Practical Time Series Analysis - Class Notes

Week2

- Data points-time-correlation-data set-1 r.v.
- 1r.v.

-no systematic change in mean, variable-stationary
-X:s->R->dataset-describe X

- 2 r.v. cov(X,Y)
- >=3 r.v.

-X1, X2, X3 …:stochastic process
-Simple Random Samples(SRS)-indexed set of r.v. -trajactous
-multi:ensemble
-single:1 realization of process:Time Series structure
-estimate process-pool-stationary
-Autocovariance function-Autocorrelation function-each lag give coefficient
Random walk:x_t=x_t-1+z_t z_t~N(mu, sigma^2)
-x_t=Sum(z_i)-1 weighted sum-mu_t=mu*t, sigma_t=sigma^2 *t-not stationary
-diff(x_t)=z_t ->stationary
MA(q):x_t=z_t+theta_1*x_t-1+theta_q*x_t-q

Week3

Sequence {an}
Partial Sum {Sn}
Series sum(a_k)=Lim(Sn)-n -Sum(a_k) convergence
-Lim|a_k| exist- Sum(a_k) absolute convergence
Geometric
-Sequence {ar^n-1}
-Series: Sum(ar^n-1)
Backwards shift operator B
Time Series cut off-MA(q)-ACF
MA(q)-AR(p):Duality
-AR->MA:Invertibility
—z_t=Sum((-beta)^n)*x_t-n:weighted sum of x_t - Sum((-beta)^n) convergent - |beta|<1
—x_t=beta(B)*z_t - beta(B)=0 - |B|>1
-MA->AR:Stationary - phi(B)*x_t=z_t - phi(B)=0 - |B|>1
AR(p) process
x_t = z_t+HISTORY = z_t+phi_1*x_t-1+…+phi_p*x_t-p
AR process simulation
-AR(1):given order p, coefficients phi -for loop-measure process behavior
—many times-choose various coefficients - make observations - time series plot, ACF look
-AR(2):given p, coef - auto simulation:arima.sim - time series plot, ACF look
-phi 1:random walk, ->0 correlation decay quickly, =0 white noise, <0 alter + -

Week4

MA(p) has ACF cut off after q lags
AR(p) has PACF cut off p lags
-AR(2), AR(3) simulation -given p, coef, -auto simulate:arima.sim -look time series, ACF, PACF
-Dataset-smooth data points:filter - estimate coef.:ar
Time series-a set of related r.v.-redundancy
-See related r.v.-pair plot:pairs-numeric supplement:cov
-control for/partial out r.v.-linear regression-remove effect
-find PACF-cov
Yule-Walker equation in Matrix form-estimate coefficients, variance:sigma_z, constant

Week5

Time Series dataset-set of r.v.-realization of process-generating process-fit model
Fit AR(p) model-PACF->find order p

AR(2) simulation
-Given order p, ar coef. - generate data points - measure process behavior
-Given order p, estimate ar coef
—2 r.v.(2D)-model fit -plot
—serveral r.v.(nD)-model fit:arima-numeric measure of quality:AIC
-x know order p, ar coef.-fit model:arima - AIC, SSE
ARMA(p,q) simulation
-Given order p, ar ma coef. - generate data points-measure process behavior:ACF, PACF
-Given order p, estimate ar ma coef
-auto estimate order p, ar ma coef., d=0
-auto estimate order p, ar ma coef, d=0, aic
-Real-life dataset- non-stationary-remove trend -ARIMA(p,d,q)
ARIMA simulation
Modeling
Non-stationary
—systematic change in trend - diff
—systematic change in variation-transformation-log-return
-Ljung-Box Q-statistic-autocorrelation test-Box.test
-ACF-> MA(q), PACF->AR(q)
-auto fit model:auto.arima, fit various ARIMA models
-criteria:AIC, SSE, Box.test$p.value
Week6.1
Time series autocorrelation
-recent lags
-seasonal periodic lags-every s observations - Seasonality:s
SARIMA(0,0,1,0,0,1)_12 simulation
Modeling
-Time plot-stationary:systematic change in trend, variance-outlier
—Transformation -stablize variance-log-return
—Diff-remove trend(non-seasonal, seasonal)
-Box.test
-ACF
—closer spikes-MA q
—seasonal spikes-SMA Q
-PACF
-closer spikes-AR p
—seasonal spikes-SAR P
-Fit different models
—AIC
—parsimony principle:p+d+q+P+D+Q<=6
-residual analysis
—Time plot, ACF, PACF of residuals
—LBQ test for residuals
Week6.2
Forecast:Simple Exponential Smoothing(SES)
-plot-summarize data nature
—histogram-shape, symmetrical
—qqnorm, qqline-normal distributed
—Time series: time plot, ACF, PACF
-Forecast
—Naive method:x_n_n+1=x_n
—seasonal naive method: x_n_n+1=x_n+1_s
—Average method
—-Simple Moving Average-equally weighted average-mean all previous values

-Simple Exponential Smoothing(SES)
—greater weight-closer values
—decaying sequence weights-further past values-geometric series
-x_n_n+1=alpha*x_n+(1-alpha)*x_n-1_n
-find alpha -Least SSE
-auto SSE
—HoltWinters for SSE-turn off trend, seasonal effects-beta=FALSE, gamma=FALSE
—HoltWinters for level:alpha, trend:beta-turn off seasonal:gamma=FALSE
—SES with level, Trend, Seasonality
—-additive seasonality
—-multiplicative seasonality
—forcast