

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from datetime import datetime
from datetime import timedelta
from pandas.plotting import register_matplotlib_converters
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima_model import ARMA
register_matplotlib_converters()
from time import time
```

## Ice Cream Production Data

```
In [2]: def parser(s):
return datetime.strptime(s, '%Y-%m-%d')
```

```
In [3]: #read data
production_ice_cream = pd.read_csv('ice_cream.csv', parse_dates=[0], index_
```

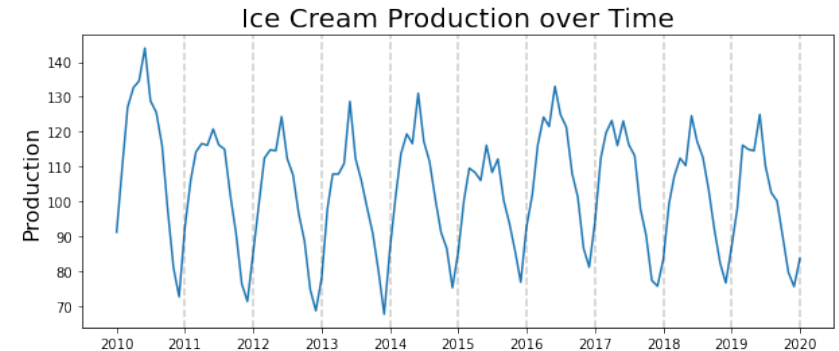
```
In [4]: production_ice_cream.rename('production', inplace = True)
```

```
Out[4]: DATE
1972-01-01    59.9622
1972-02-01    67.0605
1972-03-01    74.2350
1972-04-01    78.1120
1972-05-01    84.7636
...
2019-09-01   100.1741
2019-10-01    90.1684
2019-11-01    79.7223
2019-12-01    75.7094
2020-01-01    83.6290
Name: production, Length: 577, dtype: float64
```

```
In [5]: #infer the frequency of the data
catfish_sales = production_ice_cream.asfreq(pd.infer_freq(production_ice_cr
```

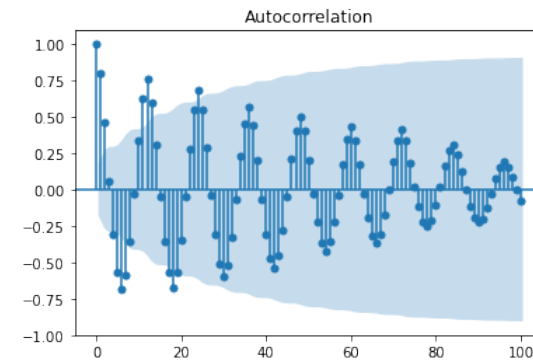
```
In [6]: start_date = pd.to_datetime('2010-01-01')
production_ice_cream = production_ice_cream[start_date:]
```

```
In [7]: plt.figure(figsize=(10,4))
plt.plot(production_ice_cream)
plt.title('Ice Cream Production over Time', fontsize=20)
plt.ylabel('Production', fontsize=16)
for year in range(2011, 2021):
    plt.axvline(pd.to_datetime(str(year)+'-01-01'), color='k', linestyle='-'
```



## ACF

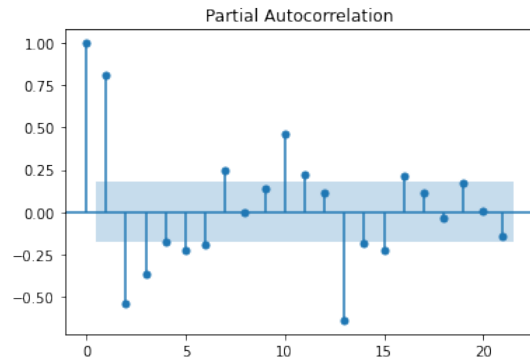
```
In [8]: acf_plot = plot_acf(production_ice_cream, lags=100)
```



Based on decaying ACF, we are likely dealing with an Auto Regressive process

## PACF

```
In [9]: pacf_plot = plot_pacf(production_ice_cream)
```



Based on PACF, we should start with an Auto Regressive model with lags 1, 2, 3

## Get training and testing sets

```
In [10]: train_end = datetime(2018,12,1)
test_end = datetime(2019,12,1)

train_data = production_ice_cream[:train_end]
test_data = production_ice_cream[train_end + timedelta(days=1):test_end]
```

## Fit the AR Model

```
In [11]: # define model
model = ARMA(train_data, order=(3,0))
```

```
/Users/siamakfarjami/opt/anaconda3/envs/UNI/lib/python3.8/site-packages/statsmodels/tsa/arma_model.py:472: FutureWarning:
statsmodels.tsa.arma_model.ARMA and statsmodels.tsa.arma_model.ARIMA have
been deprecated in favor of statsmodels.tsa.arma.model.ARIMA (note the .
between arma and model) and
statsmodels.tsa.SARIMAX. These will be removed after the 0.12 release.
```

statsmodels.tsa.arma.model.ARIMA makes use of the statespace framework and is both well tested and maintained.

To silence this warning and continue using ARMA and ARIMA until they are removed, use:

```
import warnings
warnings.filterwarnings('ignore', 'statsmodels.tsa.arma_model.ARMA',
                        FutureWarning)
warnings.filterwarnings('ignore', 'statsmodels.tsa.arma_model.ARIMA',
                        FutureWarning)
```

