## Course: Time Series

Session: Spring 2013 VEE Student Project

## Modeling Population in Canada (1946-2013)

## Introduction

Population growth rates vary greatly among countries. Many countries have experienced rapid growth rates while others have experienced the opposite. My time series project will analyze population in Canada using data from 1946 to 2013 and forecast the expected 2014, 2015 and 2016 population with the resulted model. Canada is a multicultural country, I would expect it has a steady population growth rate as its natural growth rate can be balanced with immigration controls.

## Data Source

Data of population in Canada can be extracted from Statistics Canada (www.statcan.gc.ca). These are annual population estimates at each calendar year ending June 30, averaging of four quarterly estimates. Population figures below are all in thousands.

## Analysis

Figure 1 shows annual population and growth rate in Canada from 1946 to 2013.


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Population remained relatively stable with a period of high population growth from 1946 to 1961 due to strong natural increase and migratory increase. Starting 2001 population grew at an average annual rate of approximately $1.0 \%$.

Before modeling the population data, I will examine autocorrelation to check if this series is stationary and whether the series need to be differenced in order to get a stationary series.
The sample autocorrelation is calculated using the following equation where k is from 1 to 65.
$r_{k}=\frac{\sum_{t=k+1}^{n}\left(Y_{t}-\bar{Y}\right)\left(Y_{t-k}-\bar{Y}\right)}{\Sigma_{t=1}^{n}\left(Y_{t}-\bar{Y}\right)^{2}}$

Figure 2 shows sample autocorrelation of Canada population for different lags.


This sample autocorrelation plot shows that the time series is not random, but rather has a high degree of autocorrelation between adjacent and near-adjacent observations. It shows high autocorrelation at lag 1 then slowly and steadily declines. It continues decreasing and becomes negative then starts showing an increasing negative autocorrelation. This indicates an $\operatorname{AR}(\mathrm{p})$ time series rather than MA(q) since the autocorrelation shows no sudden drop but gradually decreasing then increasing back up.

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Before proceeding with the $\operatorname{AR}(\mathrm{p})$ model, I would like to examine the correlogram on the first differences to achieve stationary through differencing which may lead to a simpler model compared to an $\operatorname{AR}(\mathrm{p})$ model. The model on first difference of the population is:
$\mathrm{W}_{\mathrm{t}}=\mathrm{Y}_{\mathrm{t}}-\mathrm{Y}_{\mathrm{t}-1}$
Figure 3 shows sample autocorrelation on first difference of Canada population for different lags.

Correlogram on First Difference of Canada Population


For a stationary series, we would expect to see a quick drop off to zero which is not the case shown here. This sample autocorrelation plot indicates non-random patterns and hence nonstationary.

Therefore, we will try to fit two $\operatorname{AR}(p)$ models to model the population data.
$\operatorname{AR}(1)$ process: $\mathrm{Y}_{\mathrm{t}}=\Phi_{1} \mathrm{Y}_{\mathrm{t}-1}+\Theta_{0}+\mathrm{e}_{\mathrm{t}}$.
$\operatorname{AR}(2)$ process: $\mathrm{Y}_{\mathrm{t}}=\Phi_{1} \mathrm{Y}_{\mathrm{t}-1}+\Phi_{2} \mathrm{Y}_{\mathrm{t}-2}+\Theta_{0}+\mathrm{e}_{\mathrm{t}}$.
SAS function was used to fit the population data to $\operatorname{AR}(1)$ and $\operatorname{AR}(2)$ models and the linear regression results are as follows:

