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hoffm386 update StatsModels ARMA --> ARIMA ...

on Aug 23

 5[View code](#) README.md

ARMA Models in StatsModels - Lab

Introduction

In this lesson, you'll fit an ARMA model using `statsmodels` to a real-world dataset.

Objectives

In this lab you will:

- Decide the optimal parameters for an ARMA model by plotting ACF and PACF and interpreting them
- Fit an ARMA model using StatsModels

Dataset

Run the cell below to import the dataset containing the historical running times for the men's 400m in the Olympic games.

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import warnings
from statsmodels.tools.sm_exceptions import ConvergenceWarning
warnings.simplefilter('ignore', ConvergenceWarning)

data = pd.read_csv('winning_400m.csv')
data['year'] = pd.to_datetime(data['year'].astype(str))
data.set_index('year', inplace=True)
data.index = data.index.to_period("Y")

# Preview the dataset
data
```

<style scoped> .dataframe tbody tr th:only-of-type { vertical-align: middle; }

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

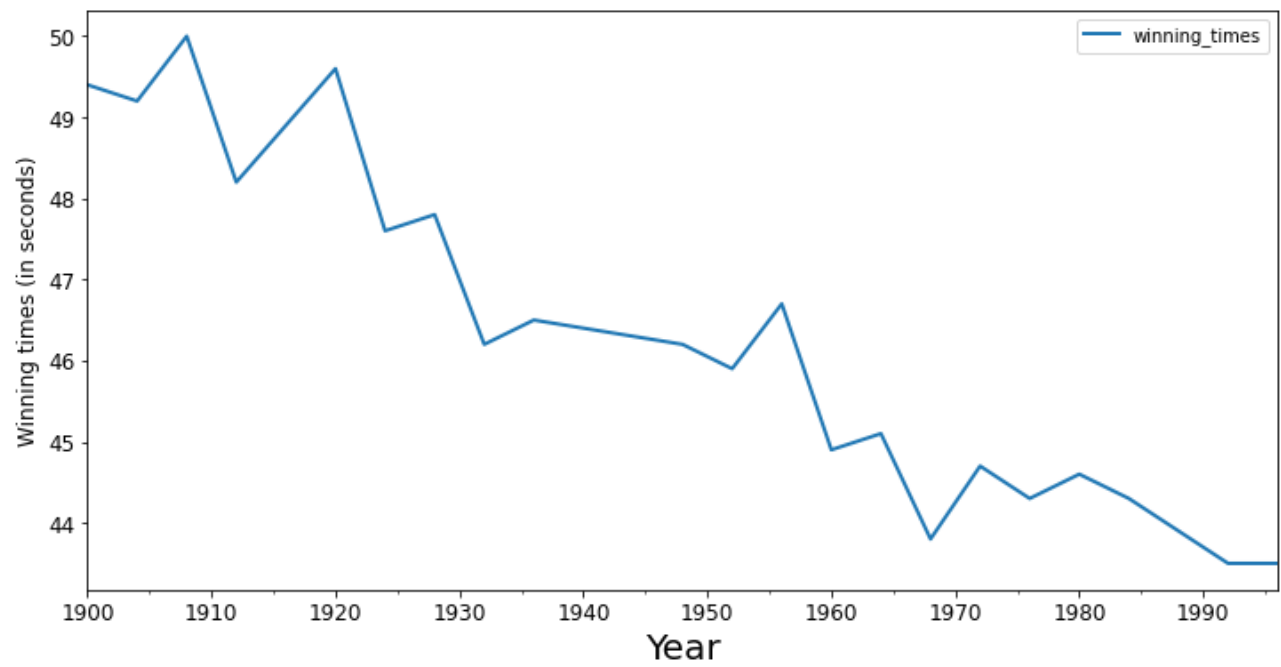
</style>

	winning_times
year	
1900	49.4
1904	49.2
1908	50.0
1912	48.2
1920	49.6

	winning_times
year	
1924	47.6
1928	47.8
1932	46.2
1936	46.5
1948	46.2
1952	45.9
1956	46.7
1960	44.9
1964	45.1
1968	43.8
1972	44.7
1976	44.3
1980	44.6
1984	44.3
1988	43.9
1992	43.5
1996	43.5

Plot this time series data.

```
# Plot the time series
data.plot(figsize=(12,6), linewidth=2, fontsize=12)
plt.xlabel('Year', fontsize=20)
plt.ylabel('Winning times (in seconds)', fontsize=12);
```



If you plotted the time series correctly, you should notice that it is not stationary. So, difference the data to get a stationary time series. Make sure to remove the missing values.

```
# Difference the time series
data_diff = data.diff().dropna()
data_diff
```

<style scoped> .dataframe tbody tr th:only-of-type { vertical-align: middle; }

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

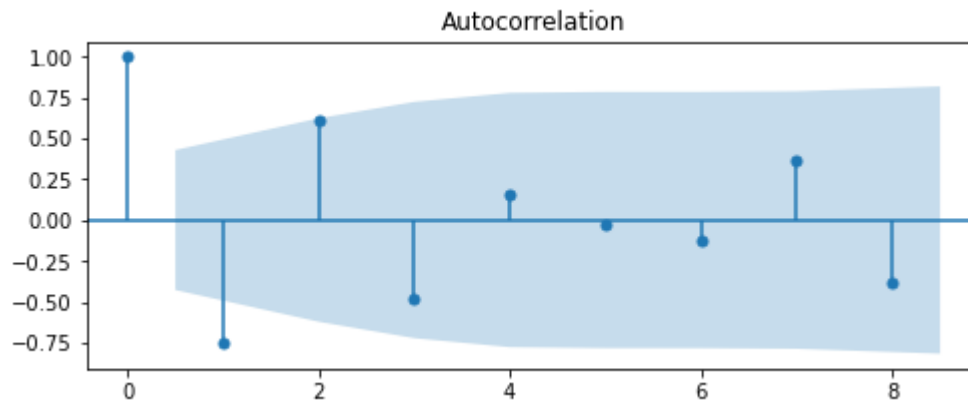
</style>

	winning_times
year	
1904	-0.2
1908	0.8
1912	-1.8

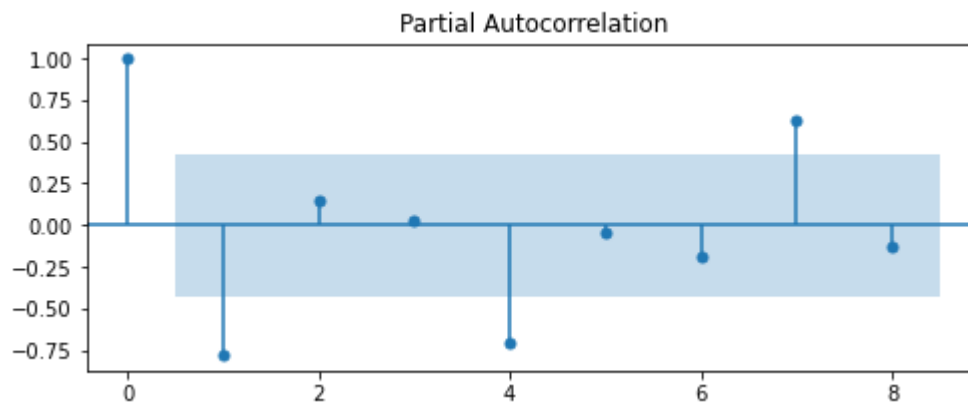
	winning_times
year	
1920	1.4
1924	-2.0
1928	0.2
1932	-1.6
1936	0.3
1948	-0.3
1952	-0.3
1956	0.8
1960	-1.8
1964	0.2
1968	-1.3
1972	0.9
1976	-0.4
1980	0.3
1984	-0.3
1988	-0.4
1992	-0.4
1996	0.0

Use `statsmodels` to plot the ACF and PACF of this differenced time series.

```
# Plot the ACF
from statsmodels.graphics.tsaplots import plot_acf
fig, ax = plt.subplots(figsize=(8,3))
plot_acf(data_diff,ax=ax, lags=8);
```



```
# Plot the PACF
from statsmodels.graphics.tsaplots import plot_pacf
fig, ax = plt.subplots(figsize=(8,3))
plot_pacf(data_diff,ax=ax, lags=8);
```



Based on the ACF and PACF, fit an ARMA model with the right orders for AR and MA. Feel free to try different models and compare AIC and BIC values, as well as significance values for the parameter estimates.

```
# Import ARIMA
from statsmodels.tsa.arima.model import ARIMA

# Fit an ARMA(1,0) model
mod_arma = ARIMA(data_diff, order=(1,0,0))
res_arma = mod_arma.fit()

# Print out summary information on the fit
print(res_arma.summary())
```

SARIMAX Results

```
=====
Dep. Variable:      winning_times    No. Observations:      21
```

```

Model:          ARIMA(1, 0, 0)    Log Likelihood      -20.054
Date:           Mon, 22 Aug 2022  AIC              46.107
Time:           17:08:26          BIC              49.241
Sample:         12-31-1904        HQIC              46.787
                  - 12-31-1996

```

Covariance Type: opg

```

=====
              coef    std err          z      P>|z|      [0.025    0.975]
-----
const        -0.2885     0.081     -3.559     0.000     -0.447     -0.130
ar.L1         -0.7186     0.144     -5.005     0.000     -1.000     -0.437
sigma2         0.3819     0.180      2.121     0.034      0.029      0.735
=====
Ljung-Box (L1) (Q):                0.04    Jarque-Bera (JB):
1.19
Prob(Q):                0.84    Prob(JB):
0.55
Heteroskedasticity (H):            0.33    Skew:
0.20
Prob(H) (two-sided):            0.16    Kurtosis:
1.91
=====

```

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

```

# Fit an ARMA(2,1) model
mod_arma = ARIMA(data_diff, order=(2,0,1))
res_arma = mod_arma.fit()

# Print out summary information on the fit
print(res_arma.summary())

```

SARIMAX Results

```

=====
Dep. Variable:    winning_times    No. Observations:      21
Model:           ARIMA(2, 0, 1)    Log Likelihood         -19.931
Date:           Mon, 22 Aug 2022  AIC              49.862
Time:           17:08:27          BIC              55.084
Sample:         12-31-1904        HQIC              50.995
                  - 12-31-1996
Covariance Type: opg
=====
              coef    std err          z      P>|z|      [0.025    0.975]
-----

```

const	-0.2834	0.092	-3.079	0.002	-0.464	-0.103
ar.L1	-0.6102	2.583	-0.236	0.813	-5.673	4.453
ar.L2	0.1280	1.848	0.069	0.945	-3.493	3.749
ma.L1	-0.0208	2.564	-0.008	0.994	-5.046	5.004
sigma2	0.3774	0.181	2.088	0.037	0.023	0.732

=====

Ljung-Box (L1) (Q): 0.04 Jarque-Bera (JB):

1.21

Prob(Q): 0.83 Prob(JB):

0.55

Heteroskedasticity (H): 0.31 Skew:

0.22

Prob(H) (two-sided): 0.14 Kurtosis:

1.91

=====

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

```
# Fit an ARMA(2,2) model
mod_arma = ARIMA(data_diff, order=(2,0,2))
res_arma = mod_arma.fit()

# Print out summary information on the fit
print(res_arma.summary())
```

SARIMAX Results

=====

Dep. Variable:	winning_times	No. Observations:	21
Model:	ARIMA(2, 0, 2)	Log Likelihood	-16.472
Date:	Mon, 22 Aug 2022	AIC	44.943
Time:	17:08:29	BIC	51.210
Sample:	12-31-1904	HQIC	46.303
	- 12-31-1996		

Covariance Type: opg

=====

	coef	std err	z	P> z	[0.025	0.975]
const	-0.2717	0.103	-2.629	0.009	-0.474	-0.069
ar.L1	-1.7573	0.117	-14.990	0.000	-1.987	-1.528
ar.L2	-0.9179	0.120	-7.664	0.000	-1.153	-0.683
ma.L1	1.5669	50.157	0.031	0.975	-96.739	99.873
ma.L2	0.9986	63.913	0.016	0.988	-124.268	126.265
sigma2	0.2126	13.545	0.016	0.987	-26.336	26.761

=====


```

Ljung-Box (L1) (Q):          0.03   Jarque-Bera (JB):
0.87
Prob(Q):                    0.86   Prob(JB):
0.65
Heteroskedasticity (H):      0.41   Skew:
-0.30
Prob(H) (two-sided):         0.26   Kurtosis:
2.20
=====

```

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

What is your final model? Why did you pick this model?

```
"""
```

```

ARMA(1,0), ARMA(2,2) and ARMA(2,1) all seem to have decent fits with significant par
Depending on whether you pick AIC or BIC as a model selection criterion,
your result may vary. In this situation, you'd generally go for a model with fewer p
so ARMA(1,0) seems fine. Note that we have a relatively short time series,
which can lead to a more difficult model selection process.

```

```
"""
```

Summary

Well done. In addition to manipulating and visualizing time series data, you now know how to create a stationary time series and fit ARMA models.

Releases

No releases published

Packages

No packages published

Contributors 2



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Languages

● **Jupyter Notebook** 100.0%