robKalman — a package on Robust Kalman Filtering

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Classical setup: Linear state space models (SSMs)

- State equation:

$$\boxed{X_t = F_t X_{t-1} + v_t}$$

- Observation equation:

$$\boxed{Y_t = Z_t X_t + \varepsilon_t}$$

- Ideal model assumption:

$$X_0 \sim \mathcal{N}_p(a_0, \Sigma_0), \quad v_t \sim \mathcal{N}_p(0, Q_t), \quad \varepsilon_t \sim \mathcal{N}_q(0, V_t),$$

  all independent
- (preliminary ?) simplification: Hyper parameters F_t, Z_t, V_t, Q_t constant in t

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Problem and classical solution

- Problem: Reconststruction of X_t by means of $Y_s, s \leq t$
- Criterium: MSE
- $\rightsquigarrow$ general solution: $\mathrm{E}\, X_t | (Y_s)_{s \leq t}$
- Computational difficulties:
  $\Longrightarrow$ restriction to **linear** procedures
  / or: Gaussian assumptions
- $\rightsquigarrow$ classical **Kalman Filter**

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Kalman filter

0. Initialization $(t=0)$:

$$X_{0|0} = a_0, \quad \Sigma_{0|0} = \Sigma_0$$

1. Prediction $(t \geq 1)$:

$$X_{t|t-1} = FX_{t-1|t-1}, \quad \mathrm{Cov}(X_{t|t-1}) = \Sigma_{t|t-1} = F\Sigma_{t-1|t-1}F' + Q$$

2. Correction $(t \geq 1)$:

$$\begin{aligned} X_{t|t} &= X_{t|t-1} + K_t(Y_t - ZX_{t|t-1}) \\ K_t &= \Sigma_{t|t-1}Z'(Z\Sigma_{t|t-1}Z' + V)^-, \qquad \text{(Kalman gain)} \\ \mathrm{Cov}(X_{t|t}) &= \Sigma_{t|t} = \Sigma_{t|t-1} - K_t Z \Sigma_{t|t-1} \end{aligned}$$

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Types of outliers and robustification

- IOs (system intrinsic): state equation is distorted
  — not considered here
- AO/SOs (exogeneous): observations are distorted:
  - either error ε_t is affected (AO)
  - or observations Y_t are modified (SO)
- a robustifications as to AO/SOs is to
  - retain recursivity (three-step approach)
  - modify correction step $\rightsquigarrow$ bound influence of Y_t
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Considered approaches

Approximate conditional mean (ACM): [Martin(79)]

- dim $Y_t = 1$
- particular model: $Y_t \sim \mathrm{AR}(p)$
  - $\rightsquigarrow X_t = (Y_t, \ldots, Y_{t-p+1})$,
  - hyper parameters $Z = (1, 0, \ldots, 0)$, $V^{\rm id} = 0$, F, Q unknown
- estimation of F, Q by means of GM-Estimators
- modified Corr.step: for suitable location influence curve ψ

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\begin{aligned}
X_{t|t} &= X_{t|t-1} + \Sigma_{t|t-1} Z' \psi(Y_t - Z X_{t|t-1}) \\
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rLS filter: [P.R.(01)]

- dim X_t, dim Y_t arbitrary, finite
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- optimality for SO's in some sense

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Concept and strategy

Goal: package `robKalman`
Contents

- Kalman filter: filter, Kalman gain, covariances
- ACM-filter: filter, GM-estimator
- rLS-filter: filter, calibration of clipping height
- further recursive filters?
  ⇝ general interface `recursiveFilter`
  with arguments:
  - state space model (hyper parameters)
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  - completely in S
  - perhaps some code in C (much) later
- Use existing infrastructure
  - from where to "borrow":
    - univariate setting: `KalmanLike` (package `stats`);
      time series classes: `ts`, `its`, `irts`, `zoo`, `zoo.reg`, `tframe`
    - multivariate setting: `dse` bundle by Paul Gilbert; perhaps `zoo`?
  - use for: graphics, diagnostics, management of date/time
- Split user interface and "Kalman code"
  - internal functions: no S4-objects
  - user interface: S4-objects

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- Use of S4
  - Hierarchic Classes:
    - state space models (SSMs) (Hyper-Parameter, distributional assumptions, outlier types)
    - filter results (specific subclass of (multivariate) time series)
    - control structures for filters (tuning parameters)
  - Methods:
    - filters (for different types of SSMs)
    - accessor/replacement functions
    - `simulate` for SSMs
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    - tests?
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Robust Kalman Filtering | Concept / Strategy
Implementation proposal | Implementation so far
Demonstration | Next steps

Implementation so far: interfaces

- preliminary, "S4-free" interfaces
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    — with routines for calibration at given
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    - contamination radius
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    - with function `arGM` for AR-parameters by GM-estimates
    - various ψ-functions are available:
      Hampel (ACM-filter), Huber, Tukey (both GM-estimators)
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  - all: wrappers to `recursiveFilter`

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    ⇝ close contact to
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    - Paul Gilbert,
    - possibly Gabor Grothendiek and Achim Zeileis (zoo)
  - casting/conversion functions for various time series classes
- User interface robfilter (?)
  - goal: four arguments: data, SSM, control-structure, filter type
  - should cope with various definitions of SSMs, data in various time series classes,
  - possibly simpler interfaces for ACM (Splus-compatibility) ⇝ ACMfilt-like
- Release schedule
  - wait for results of discussion as to class definition
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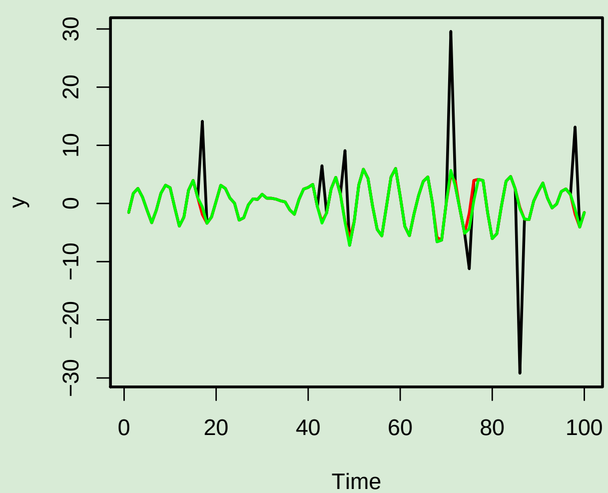
Demonstration: ACMfilt

```
## generation of data from AO model:
set.seed(361)
Eps ← as.ts(rnorm(100))
ar2 ← arima.sim(list(ar = c(1, −0.9)),
        100, innov = Eps)
Binom ← rbinom(100, 1, 0.1)
Noise ← rnorm(100,sd = 10)
y ← ar2 + as.ts(Binom*Noise)

## determination of GM−estimates
y.arGM ← arGM(y, 3)
## ACM−filter
y.ACMfilt ← ACMfilt(y, y.arGM)

plot(y)
lines(y.ACMfilt$filt , col=2)
lines(ar2 ,col="green")
```


Robust Kalman Filtering | ACMfilt
Implementation proposal | rLSFilter
Demonstration



green:	ideal time series,
black:	AO contam. time series,
red:	result ACM

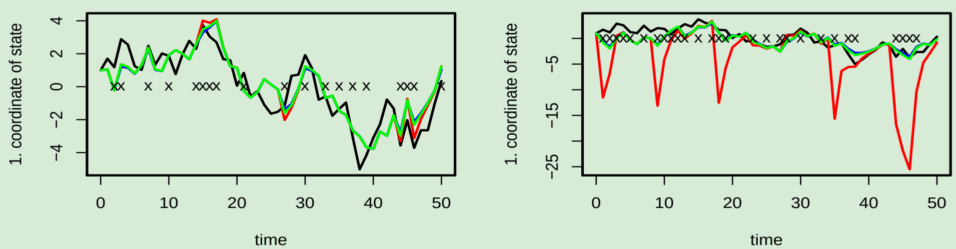
Demonstration: rLSFilter

```
## specification of SSM: (p=2, q=1)
a0   ← c(1, 0); S0   ← matrix(0, 2, 2)
F   ← matrix(c(.7, 0.5, 0.2, 0), 2, 2)
Q   ← matrix(c(2, 0.5, 0.5, 1), 2, 2)
Z   ← matrix(c(1, −0.5), 1, 2)
Vi   ← 1;
## time horizon:
TT←50
## AO−contamination
mc   ← −20; Vc   ← 0.1; ract ← 0.1
## for calibration
r1←0.1; eff1←0.9

#Simulation::
X   ← simulateState(a, S0, F, Q, TT)
Yid   ← simulateObs(X, Z, Vi, mc, Vc, r=0)
Yre   ← simulateObs(X, Z, Vi, mc, Vc, ract)
```

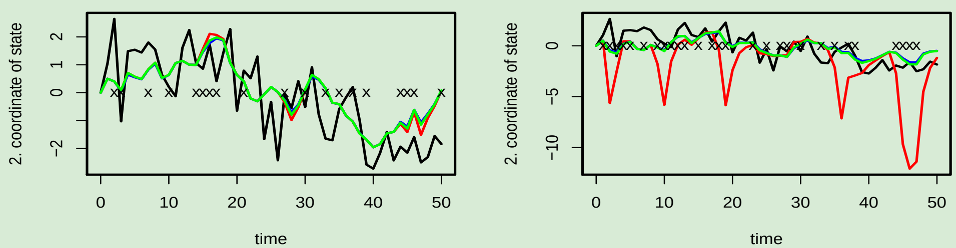

Demonstration: rLSfilter II

```
### calibration b
#limiting S_{t|t−1}
SS ← limitS(S, F, Q, Z, Vi)
# by efficiency in the ideal model
(B1 ← rLScalibrateB(eff=eff1, S=SS, Z=Z, V=Vi))
# by contamination radius
(B2 ← rLScalibrateB(r=r1, S=SS, Z=Z, V=Vi))

### evaluation of rLS
rerg1.id ← rLSFilter(Yid, a, Ss, F, Q, Z, Vi, B1$b)
rerg1.re ← rLSFilter(Yre, a, Ss, F, Q, Z, Vi, B1$b)
rerg2.id ← rLSFilter(Yid, a, Ss, F, Q, Z, Vi, B2$b)
rerg2.re ← rLSFilter(Yre, a, Ss, F, Q, Z, Vi, B2$b)
```


ideal situation — AO-contaminated situation



black: real state, — green: rLS filter (B1),
red: class. Kalman filter — blue: rLS filter (B2)



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