Python Companion Course

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Contents

1	Data	1	1
	1.1	Data Set Construction	1
	1.2	Simulation	2
	1.3	Expectations	3
2	Esti	mation	5
	2.1	Method of Moments	5
	2.2	Maximum Likelihood	6
	2.3	Bias and Verification of Standard Errors	7
3	Line	ear Regression	9
	3.1	Basic Linear Regression	9
	3.2	Rolling and Recursive Regressions	10
	3 3	Model Selection and Cross-Validation	11

Topic 1

Data

1.1 Data Set Construction

Functions

pd.read_csv, pd.read_excel, np.diff or DataFrame.diff, DataFrame.resample

Exercise 1

- 1. Download all daily data for the S&P 500 and the FTSE 100 from Yahoo! Finance.
- 2. Import both data sets into Python. The final dataset should have a DateTimeIndex, and the date column should not be part of the DataFrame.
- 3. Construct weekly price series from each, using Tuesday prices (less likely to be a holiday).
- 4. Construct monthly price series from each using last day in the month.

Exercise 2

Write a function which will return month-end prices. The function signature should be

```
def month_end_prices(price,date):
    ...
    return month_end_price, month_end_date
```

Exercise 3

- 1. Import the Fama-French benchmark portfolios as well as the 25 sorted portfolios at both the monthly and daily horizon from Ken French's Data Library. **Note** It is much easier to clean to data file before importing than to find the precise command that will load the unmodified data.
- 2. Import daily FX rate data for USD against AUD, Euro, JPY and GBP from the Federal Reserve Economic Database (FRED). Use Excel rather than csv files.

1.2 Simulation

Functions

np.random.standard_normal, np.random.standard_t, np.random.RandomState

Exercise 4

Simulate 100 standard Normal random variables

Exercise 5

Simulate 100 random variables from a $N(.08, .2^2)$

Exercise 6

Simulate 100 random variables from a Students t with 8 degrees of freedom

Exercise 7

Simulate 100 random variables from a Students t with 8 degrees of freedom with a mean of 8% and a volatility of 20%. Note: $V[X] = \frac{v}{v-2}$ when $X \sim t_v$.

Exercise 8

Simulate two identical sets of 100 standard normal random variables by resetting the random number generator.

Exercise 9

Repeat exercise 7 using only standard_normal.

1.3 Expectations

Functions

randn, trnd, chi2rnd, exp, mean, std, integral, quadl

Exercise 10

Compute E[X], $E[X^2]$, V[X] and the kurtosis of X using Monte Carlo integration when X is distributed:

- 1. Standard Normal
- 2. $N(0.08, 0.2^2)$
- 3. Students t_8
- 4. χ_5^2

Exercise 11

- 1. Compute $E[\exp(X)]$ when $X \sim N(0.08, 0.2^2)$.
- 2. Compare this to the analytical result for a Log-Normal random variable.

Exercise 12

Explore the role of uncertainty in Monte Carlo integration by increasing the number of simulations 300% relative to the base case.

Exercise 13

Compute the expectation in exercise [exer:expectations] using quadrature.

Note: This requires writing a function which will return $\exp(x) \times \phi(x)$ where $\phi(x)$ is the pdf evaluated at x.

Exercise 14

Optional (Much more challenging)

Suppose log stock market returns are distributed according to a Students t with 8 degrees of freedom, mean 8% and volatility 20%. Utility maximizers hold a portfolio consisting of a risk-free asset paying 1% and the stock market. Assume that they are myopic and only care about next period wealth, so that

$$U\left(W_{t+1}\right) = U\left(\exp\left(r_p\right)W_t\right)$$

and that $U(W) = \frac{W^{1-\gamma}}{1-\gamma}$ is CRRA with risk aversion γ . The portfolio return is $r_p = w \, r_s + (1-w) \, r_f$ where s is for stock market and f is for risk-free. A 4th order expansion of this utility around the expected wealth next period is

$$E_t[U(W_{t+1})] \approx \phi_0 + \phi_1 \mu_1' + \phi_2 \mu_2' + \phi_3 \mu_3' + \phi_4 \mu_4'$$

where

$$\phi_j = (j!)^{-1} U^{(j)} (E_t [W_{t+1}]),$$

$$U^{(j)} = \frac{\partial^j U}{\partial W^j},$$

$$\mu'_k = E_t \left[(r - \mu)_p^k \right],$$

and $\mu = E_t \ [r_p]$. Use Monte Carlo integration to examine how the weight in the stock market varies as the risk aversion varies from 1.5 to 10. Note that when $\gamma = 1$, $U(W) = \ln(W)$. Use $W_t = 1$ without loss of generality since the portfolio problem is homogeneous of degree 0 in wealth.

Topic 2

Estimation

2.1 Method of Moments

Functions

DatFrame.mean, DatFrame.sum, plt.subplots, plt.plot, DataFrame.to_numpy,

Exercise 15

Estimate the mean, variance, skewness and kurtosis of the S&P 500 and FTSE 100 using the method of moments using monthly data.

Exercise 16

Estimate the asymptotic covariance of the mean and variance of the two series (separately, but not the skewness and kurtosis).

Exercise 17

Estimate the Sharpe ratio of the two series and compute the asymptotic variance of the Sharpe ratio. See Chapter 2 of the notes for more on this problem.

Exercise 18

Plot rolling estimates of these using 120 months of consecutive data using a 4 by 1 subplot against the dates.

