get_predict(expts_xc, tol=1e-13)
        pred_jc = net.get_predict(expts_jc, tol=1e-13)
        pred = pred_xc + pred_jc
```

Spectrum refers to the list of **singular values** of Df and the number of zeros tells how well-conditioned is f.

Here, the presence of two numerical zeros mean that f has two degrees of **structural non-identifiability** if we use only steady-state concentration data, and that goes away if we *also* use steady-state flux data.

```
In [10]: print(pred_xc.get_spectrum(p))
         print(pred.get_spectrum(p))
```

```
[  1.20905442e+01   4.93033641e+00   2.52758635e-01   1.39687397e-01
   1.01009238e-01   3.91820667e-02   8.71208005e-03   2.56166801e-16
   1.30507017e-16]
[  1.22337512e+01   4.93141522e+00   8.37274936e-01   2.49733197e-01
   1.38769116e-01   6.64837163e-02   3.77714875e-02   9.85294255e-03
   3.33095961e-03]
```

```
In [11]: # generating simulation data
         dat = pred.get_dat(p=p)
         print(dat)
```

```
                                          Y  sigma
((C1, =, 1), (C2, =, 1)), X1, inf    2.946751    1.0
((C1, =, 1), (C2, =, 1)), X2, inf    1.810122    1.0
((C1, =, 1), (C2, =, 2)), X1, inf    3.415678    1.0
((C1, =, 1), (C2, =, 2)), X2, inf    2.923024    1.0
((C1, =, 1), (C2, =, 3)), X1, inf    3.719251    1.0
((C1, =, 1), (C2, =, 3)), X2, inf    3.971140    1.0
((C1, =, 2), (C2, =, 1)), X1, inf    5.312293    1.0
((C1, =, 2), (C2, =, 1)), X2, inf    2.366553    1.0
((C1, =, 2), (C2, =, 2)), X1, inf    6.115603    1.0
((C1, =, 2), (C2, =, 2)), X2, inf    3.616832    1.0
((C1, =, 2), (C2, =, 3)), X1, inf    6.658750    1.0
((C1, =, 2), (C2, =, 3)), X2, inf    4.772198    1.0
((C1, =, 3), (C2, =, 1)), X1, inf    7.452233    1.0
((C1, =, 3), (C2, =, 1)), X2, inf    2.820369    1.0