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Figure 4 shows SAS Linear Regression results of the AR(1) model

| Analysis of Variance |  |  |  |  |  |
| :--- | ---: | ---: | ---: | ---: | ---: |
|  |  | Sum of | Mean | F |  |
| Source | DF | Squares | Square | Value | Pr > F |
| Model | 1 | 2756871852 | 2756871852 | 4E+05 | $<.0001$ |
| Error | 65 | 404127 | 6217.34342 |  |  |
| Corrected Total | 66 | 2757275979 |  |  |  |


| Root MSE | 78.85013 | R-Square | 0.9999 |
| :--- | ---: | :--- | ---: |
| Dependent Mean | 24196 | Adj R-Sq | 0.9999 |
| Coeff Var | 0.32588 |  |  |


| Parameter Estimates |  |  |  |  |  |  |
| :--- | ---: | ---: | ---: | ---: | ---: | :---: |
|  | DF | Parameter <br> Estimate | Standard <br> Error | t Value | Pr > \|t| |  |
| Variable | 1 | 409.32812 | 36.99714 | 11.06 | $<.0001$ |  |
| Intercept | 1 | 0.99717 | 0.0015 | 665.9 | $<.0001$ |  |
| Yt-1 |  |  |  |  |  |  |

Figure 5 shows SAS Linear Regression results of the AR(2) model

| Analysis of Variance |  |  |  |  |  |
| :--- | ---: | ---: | ---: | ---: | ---: |
| Source | DF | Sum of <br> Squares | Mean <br> Square | F <br> Value | Pr > F |
| Model | 2 | 2618201140 | 1309100570 | 218829 | $<.0001$ |
| Error | 63 | 376885 | 5982.29575 |  |  |
| Corrected Total | 65 | 2618578024 |  |  |  |


| Root MSE | 77.3453 | R-Square | 0.9999 |
| :--- | ---: | :--- | :--- |
| Dependent Mean | 24373 | Adj R-Sq | 0.9999 |
| Coeff Var | 0.31734 |  |  |


| Parameter Estimates |  |  |  |  |  |  |
| :--- | ---: | ---: | ---: | ---: | ---: | :---: |
|  | DF | Parameter <br> Estimate | Standard <br> Error | t Value | Pr > \|t| |  |
| Variable | 1 | 343.6131 | 62.89706 | 5.46 | $<.0001$ |  |
| Intercept | 1 | 1.18844 | 0.12263 | 9.69 | $<.0001$ |  |
| Yt-1 | 1 | -0.19118 | 0.12225 | -1.56 | 0.1229 |  |
| yt-2 |  |  |  |  |  |  |

Note that the $R^{2}$ and adjusted $R^{2}$ statistics for both models are almost equal to 1 . This indicates both models would be a good fit to the population data. The residual plots of the $\operatorname{AR}(1)$ and $\operatorname{AR}(2)$ models are shown in Figures 6 to 9 below.

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Figure 6 shows residual plot from $\operatorname{AR}(1)$ model

Residuals from AR(1) Model


Figure 7 shows standardized residual plot from AR(1) model

Standardized Residuals from AR(1) Model


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Figure 8 shows residual plot from $\operatorname{AR}(2)$ model

Residuals from AR(2) Model


Figure 9 shows standardized residual plot from AR(2) model

Standardized Residuals from AR(2) Model


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We can see that the residuals are very small and almost all the standardized residuals are within 2 standard deviations. Most of the standardized residuals fall within 1 standard deviation with some random fluctuations as expected in the data. This indicates that both models fitted the population data very well.

## Conclusion

Based on the analysis provided and the principle of parsimony, the $\operatorname{AR}(1)$ model would work best for modeling the population in Canada. The model can be used to forecast the future population using the near-adjacent population data as follows:
$\mathrm{Y}_{\mathrm{t}}=0.99717 \mathrm{Y}_{\mathrm{t}-1}+409.32812+\mathrm{e}_{\mathrm{t}}$
Knowing the 2013 Canada population is 35,142 , the expected future populations are:
2014 forecast is $35,142 * 0.99717+409.32812=35,452$
2015 forecast is $35,452 * 0.99717+409.32812=35,761$
2016 forecast is $35,761 * 0.99717+409.32812=36,069$