2.2 Maximum Likelihood

Functions

log, gamma, gammaln, normcdf, erf, fminunc, fmincon, trnd, var, std, normpdf

Exercise 19

Simulate a set of i.i.d. Student's t random variables with degree of freedom parameter $\nu = 10$. Standardize the residuals so that they have unit variance using the fact that $V[x] = \frac{\nu}{\nu - 2}$. Use these to estimate the degree of freedom using maximum likelihood. Note that the likelihood of a standardized Student's t is

$$f(x; \nu, \mu, \sigma_t^2) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)} \frac{1}{\sqrt{\pi(\nu-2)}} \frac{1}{\sigma_t} \frac{1}{\left(1 + \frac{(x-\mu)^2}{\sigma_t^2(\nu-2)}\right)^{\frac{\nu+1}{2}}}$$

where Γ () is known as the gamma function.

Exercise 20

Repeat the previous exercise using daily, weekly and monthly S&P 500 and FTSE 100 data. Note that it is necessary to remove the mean and standardize by the standard deviation error before estimating the degree of freedom. What happens over longer horizons?

Exercise 21

Repeat the previous problem by estimating the mean and variance simultaneously with the degree of freedom parameter.

Exercise 22

Simulate a set of Bernoulli random variables y_i where

$$p_i = \Phi(x_i)$$

where $X_i \sim N(0, 1)$. (Note: p_i is the probability of success and $\Phi()$ is the standard Normal CDF). Use this simulated data to estimate the Probit model where $p_i = \Phi(\alpha_0 + \alpha_1 x_i)$ using maximum likelihood.

Exercise 23

Estimate the asymptotic covariance of the estimated parameters in exercise [exer:probit].

2.3 Bias and Verification of Standard Errors

Functions

sum, mean, cov, bsxfun, fminunc, normcdf, normpdf, norminv, pltdens, chi2rnd, rand, plot, title, axis, legend

Exercise 24

Simulate a set of i.i.d. χ_5^2 random variables and use the method of moments to estimate the mean and variance.

Exercise 25

Compute the asymptotic variance of the method of moment estimator.

Exercise 26

Repeat [exer:method-of-moments] and [exer:asymptotic-variance] a total of 1000 times. Examine the finite sample bias of these estimators relative to the true values.

Exercise 27

Repeat [exer:method-of-moments] and [exer:asymptotic-variance] a total of 1000 times. Compare the covariance of the estimated means and variance (1000 of each) to the asymptotic covariance of the parameters (use the average of the 1000 estimated variance-covariances). Are these close? How does the sample size affect this?

Exercise 28

In the previous problem, for each parameter, form a standardized parameter estimate as

$$z_i = \frac{\sqrt{n} \left(\hat{\theta}_i - \theta_{i,0} \right)}{\sqrt{\hat{\Sigma}_{ii}}}$$

where

$$\sqrt{n} (\hat{\theta} - \theta_0) \stackrel{d}{\rightarrow} N(0, \Sigma)$$

so that $\hat{\Sigma}$ is the estimated asymptotic covariance. What percent of these z_i are larger in absolute value than 10%, 5% and 1% 2-sided critical values from a normal?

Exercise 29

Produce a density plot of the z_i standardized parameters and compare to a standard normal.

Exercise 30

Repeat the same exercise for the Bernoulli problem from the previous question.

Topic 3

Linear Regression

3.1 Basic Linear Regression

Functions mean, bsxfun, repmat

Exercise 44

Use the OLS function to estimate the coefficients of the Fama-French portfolios (monthly data) on the market, size and value factors. Include a constant in the regressions. Use only the four extremum portfolios – that is the 1-1, 1-5, 5-1 and 5-5 portfolios.

Exercise 45

Are the parameter standard errors similar using the two covariance estimators? If not, what does this mean?

Exercise 46

How much of the variation is explained by these three regressors?

3.2 Rolling and Recursive Regressions

Functions

ols, title, datetick, legend, axis, subplot, plot, figure

Exercise 47

For the same portfolios in the previous exercise, compute rolling β s using 60 consecutive observations.

Exercise 48

For each of the four market β s, produce a plot containing four series:

- A line corresponding to the constant β (full sample)
- The β estimated on the rolling sample
- The constant β plus $1.96 \times$ the variance of a 60-observation estimate of β . The 60-month covariance can be estimated using a full sample VCV and rescaling it by T/60 where T is the length of the full sample used to estimate the VCV. Alternatively, the VCV could be estimated by first estimating the 60-month VCV for each sub-sample and then averaging these.
- The constant β minus 1.96× the variance of a 60-observation estimate of β .

Exercise 49

Do the market exposures appear constant?

Exercise 50

What happens if only the market is used as a factor (repeat the exercise excluding SMB and HML).

Exercise 51

In problems 1 and 2, is there any evidence of time-variation in the SMB of HML loadings?

3.3 Model Selection and Cross-Validation

Functions

randperm, ols, setdiff, norminy, linspace, mean

Exercise 52

For these portfolios, and considering all 8 sets of regressors which range from no factor to all 3 factors, which model is preferred by AIC, BIC, GtS and StG?

Exercise 53

Cross-validation is a method of analyzing the in-sample forecasting ability of a cross-sectional model by using $\alpha\%$ of the data to estimate the model and then measuring the fit using the remaining $100-\alpha\%$. The most common forms are 5- and 10-fold cross-validation which use $\alpha=20\%$ and 10%, respectively. k-fold cross validation is implemented by randomly grouping the data into k-equally-sized groups, using k-1 of the groups to estimate parameters, and then evaluating using the bin that was held out. This is then repeated so that each bin is held out.

- 1. Implement cross-validation using the 5- and 10-fold methods for all 8 models.
- 2. For each model, compute the full-sample sum of squared errors as well as the sum-of-squared errors using the held-out sample. Note that all data points will appear exactly once in both of these sum or squared errors. What happens to the cross-validated R^2 when computed on the held out sample when compared to the full-sample R^2 ? (k-fold cross validated SSE by the TSS).