((C1, =, 3), (C2, =, 2)), X1, inf    8.545576    1.0
((C1, =, 3), (C2, =, 2)), X2, inf    4.179453    1.0
((C1, =, 3), (C2, =, 3)), X1, inf    9.301372    1.0
((C1, =, 3), (C2, =, 3)), X2, inf    5.422006    1.0
((C1, =, 1), (C2, =, 1)), J_R1, inf  0.578283    1.0
((C1, =, 1), (C2, =, 2)), J_R1, inf  0.419593    1.0
((C1, =, 1), (C2, =, 3)), J_R1, inf  0.326581    1.0
((C1, =, 2), (C2, =, 1)), J_R1, inf  0.845595    1.0
((C1, =, 2), (C2, =, 2)), J_R1, inf  0.655089    1.0
((C1, =, 2), (C2, =, 3)), J_R1, inf  0.539740    1.0
((C1, =, 3), (C2, =, 1)), J_R1, inf  1.016070    1.0
((C1, =, 3), (C2, =, 2)), J_R1, inf  0.811509    1.0
((C1, =, 3), (C2, =, 3)), J_R1, inf  0.685206    1.0
```

In [12]:
```
# make a residual object that contains the predict object and data,
# and do the fitting (using Levenberg-Marquardt algorithm)
res = residual.Residual(pred=pred, dat=dat)
fit = fitting.fit_lm_scipy(res, p0=p.randomize(sigma=0.2))
```

In [13]:
```
fit.p
```

Out[13]:
```
V1f     5.836039
K1C1    1.492059
K1X1    2.661096
V2f     9.401725
K2X1    6.472471
K2X2    0.376334
V3f     2.585938
K3X2    0.859541
K3C2    0.901930
dtype: float64
```

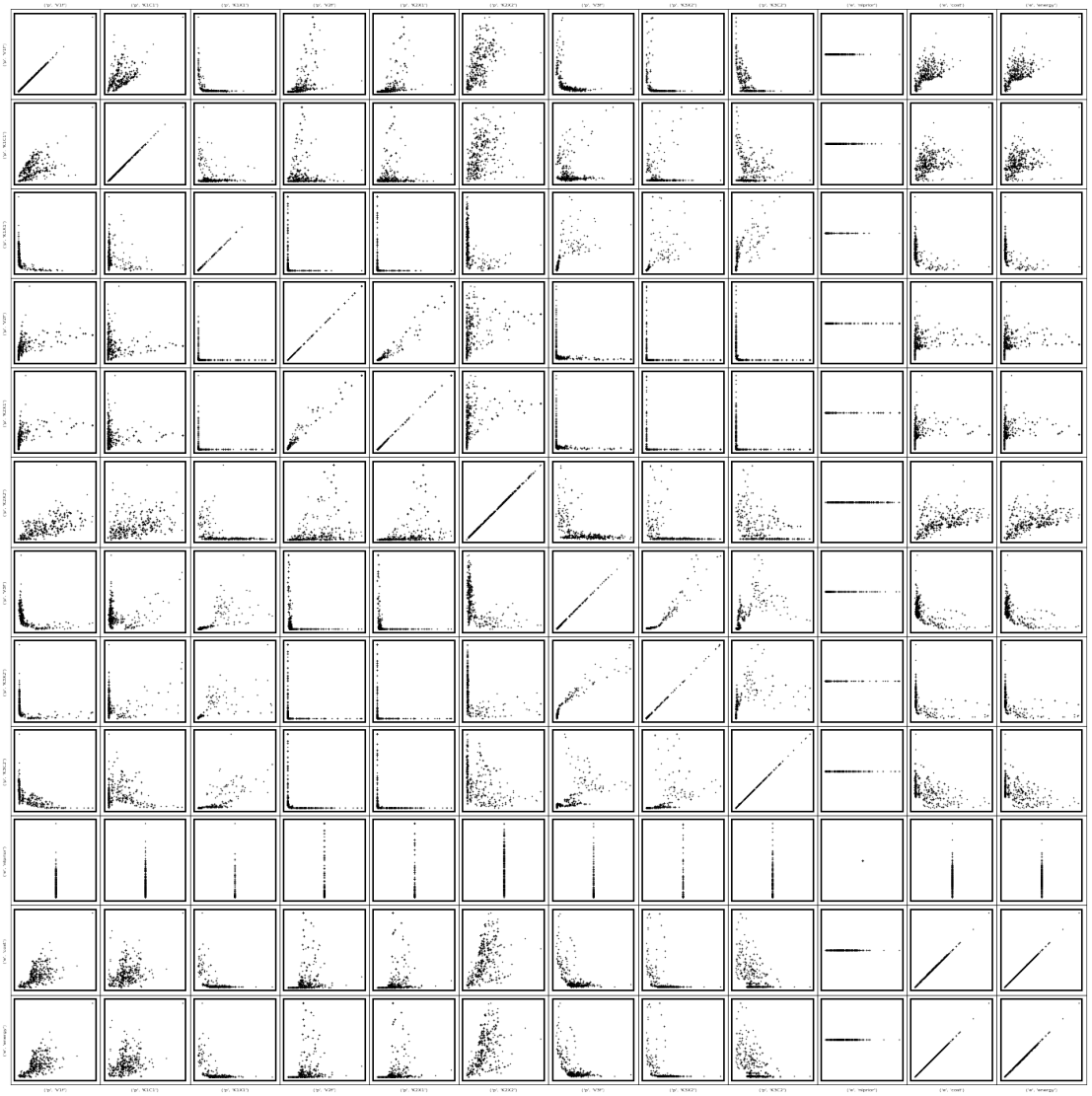
In [14]:
```
# confirm that the best fit parameter recovers the original parameter used for genera
fit.p - p
```

Out[14]:
```
V1f    -2.842171e-14
K1C1   -5.107026e-15
K1X1    1.376677e-14
V2f     9.237056e-14
K2X1    1.012523e-13
K2X2    2.164935e-15
V3f     3.552714e-15
K3X2    1.776357e-15
K3C2   -1.776357e-15
dtype: float64
```

In [15]:
```
# generating ensembles
ens = sampling.sampling(res, 1000, stepscale=0.1, interval_print_step=100)
```

```
100
200
300
400
500
600
700
800
900
1000
```

In [16]:
```
# scatter-plot the ensembles
ens.scatter()
```



In [ ]: