

Dis 11: Big Data (Cont'd); Time Series

1 Shrinkage estimators (from last week)

1. (Adapted from Problem #2 of PS 10)

You have a sample of size $n = 2$ with data $(x_1, y_1) = (1, 2)$ and $(x_2, y_2) = (3, 6)$. You are interested in the value of β in the regression model

$$Y = X\beta + u$$

(notice that this model has no intercept term)

(a) Plot sum of squared residuals $\sum_i (y_i - bx_i)^2$ as a function of b . Which level of b indicated on the plot is the solution to the OLS estimator?

(b) Find OLS estimate of β (i.e. $\hat{\beta}_{OLS}$)

(c) Plot penalized sum of squared residuals for Lasso regression (which is sum of squared residuals + penalty term) as a function of b with $\lambda_{Lasso} = 10$. Which level of b indicated on the plot is the solution to the Lasso estimator?

(d) Find Lasso estimate of β (i.e. $\hat{\beta}_{Lasso}$) under $\lambda_{Lasso} = 10$

(e) Repeat (c), but set $\lambda_{Lasso} = 100$

(f) Find Lasso estimate of β (i.e. $\hat{\beta}_{Lasso}$) under $\lambda_{Lasso} = 100$

2 Time Series

2.1 Terminology

- **Time series data:** Time ordered data with all observations associated with the same sampling unit

year	Y	X_1	X_2
2000	10	5	4
2001	21	3	10
2002	23	10	23
\vdots	\vdots	\vdots	\vdots
2019	124	40	83
2020	112	51	93

- How frequent does the time period needs to be?
 - Depends on your analysis.
Could be hourly, daily, weekly, monthly, quarterly, yearly, etc.
 - But time frequency must be consistent throughout the dataset (for example, you can't have the first ten rows of data in quarterly frequency, and then the rest in yearly frequency)
- Time period is usually denoted as t , and value in that time is subscripted with t (Y_t , X_{1t} , X_{2t} , etc.)
- Lags and differences:
 - The **first lag** of Y_t is Y_{t-1} . The j -th lag of Y_t is Y_{t-j} .
 - The **first difference** of Y_t is $\Delta Y_t = Y_t - Y_{t-1}$
 - The **first difference of the logarithm** of Y_t is $\Delta \ln(Y_t) = \ln(Y_t) - \ln(Y_{t-1})$
 - The **percentage change** of Y_t between t and $t - 1$ is approximately $100\Delta \ln(Y_t)$

2.2 What do we do with time series data?

- Time series data, unlike cross sectional or panel data, is usually used for **prediction**.
 - So, like what we talked about last week regarding Big Data, we're interested in the prediction aspect of econometric analysis when dealing with time series data
 - However, unlike last week regarding X and Y variables have to be standardized / demeaned in big data prediction model, we usually **don't** do that for small scale time series prediction.
(The reason why we standardize / demean variables in big data models is to make all β s to be in terms of increase one standard deviation of X , since we have so many X variables to include in a big data model, and the units of X become hard to keep track of.)
- So how to conduct prediction for time series data?
 - Time series data are often **autocorrelated** (also known as **serially correlated**): Past value(s) of Y should be correlated with current or future value of Y .

- * j -th autocovariance = $Cov(Y_t, Y_{t-j})$
- * j -th autocorrelation = $Corr(Y_t, Y_{t-j}) = \frac{Cov(Y_t, Y_{t-j})}{\sqrt{Var(Y_t)Var(Y_{t-j})}}$

- **Stationarity:** A time series Y_t is stationary if its probability distribution does NOT change over time. In other words, the distribution of the time series today is the same as its distribution in the past.

Variables can also be jointly stationary. For example, (X_t, Y_t) can jointly have probability distribution that does NOT change over time.

- Therefore,
 - * If the variable to forecast is stationary, then try to include lagged value of Y_t (and potentially lagged value of a different variable X_t) to predict future Y .
 \Rightarrow Autoregression & Autoregressive distributed lag model
 - * If the forecast variable is NOT stationary, then **trend** and **breaks** need to be accounted for.

- **Autoregression**

- A p -th order autoregressive model, or $AR(p)$, looks like the following:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \dots + \beta_p Y_{t-p} + u_t$$

- What are these β s?

Recall that β_1 is calculated as

$$\beta_1 = \frac{Cov(Y_t, Y_{t-1})}{Var(Y_t)}$$

this looks awful a lot like the first autocorrelation formula.

In fact, since we assume that Y_t is stationary,

$$Var(Y_t) = Var(Y_{t-1})$$

given that distribution of Y at time t is exactly the same as the distribution of Y at time $t - 1$. This gives us

$$\text{first autocorrelation} = \frac{Cov(Y_t, Y_{t-1})}{\sqrt{Var(Y_t)Var(Y_{t-1})}} = \frac{Cov(Y_t, Y_{t-1})}{Var(Y_t)} = \beta_1$$

Thus, under stationarity, β_1 records the first order autocorrelation.

By extension, under stationarity, β_p records the p -th order autocorrelation.

- **Autoregressive distributed lag model**

- A autoregressive distributed lag model with p lags of Y_t and q lags of X_t , or $ADL(p, q)$, looks like the following:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \dots + \beta_p Y_{t-p} + \delta_1 X_{t-1} + \dots + \delta_q X_{t-q} + u_t$$

- Both $AR(p)$ and $ADL(p, q)$ are estimated using OLS. But let's see how OLS assumptions under a multivariate environment hold up under time series environment:

	OLS Assumptions	Time Series Assumptions
1	Zero conditional mean: $E[u_i X_{1i}, X_{2i}, \dots, X_{Ki}] = 0$	Zero conditional mean: $E[u_t Y_{t-1}, \dots, Y_{t-p}, X_{1,t-1}, \dots, X_{1,t-q}, \dots, X_{K,t-1}, \dots, X_{K,t-q}] = 0$
2	I.I.D. Data: $(x_{1i}, x_{2i}, \dots, x_{ki}, y_i)$ are i.i.d. (independent and identically distributed)	a. Stationarity: The distribution of the time series today is the same as its distribution in the past. (\Rightarrow replace “identically distributed”) b. Independence for large time gap: $(Y_t, X_{1t}, \dots, X_{Kt})$ and $(Y_{t-j}, X_{1,t-j}, \dots, X_{K,t-j})$ becomes independent as j gets large. (\Rightarrow replace “independent”)
3	Large outliers are unlikely: There doesn't exist $(X_{1i}, X_{2i}, \dots, X_{Ki}, Y_i)$ that live in a dramatically different region.	Large outliers are unlikely: There doesn't exist $(X_{1t}, X_{2t}, \dots, X_{Kt}, Y_t)$ that live in a dramatically different region.
4	No perfect multicollinearity: One of the regressors cannot be a perfect linear function of the other regressors.	No perfect multicollinearity: One of the regressors cannot be a perfect linear function of the other regressors.

- How to determine how many lags to include in an $AR(p)$ or $ADL(p, q)$ model?
Idea: The marginal benefits of including one more lag outweighs the marginal costs of doing so.
- **Marginal benefits of one more lag term:** More information, reduces omitted variable bias.
- **Marginal costs of one more lag term:** Introduces additional estimation error.
 - In time series context, the predicted future Y is referred to as **forecast**, and the prediction error is referred to as **forecast error**, where

$$\text{Forecast Error} = Y_{T+1} - \hat{Y}_{T+1|T}$$

- * Y_{T+1} represents the true value of Y at time $T + 1$
- * $\hat{Y}_{T+1|T}$ represents the forecast of Y at time $T + 1$, using all data up to time period T to construct the forecast
- Similar to what we saw from Big Data, we often are interested in the average level of forecast error, which we call **mean squared forecast error (MSFE)**:

$$MSFE = E \left[(Y_{T+1} - \hat{Y}_{T+1|T})^2 \right]$$

- The tricky bit is, how do we estimate MSFE? Let's try some transformation on it first:

$$\begin{aligned} MSFE &= E \left[(Y_{T+1} - \mu_Y - (\hat{Y}_{T+1|T} - \mu_Y))^2 \right] \\ &= E \left[(Y_{T+1} - \mu_Y)^2 + (\hat{Y}_{T+1|T} - \mu_Y)^2 - 2(Y_{T+1} - \mu_Y)(\hat{Y}_{T+1|T} - \mu_Y) \right] \end{aligned}$$

$$\begin{aligned}
&= \underbrace{E[(Y_{T+1} - \mu_Y)^2]}_{\text{variance from randomness}} + \underbrace{E[(\hat{Y}_{T+1|T} - \mu_Y)^2]}_{\text{variance from estimation}} - 2 \underbrace{E[(Y_{T+1} - \mu_Y)(\hat{Y}_{T+1|T} - \mu_Y)]}_{=0 \text{ since prediction arises independently of the truth}} \\
&= E[(Y_{T+1} - \mu_Y)^2] + E[(\hat{Y}_{T+1|T} - \mu_Y)^2]
\end{aligned}$$

For example, for an $AR(p)$ model,

$$\begin{aligned}
MSFE &= \text{variance from randomness} + \text{variance from estimation} \\
&= \sigma_u^2 + \text{Var}(\hat{\beta}_0 + \hat{\beta}_1 Y_T + \dots + \hat{\beta}_p Y_{T-p+1})
\end{aligned}$$

– For an $AR(p)$ model, there are 3 methods to estimate MSFE:

1. Using standard error of the regression:

- * Only use when T is large relative to p
- * Idea: When T is large enough, the variance from estimation will become negligible. This makes $MSFE \approx \sigma_u^2$, which means the estimate of MSFE becomes

$$\widehat{MSFE}_{SER} = s_u^2 = \frac{SSR}{T - p - 1} = \frac{\sum_t (Y_t - \hat{Y}_t)^2}{T - p - 1}$$

2. Using the final prediction error:

- * Use when T is NOT large relative to p & error is homoskedastic
- * Idea: Under homoskedastic error, we can simplify the variance from estimation as the following:

$$\text{Var}(\hat{\beta}_0 + \hat{\beta}_1 Y_T + \dots + \hat{\beta}_p Y_{T-p+1}) \approx \sigma_u^2 \left(\frac{p+1}{T} \right)$$

which means that MSFE now becomes

$$MSFE \approx \sigma_u^2 + \sigma_u^2 \left(\frac{p+1}{T} \right) = \sigma_u^2 \left(\frac{T+p+1}{T} \right)$$

Thus, to estimate MSFE, we use

$$\widehat{MSFE}_{FPE} = s_u^2 \left(\frac{T+p+1}{T} \right) = \frac{SSR}{T-p-1} \left(\frac{T+p+1}{T} \right) = \frac{T+p+1}{T-p-1} \cdot \frac{\sum_t (Y_t - \hat{Y}_t)^2}{T}$$

3. Using pseudo out-of-sample forecasting:

- * Use whenever (though T cannot be too small); similar idea to big data prediction model
- * Procedure:
 - (a) For a sample with T time periods, choose W observations to set aside for prediction.
 - (b) The size of sample used for model estimation is $S = T - W$. Use $t = 1, 2, \dots, S$ to estimate the model.
 - (c) Compute forecast of $S + 1$ time period. Obtain forecast error: $e_{S+1} = Y_{S+1} - \hat{Y}_{S+1|S}$.
 - (d) Now use $W - 1$ period to set aside for prediction, meaning that the size of sample to estimate the model is now $S + 1$, with time period $t = 1, 2, \dots, S, S + 1$. Forecast outcome at time $S + 2$ and obtain forecast error.