```
warnings.warn(ARIMA_DEPRECATION_WARN, FutureWarning)
/Users/siamakfarjami/opt/anaconda3/envs/UNI/lib/python3.8/site-packages/statsmodels/tsa/base/tsa_model.py:524: ValueWarning: No frequency information
was provided, so inferred frequency MS will be used.
warnings.warn('No frequency information was'
```

```
In [12]: #fit the model
start = time()
model_fit = model.fit()
end = time()
print('Model Fitting Time:', end - start)
```

Model Fitting Time: 10.277784824371338

```
In [13]: #summary of the model
print(model_fit.summary())
```

```

=====
ARMA Model Results
=====
Dep. Variable:      production    No. Observations:
108
Model:              ARMA(3, 0)    Log Likelihood      -374.
085
Method:             css-mle       S.D. of innovations    7.
642
Date:               Thu, 26 Nov 2020    AIC                  758.
170
Time:               00:18:44           BIC                  771.
580
Sample:             01-01-2010         HQIC                 763.
607
- 12-01-2018
=====
=====

```

	coef	std err	z	P> z	[0.025
const	103.5743	1.809	57.265	0.000	100.029
ar.L1.production	1.0469	0.088	11.960	0.000	0.875
ar.L2.production	-0.0523	0.134	-0.391	0.695	-0.314
ar.L3.production	-0.4044	0.089	-4.542	0.000	-0.579

```

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Roots
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=====

```

	Real	Imaginary	Modulus	Frequen
AR.1	0.9446	-0.5767j	1.1068	-0.08
AR.2	0.9446	+0.5767j	1.1068	0.08
AR.3	-2.0186	-0.0000j	2.0186	-0.50

```

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```

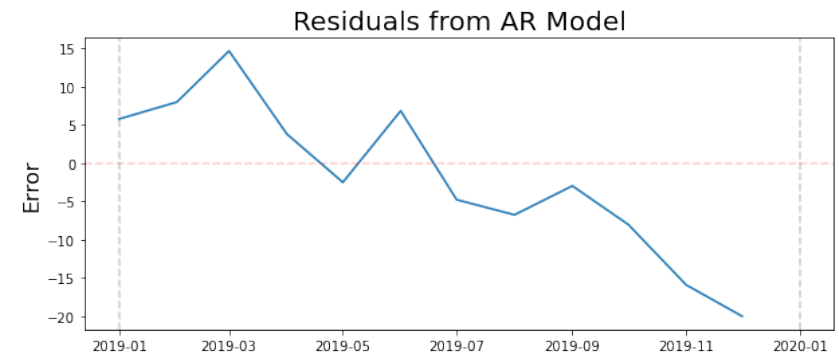
So the AR(3) model is:

$$\hat{y}_t = 103 + 1.04y_{t-1} - 0.05y_{t-2} - 0.40y_{t-3}$$

```

In [16]: plt.figure(figsize=(10,4))
plt.plot(residuals)
plt.title('Residuals from AR Model', fontsize=20)
plt.ylabel('Error', fontsize=16)
plt.axhline(0, color='r', linestyle='--', alpha=0.2)
for year in range(2019,2021):
    plt.axvline(pd.to_datetime(str(year)+'-01-01'), color='k', linestyle='--')

```



```

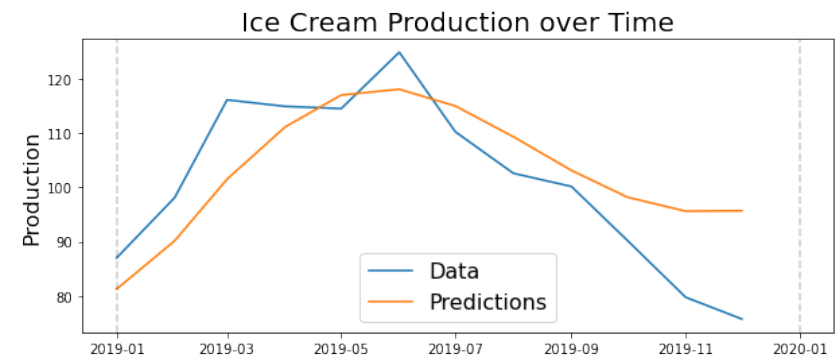
In [17]: plt.figure(figsize=(10,4))

plt.plot(test_data)
plt.plot(predictions)

plt.legend(('Data', 'Predictions'), fontsize=16)

plt.title('Ice Cream Production over Time', fontsize=20)
plt.ylabel('Production', fontsize=16)
for year in range(2019,2021):
    plt.axvline(pd.to_datetime(str(year)+'-01-01'), color='k', linestyle='--')

```



```

In [19]: print('Mean Absolute Percent Error:', round(np.mean(abs(residuals/test_data)), 2))

Mean Absolute Percent Error: 0.0895

```

```

In [20]: print('Root Mean Squared Error:', np.sqrt(np.mean(residuals**2)))

```

```

In [14]: #get prediction start and end dates
pred_start_date = test_data.index[0]
pred_end_date = test_data.index[-1]

```

```

In [15]: #get the predictions and residuals
predictions = model_fit.predict(start=pred_start_date, end=pred_end_date)
residuals = test_data - predictions

```

Root Mean Squared Error: 9.884059832193314

In [ ]: