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// T51mixExpNor1.sce
// MIXTURE ESTIMATION (descriptive normal)
// - static normal componens
// - scalar y and multinomial continuous v
// |y| = |a1 a2 a3||v1| + e
//           |v2|
//           |v3|
// Experiments
// - change simulated expectations thS
// - change initial expectations thE (through the statistics S, ka)
// -----
exec("ScIntro.sce",-1),
getd(), mode(0)

nd=100; // 1
// SIMULATION // 2
thS=list(); // 3
thS(1)=[1 6 10]; // simulated regr. coefficants // 4
thS(2)=[8 1 5]; // 5
thS(3)=[6 9 1]; // 6
sd=.1; // common and known noise std. // 7
for t=1:nd // 8
    jS=ceil(3*randu()); // pointer value generation // 9

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    cS(t)=jS; // 10
    v(t,:)=randn(1,3); // explan. variables // 11
    y(t)=thS(jS)*v(t,:)+sd*randn(); // output value generation // 12
end // 13
nc=length(thS); // 14
// 15
// INITIALIZATION // 16
V=list(); thE=list(); // 17
ka=[1 1 1]; // initial counter // 18
for j=1:nc // 19
    thE(j)=thS(j)+5*rand(1,3); // initial parameters // 20
    V(j)=eye(4,4); // initial inf. matrix // 21
    V(j)(1,2:4)=thE(j)'; // 22
    V(j)(2:4,1)=thE(j); // 23
    thE(j)=v2thN(V(j)/ka(j),1); // initial point estimates // 24
end // 25
// 26
// TIME LOOP // 27
for t=1:nd // 28
    // estimation // 29
    for j=1:nc // 30
        [nll,qp(j)]=GaussN(y(t),thE(j)*v(t,:)',sd); // proximity // 31
    end // 32

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q=exp(qp-max(qp));           // log q -> w           // 33
w=q/sum(q);                 // weights           // 34
wt(:,t)=w;                  // 35
for j=1:nc                   // 36
    Ps=[y(t) v(t,:)]';      // extended reg. vector // 37
    V(j)=V(j)+w(j)*Ps*Ps';  // update of statistics V // 38
    ka(j)=ka(j)+w(j);       // and counter           // 39
    thE(j)=v2thN(V(j)/ka(j),1); // point estimates      // 40
    c(j).th(:,t)=thE(j);    // remember for plot    // 41
end                           // 42
// zero-step prediction      // 43
ypp=0;                       // 44
for j=1:nc                   // 45
    select 1                 // type of prediction: 1-point, 2-generated; // 46
    case 1, ypp=ypp+w(j)*thE(j)*v(t,:); // 47
    case 2, ypp=ypp+w(j)*(thE(j)*v(t,:)+sd*randn()); // 48
    end                       // 49
end                           // 50
yp(t)=ypp;                   // prediction           // 51
end                           // 52
// RESULTS                    // 54
set(scf(1),'position',[600 10 1200 400]) // 55

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for j=1:nc // 56
    subplot(1,3,j) // 57
    plot(c(j).th') // 58
    title('Evolution of estimated parametrs: comp. '+string(j)) // 59
end // 60
// 61

disp 'Simulated parameter values' // 62
disp(thS(:)) // 63
disp 'Final estimated parameters' // 64
disp(thE(:)) // 65
// 66

set(scf(2),'position',[900 500 600 400]) // plot data and prediction // 67
plot(1:nd,y,'ob',1:nd,yp,'xr','markersize',8) // 68
title 'Data (b) and prediction (r)' // 69
// 70

[nill,cp]=max(wt,'r'); // accuracy of classification // 71
disp 'Accuracy of classification' // 72
ACC=acc(cS,cp) // 73
// 74

disp 'Relative prediction error' // accuracy of prediction // 75
RPE=rpe(y(:),yp(:)) // 76

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Description of the program

- Rows 3–7 define parameters for simulation.
- Rows 9–12 perform simulation with switching components. Simulated model is

$$f_j(y_t | v_{1;t}, v_{2;t}, v_{3;r})$$

for components $j = 1, 2$.

- Rows 17–25 prepare initial statistics and parameters for the estimation.
- Rows 28–52 represent the time loop.
 - Rows 30–32 compute logarithmic proximities.
 - Rows 33–34 perform normalization of proximities and take their exponent.
 - Rows 36–42 do statistics update and construction of point estimates of the parameters.
 - Rows 44–52 construct the output zero-step prediction (either point one - expectation or generated one - expectation + noise).