- (e) Repeat, and stop after the sample set aside for prediction reduces its size to 1.
The estimated MSFE is

$$\widehat{MSFE}_{POOS} = \frac{1}{W} \sum_{j=S+1}^T e_j^2$$

- Side note: How to obtain forecast interval?

We usually assume error in the forecast model is normally distributed. Thus, the way to construct confidence interval for a forecast is very similar to the confidence interval we have been constructing for coefficient estimate $\hat{\beta}$:

$$\text{point forecast} \pm z_{1-\frac{\alpha}{2}} \times se(\text{point estimator}) \Leftrightarrow \hat{Y}_{T+1|T} \pm z_{1-\frac{\alpha}{2}} \times \sqrt{\widehat{MSFE}}$$

where α = significance level = 1 – confidence level.

- Going back to what we were talking about: How do we balance the marginal benefits and marginal costs of introducing an additional lag term in our forecast models?
 - **F-statistic approach**: Start with some number of lags, and keep testing whether the largest lag is statistically significant. If yes, keep it. If no, drop it and re-estimate the model.
 - **Use information criterion**: An information criterion is a function of p (or the number of lags in general). It's essentially a penalty function, so the **smaller** the information criterion is at p , the better.

Under an $AR(p)$ model:

- * AIC (Akaike information criterion):

$$AIC(p) = \ln \left[\frac{SSR(p)}{T} \right] + (p+1) \frac{2}{T}$$

- * BIC (Bayes information criterion):

$$BIC(p) = \ln \left[\frac{SSR(p)}{T} \right] + (p+1) \frac{\ln(T)}{T}$$

Under an $ADL(p, q)$ model, the total number of predictors included is $K = p + q + 1$, so that

$$AIC(K) = \ln \left[\frac{SSR(K)}{T} \right] + K \frac{2}{T} \quad BIC(K) = \ln \left[\frac{SSR(K)}{T} \right] + K \frac{\ln(T)}{T}$$

To obtain AIC and BIC in Stata, run the regression model first, then store the estimates, and finally use `estimate stats` to produce AIC and BIC:

```
reg Y l.Y, robust // first model
estimates store model1
reg Y l.Y L(1/2).Y, robust // second model
estimates store model2
estimate stats model1 model2 // obtain AIC and BIC
```

We'll see an example in the **Problems** section.

3 Problems

2. (Time Series)

Load [this week's dataset](#)* into Stata (don't forget to change your working directory).

This dataset records real GDP growth rate from the second quarter of 1947 to the second quarter of 2018. Variable that records such growth rate is `gdp`.

We will assume throughout this question that real GDP growth is stationary, and attempt to use both $AR(p)$ and $ADL(p, q)$ models to forecast real GDP growth. Assume error is heteroskedastic for all parts of analysis.

(a) Start by running an $AR(1)$ model to forecast real GDP growth.

(b) Run an $AR(2)$ model. Is there any concern about including the second lag? Explain.

(c) Proceed to run $AR(p)$ models up to $p = 4$. Use AIC, decide how many lags should be included in an $AR(p)$ model. Repeat the exercise for using BIC.

*from Econ 460 (Economic Forecasting) taught by Prof. Bruce Hansen in Fall 2018

- (d) Now consider an $ADL(1,1)$ model, with the X variable to include here being the real growth rate of private domestic investment (pdi in the dataset).
- (e) Proceed to run $ADL(p,q)$ models with all possible combinations of p and q , such that $p = 1, 2, 3, 4$ and $q = 1, 2, 3, 4$. Use AIC, how many lags should be included? What about using BIC?
- (f) Consider all the $AR(p)$ models and $ADL(p,q)$ models that we run. Using AIC, which model should we select? What about using BIC?