

Predictive Analytics

Regression and Classification

Lecture 5 : Part 1

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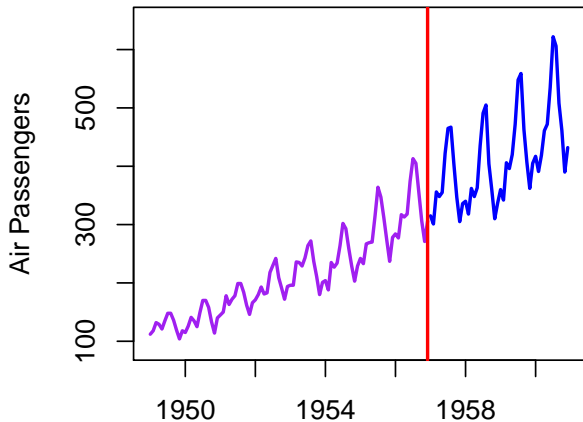
Regression Model for Time Series Data

- ▶ **Time Series** Data is ubiquitous in **Data Science**.
- ▶ **Regression Model** is one of the most commonly used statistical tools for forecasting of **time series data**.
- ▶ Two kinds of forecasting:
 1. Long term forecasting
 - ▶ modeling trend and seasonality as function of time
 2. Short term forecasting
 - ▶ detrend and auto-regression model



Long term forecasting with Trend

- ▶ Throughout we will consider the *AirPassengers* dataset



Long term forecasting with Trend

- ▶ Model the trend of AirPassengers as linear (or quadratic) function of time
- ▶ Suppose y_t is the number of Monthly totals of international airline passengers; $t = 1949$ to 1960.
- ▶ Linear Trend

$$y_t = \beta_0 + \beta_1 t + \epsilon_t$$

Long term forecasting with Trend

- ▶ Linear Trend

$$y_t = \beta_0 + \beta_1 t + \epsilon_t$$

```
> head(data_train)
```

	y	tm
1	112	1949.000
2	118	1949.083
3	132	1949.167
4	129	1949.250
5	121	1949.333
6	135	1949.417

Long term forecasting with Trend

- ▶ Linear Trend: $y_t = \beta_0 + \beta_1 t + \epsilon_t$

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

where $\mathbf{y} = (y_1, y_2, \dots, y_n)^T$;

$$\mathbf{X} = \begin{pmatrix} 1 & t_1 \\ 1 & t_2 \\ \vdots & \vdots \\ 1 & t_n \end{pmatrix}$$

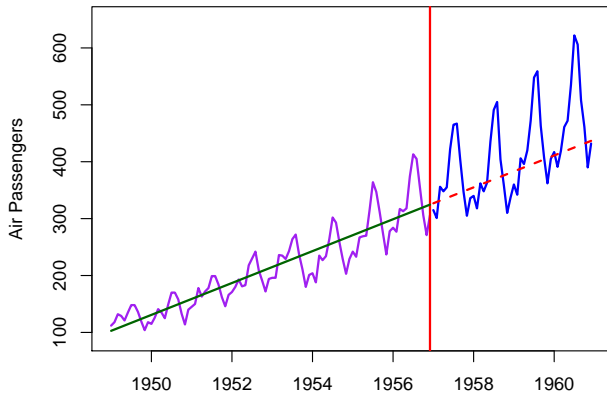
$\boldsymbol{\beta} = (\beta_0, \beta_1)^T$ and $\boldsymbol{\epsilon} = (\epsilon_1, \epsilon_2, \dots, \epsilon_n)^T$

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	213.708	3.150	67.851	0
scale(tm)	65.038	3.166	20.541	0

Adjusted R.Squared = 0.816

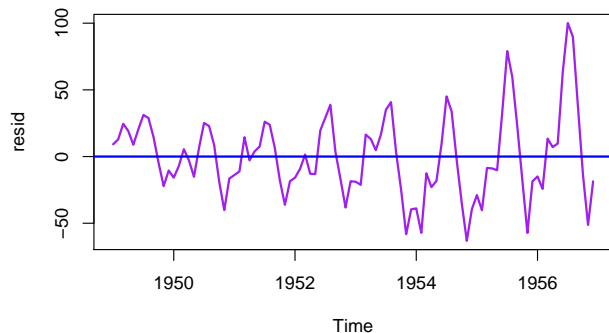


Long term forecasting with Trend



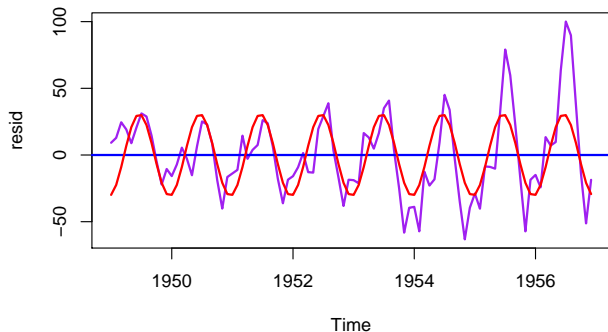
Long term forecasting with Trend

Residual shows seasonality. Now we model seasonality.



Long term forecasting with Trend

- ▶ We model seasonality as: $r_t = \alpha_0 + \alpha_1 \sin(\omega t) + \gamma_1 \cos(\omega t)$,
where $\omega = \frac{2\pi}{12}$, r_t

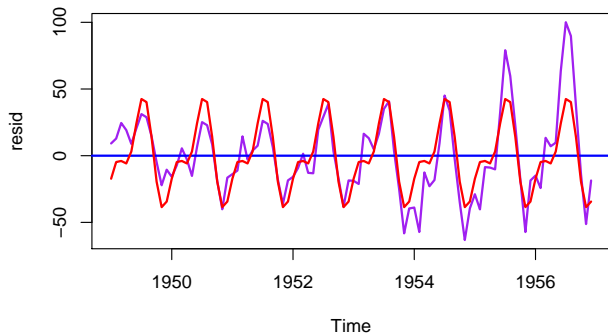


Long term forecasting with Trend

- ▶ We model seasonality as:

$$r_t = \alpha_0 + \alpha_1 \sin(\omega t) + \gamma_1 \cos(\omega t) + \alpha_2 \sin(2\omega t) + \gamma_2 \cos(2\omega t),$$

where $\omega = \frac{2\pi}{12}$

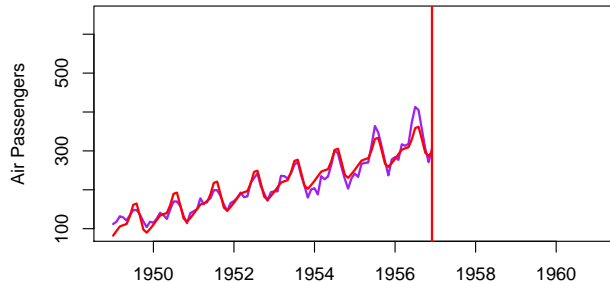


Long term forecasting with Trend & Seasonality

- ▶ We model trend & seasonality as:

$$y_t = \underbrace{\alpha + \beta t}_{\text{trend}} + \underbrace{\alpha_1 \sin(\omega t) + \gamma_1 \cos(\omega t) + \dots}_{\text{seasonality}} + \epsilon_t,$$

where $\omega = \frac{2\pi}{12}$

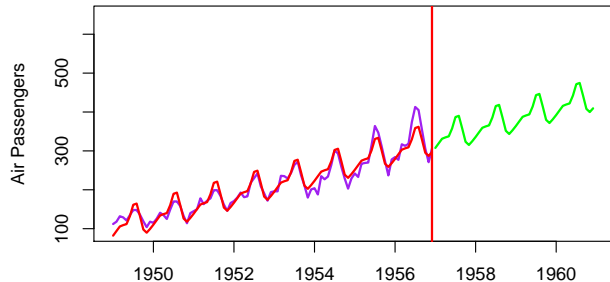


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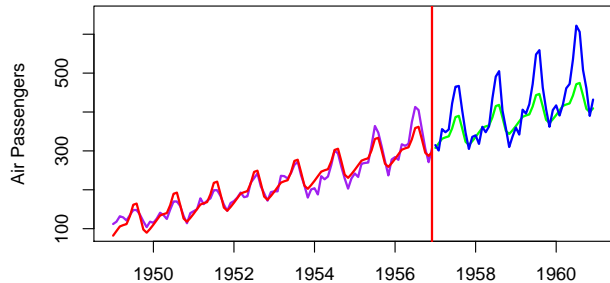


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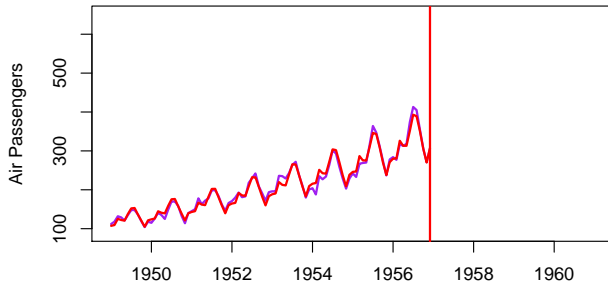


Long term forecasting with Trend & Seasonality

- ▶ Take log transformation on y :

$$\log(y_t) = \underbrace{\alpha + \beta t}_{\text{trend}} + \underbrace{\alpha_1 \sin(\omega t) + \gamma_1 \cos(\omega t) + \dots}_{\text{seasonality}} + \epsilon_t,$$

where $\omega = \frac{2\pi}{12}$

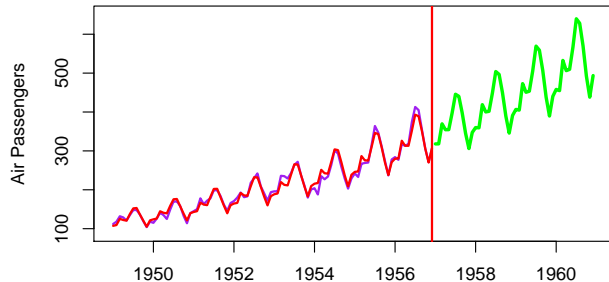


Long term forecasting with Trend & Seasonality

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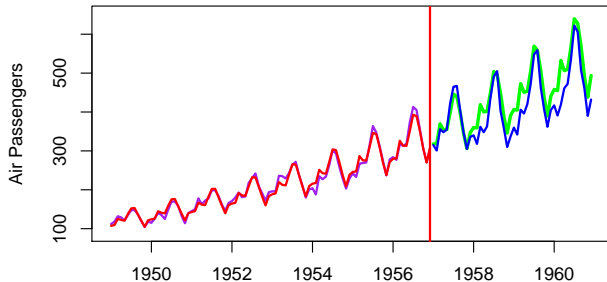


Long term forecasting with Trend & Seasonality

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where $\omega = \frac{2\pi}{12}$



Short term forecasting: Auto-Regressive Model

- ▶ Idea of Auto-Regressive Model
- ▶ Data structure with lag-variables

$$\mathcal{D} = \begin{pmatrix} t_1 & y_1 & NA \\ t_2 & y_2 & y_1 \\ \vdots & \vdots & \vdots \\ t_n & y_n & y_{n-1} \end{pmatrix}$$

	tm	y	y_lag1
1	1949.000	112	NA
2	1949.083	118	112
3	1949.167	132	118
4	1949.250	129	132
5	1949.333	121	129
6	1949.417	135	121



Short term forecasting: Auto-Regressive Model

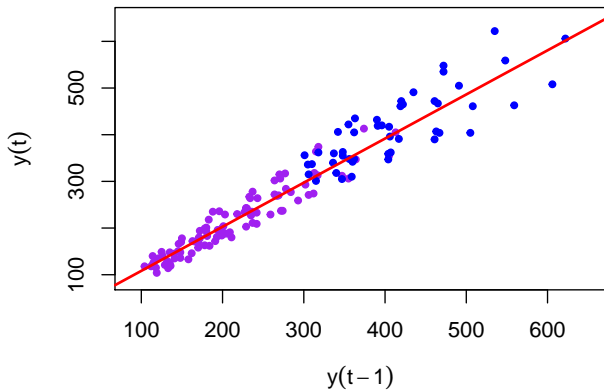
Define the first difference of $y(t)$ in log-scale

$$\delta y(t) = \ln(y(t)) - \ln(y(t-1))$$

	tm	y	y_lag1	dy	dy_lag1
1	1949.000	112	NA	NA	NA
2	1949.083	118	112	0.052	NA
3	1949.167	132	118	0.112	0.052
4	1949.250	129	132	-0.023	0.112
5	1949.333	121	129	-0.064	-0.023
6	1949.417	135	121	0.109	-0.064

Short term forecasting: Auto-Regressive Model

- ▶ Idea of Auto-Regressive Model



Short term forecasting: Auto-Regressive Model

- ▶ Auto-Regressive Model
- ▶ Model $y_t = \beta_0 + \beta_1 y_{t-1} + \epsilon_t$

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	13.758	7.477	1.840	0.069
y_lag1	0.945	0.033	28.354	0.000

studentized Breusch-Pagan test

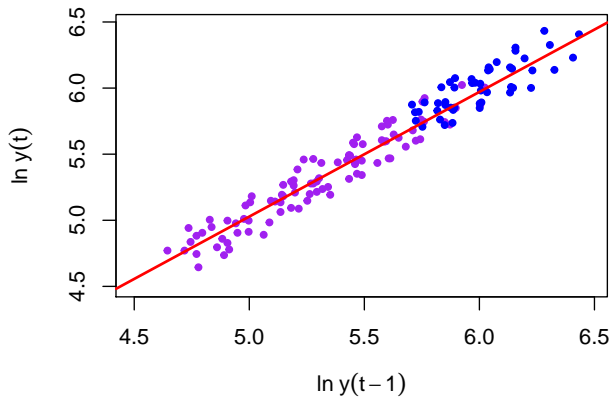
data: fit_ar1

BP = 20.289, df = 1, p-value = 6.658e-06



Short term forecasting: Auto-Regressive Model

- ▶ Taking log transformation



Short term forecasting: Auto-Regressive Model

- ▶ Auto-Regressive Model
- ▶ Model $\log(y_t) = \beta_0 + \beta_1 \log(y_{t-1}) + \epsilon_t$

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.312	0.168	1.853	0.067
log(y_lag1)	0.943	0.032	29.770	0.000

studentized Breusch-Pagan test

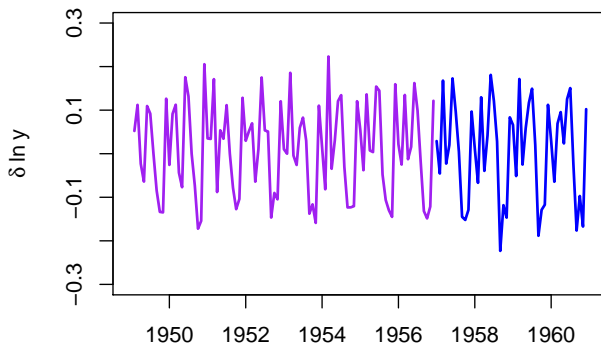
data: fit_ar1

BP = 0.051569, df = 1, p-value = 0.8204



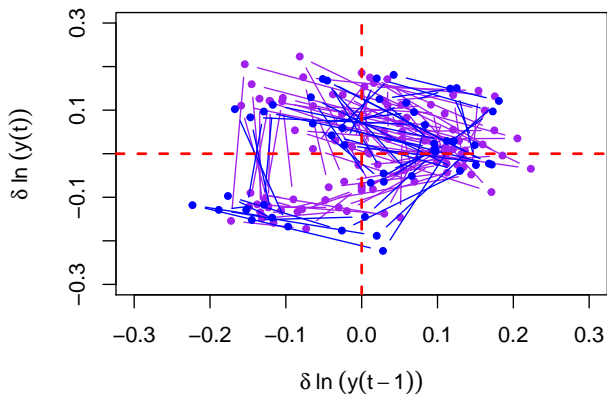
Short term forecasting: Auto-Regressive Model

- ▶ Idea of Auto-Regressive Model

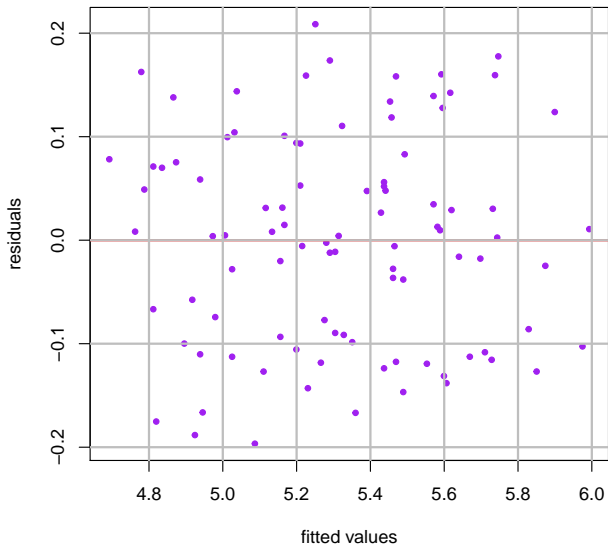


Short term forecasting: Auto-Regressive Model

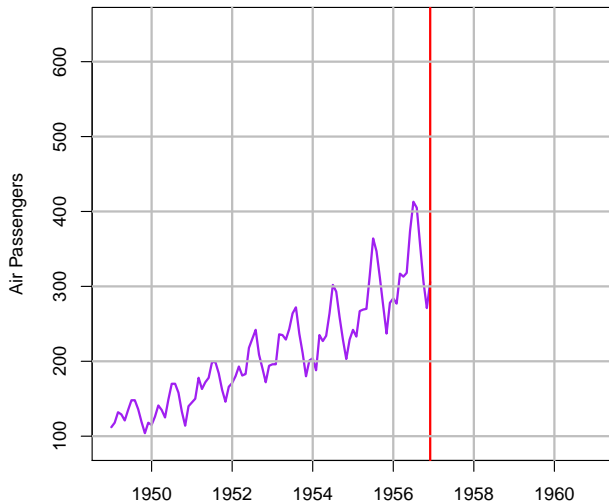
- Circular topology: **Topological Data Analysis**



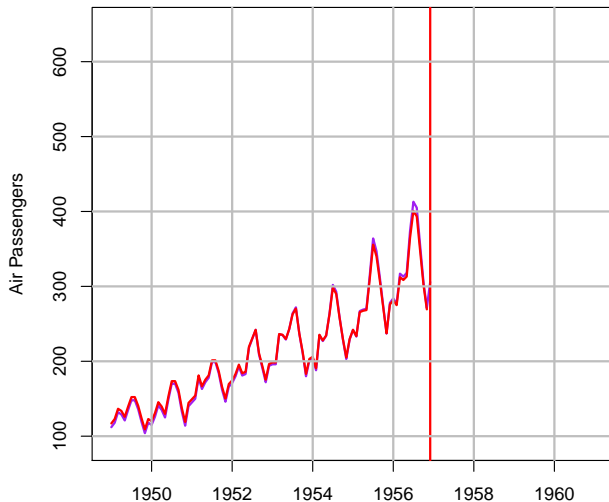
Short term forecasting: Auto-Regressive Model



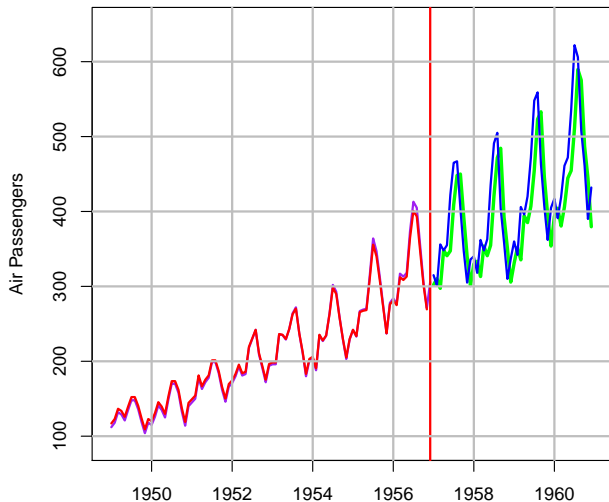
Short term forecasting: Auto-Regressive Model



Short term forecasting: Auto-Regressive Model



Short term forecasting: Auto-Regressive Model



Other Time Series Models

- ▶ ARIMA or GARCH model
- ▶ State-Space Dynamic model
- ▶ Spectral Analysis model etc.
- ▶ Most of these models are non-linear in parameter. Hence we cannot model them easily using regression model setup!!

In the next part ...

- ▶ Next we will discuss another nice application of Regression mode, known as the Granger Causality model

cm_i

Thank You

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