

# Time Series

Forecasting the Future

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# What is Time Series?

- Traditional machine learning data is assumed to be Independent & Identically Distributed
  - **Independent** (points have no information about each other's class)
  - **Identically distributed** (come from the same distribution)

# Independent Data

Color	Mass	PPAP
red	11	pen
green	45	apple
red	53	apple
yellow	0	pen
blue	2	pen
green	422	pineapple
yellow	555	pineapple
blue	7	pen

## Discovering patterns:

- Color = "red"  $\Rightarrow$  Mass < 100
- PPAP = "pineapple"  $\Rightarrow$  Color  $\neq$  "blue"
- Color = "blue"  $\Rightarrow$  PPAP = "pen"

Color	Mass	PPAP
green	45	apple
blue	2	pen
green	422	pineapple
blue	7	pen
yellow	0	pen
yellow	9	pineapple
red	555	apple
red	11	pen

## Patterns still hold when rows re-arranged:

- Color = "red"  $\Rightarrow$  Mass < 100
- PPAP = "pineapple"  $\Rightarrow$  Color  $\neq$  "blue"
- Color = "blue"  $\Rightarrow$  PPAP = "pen"

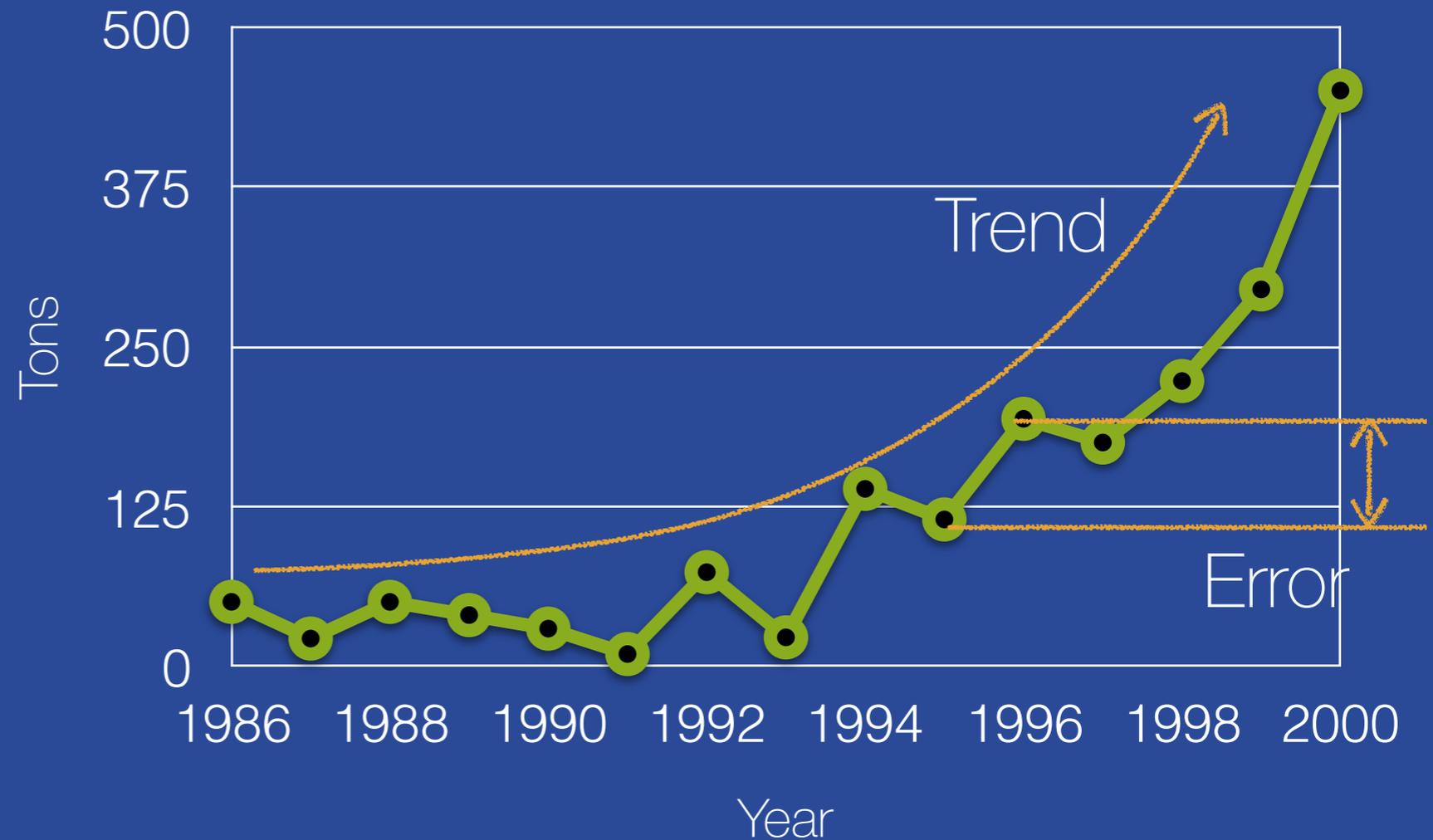
# What is Time Series?

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  - **Independent** (points have no information about each other's class)
  - **Identically distributed** (come from the same distribution)
- But what if you want to predict just the next value in a sequence?
  - 1, 2, 3, 2, ???
  - No longer independent, not identically distributed!

# Dependent Data

Year	Pineapple
1986	50.74
1987	22.03
1988	50.69
1989	40.38
1990	29.80
1991	9.90
1992	73.93
1993	22.95
1994	139.09
1995	115.17
1996	193.88
1997	175.31
1998	223.41
1999	295.03
2000	450.53

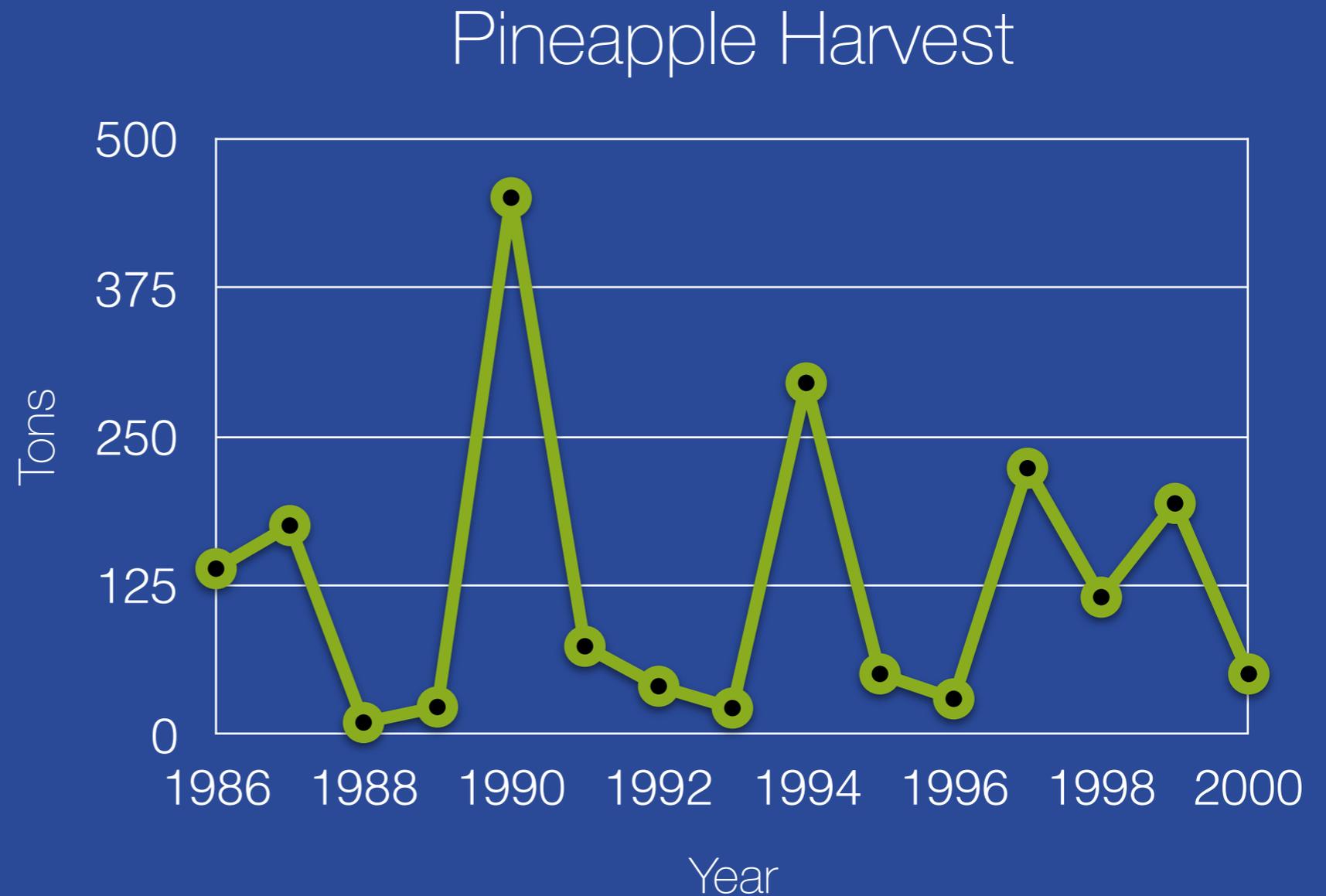
## Pineapple Harvest



# Dependent Data



Year	Pineapple
1986	139.09
1987	175.31
1988	9.91
1989	22.95
1990	450.53
1991	73.93
1992	40.38
1993	22.03
1994	295.03
1995	50.74
1996	29.8
1997	223.41
1998	115.17
1999	193.88
2000	50.69



**Rearranging Disrupts Patterns**

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  - 1, 2, 3, 2, ???
  - No longer independent, not identically distributed!
  - This also changes how we evaluate!

# Random Train / Test Split

Train

Test

plasma glucose	bmi	diabetes pedigree	age	diabetes
148	33.6	0.627	50	TRUE
85	26.6	0.351		FALSE
183	23.3	0.672		TRUE
89	28.1	0.167		FALSE
137	43.1	2.288	33	TRUE
116	25.6	0.201	30	FALSE
78	31	0.248	26	TRUE
115	35.3	0.134	29	FALSE
197	30.5	0.158	53	TRUE



# Linear Train / Test Split

**Train**

**Test**

Year	Pineapple
1986	50.74
1987	22.03
1988	50.69
1989	40.38
1990	29.80
1991	9.90
1992	73.93
1993	22.95
1994	139.09
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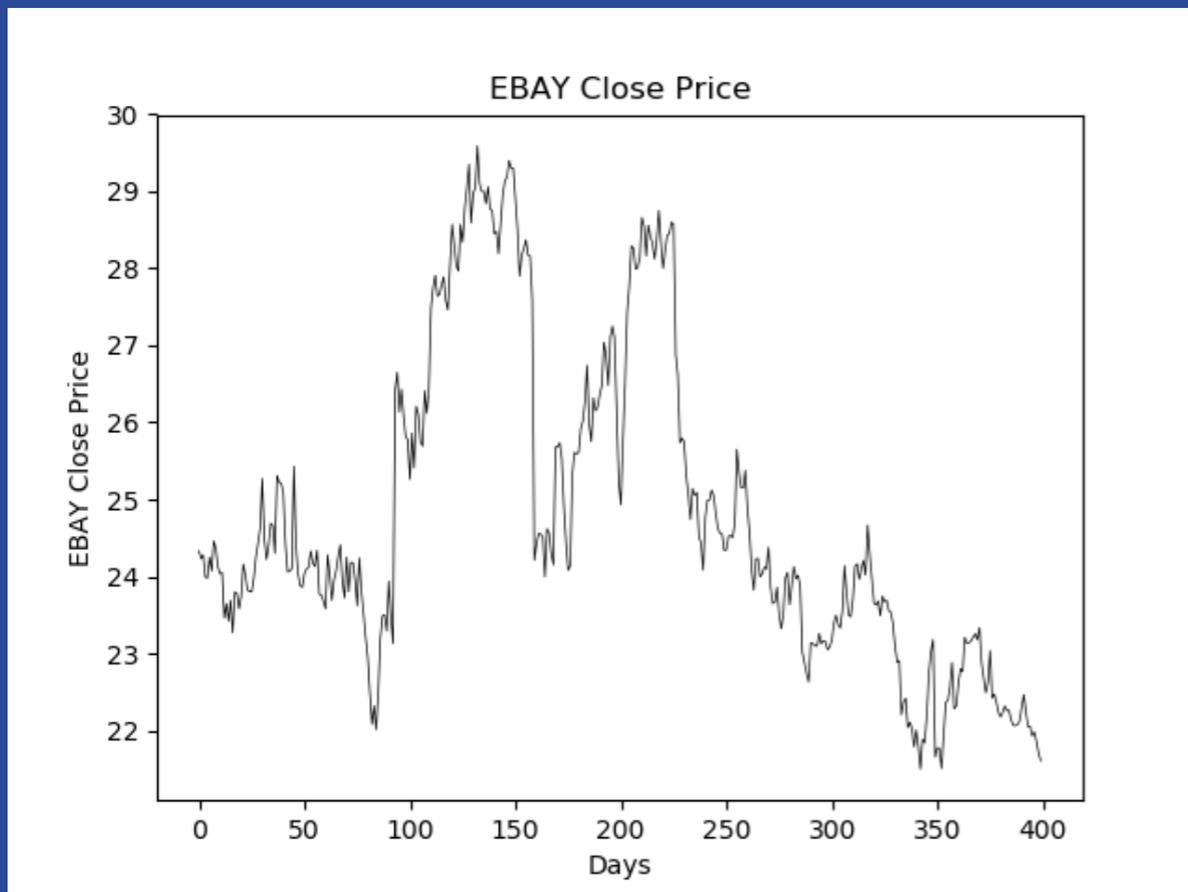
**Forecast** (indicated by a downward arrow pointing to the 1999 row)

**COMPARE** (indicated by a horizontal arrow pointing from the 1999 row to the right)

# Exponential Smoothing

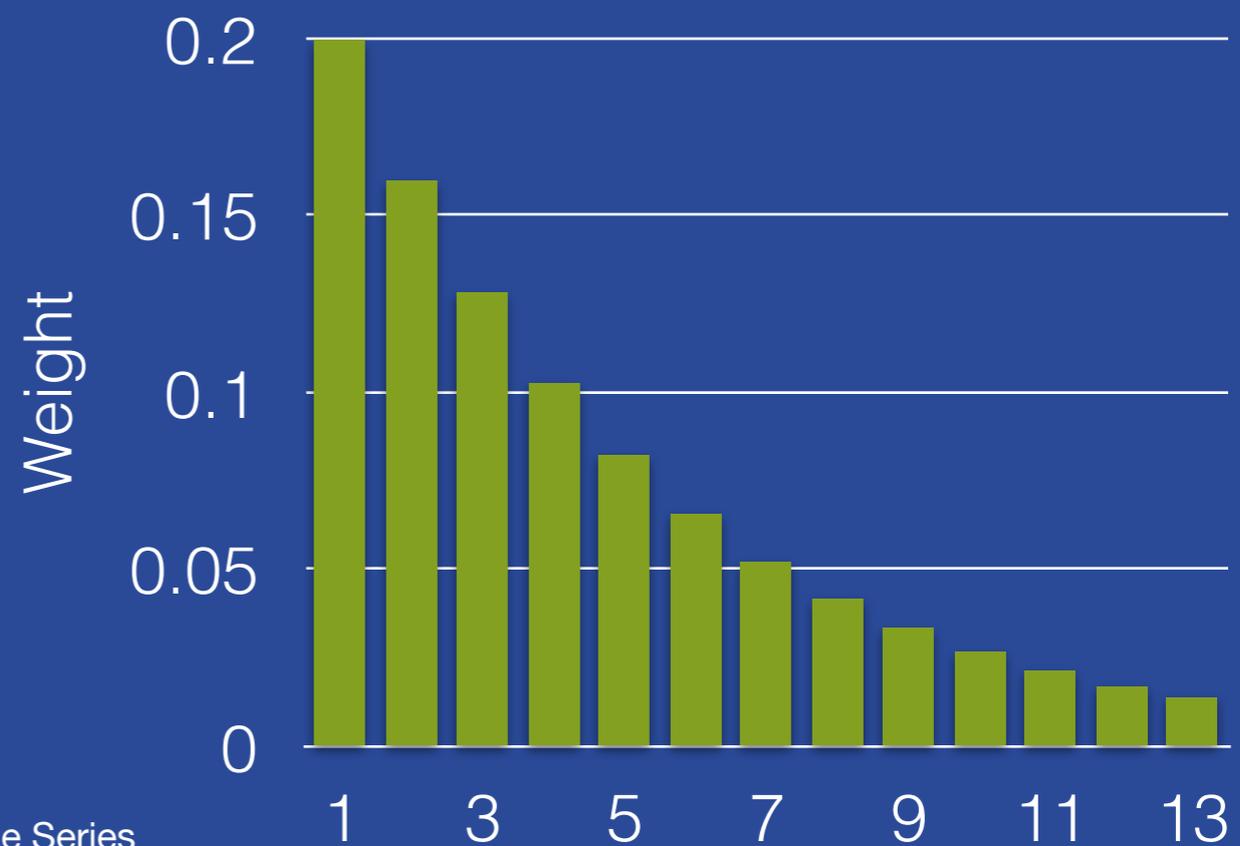
**Idea:**

Each new value in the series depends on all previous values with a decaying weight



For training values  $x_t$   
Smoothing Factor  $0 < \alpha < 1$   
Predicted values  $s_t$

$$s_t = \alpha \cdot x_t + (1 - \alpha) \cdot s_{t-1}$$



# Smoothing Factor

$$s_t = \alpha \cdot x_t + (1 - \alpha) \cdot s_{t-1}$$

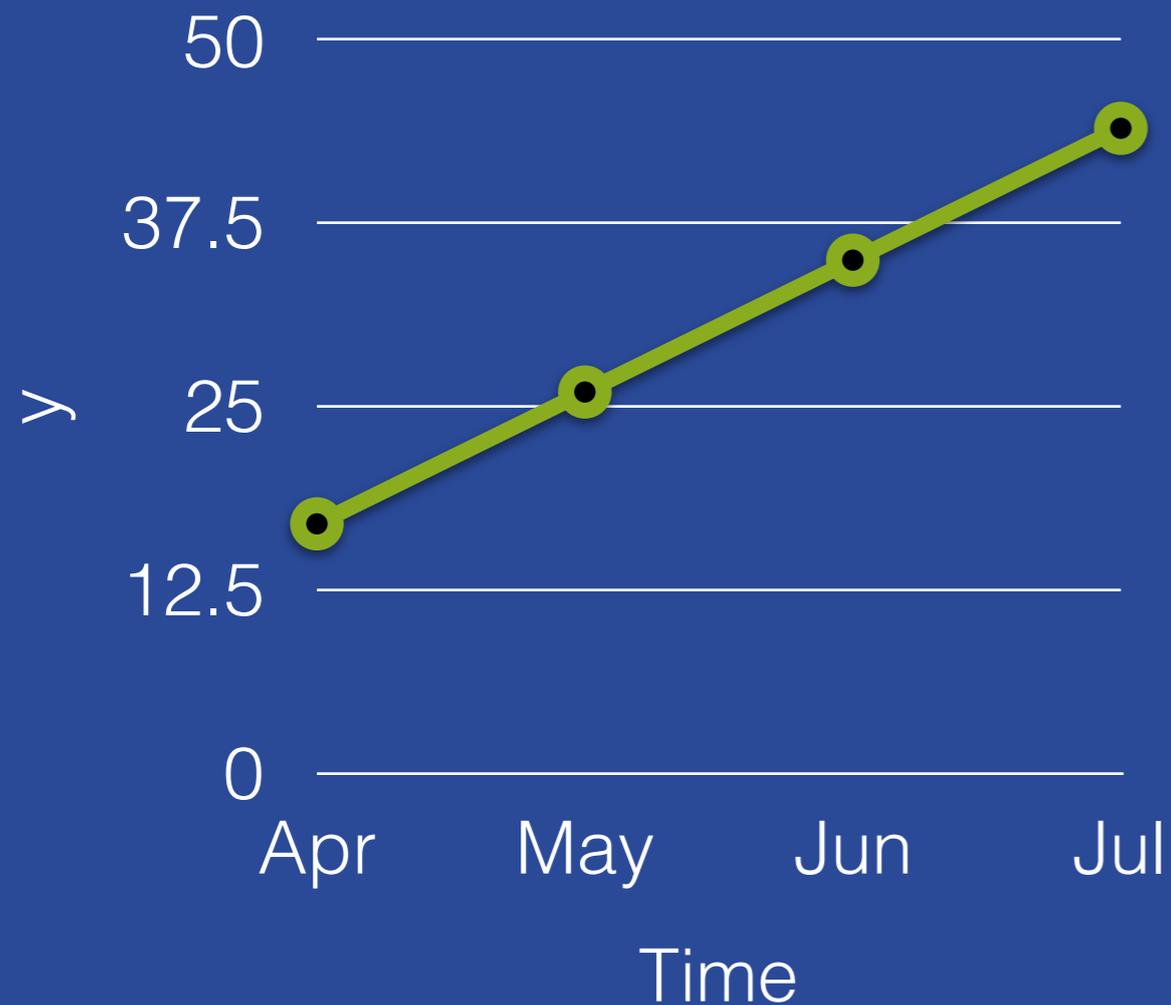
- $\alpha \rightarrow 0$ 
  - Series relies more heavily on past values
- $\alpha \rightarrow 1$ 
  - Series relies more heavily on current value
- $\alpha = 1$ 
  - Series is the current value

**Problem:** Real-world data is more complicated than this...

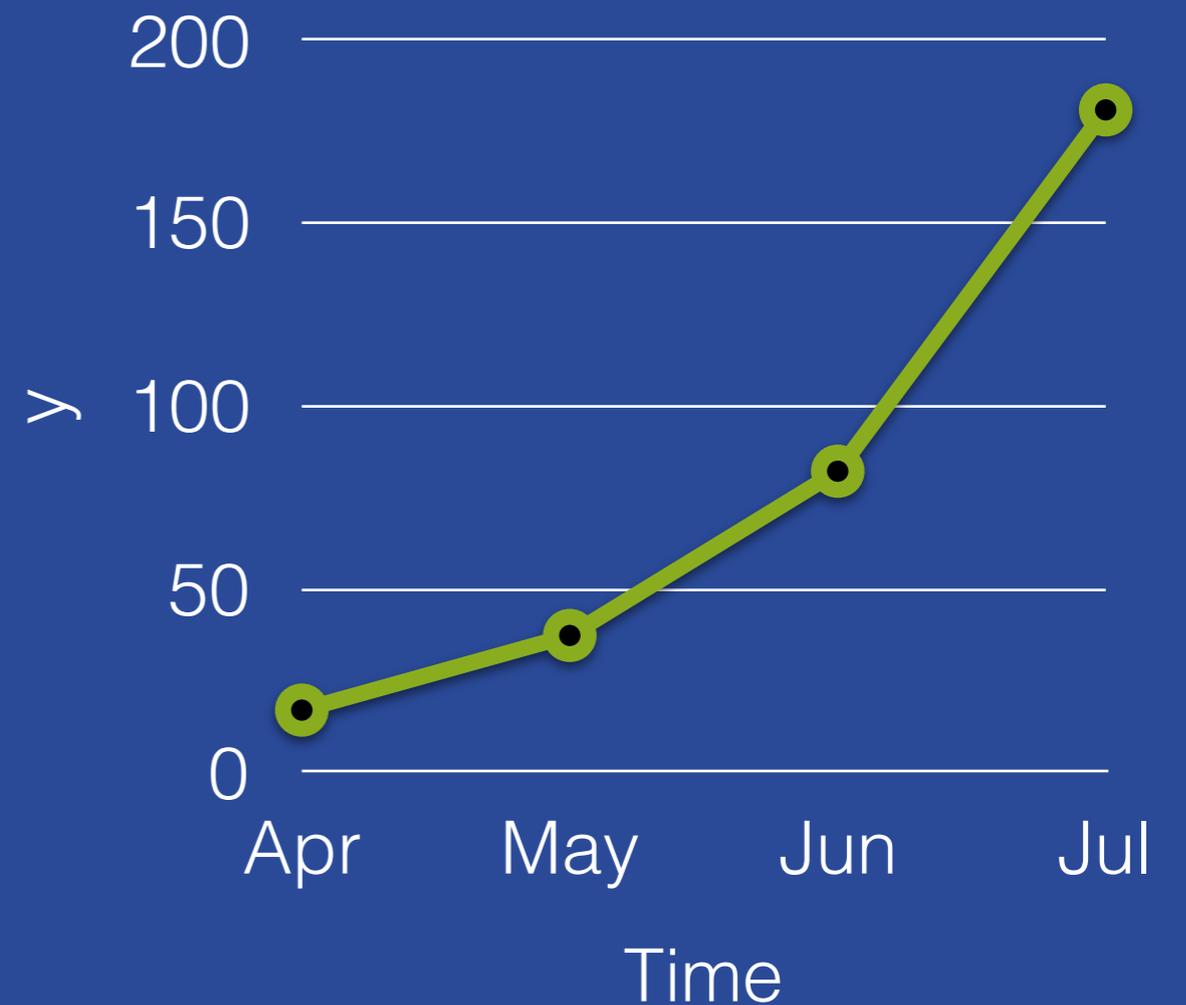
# Trend

**Trend:** A persistent long-term pattern

### Additive



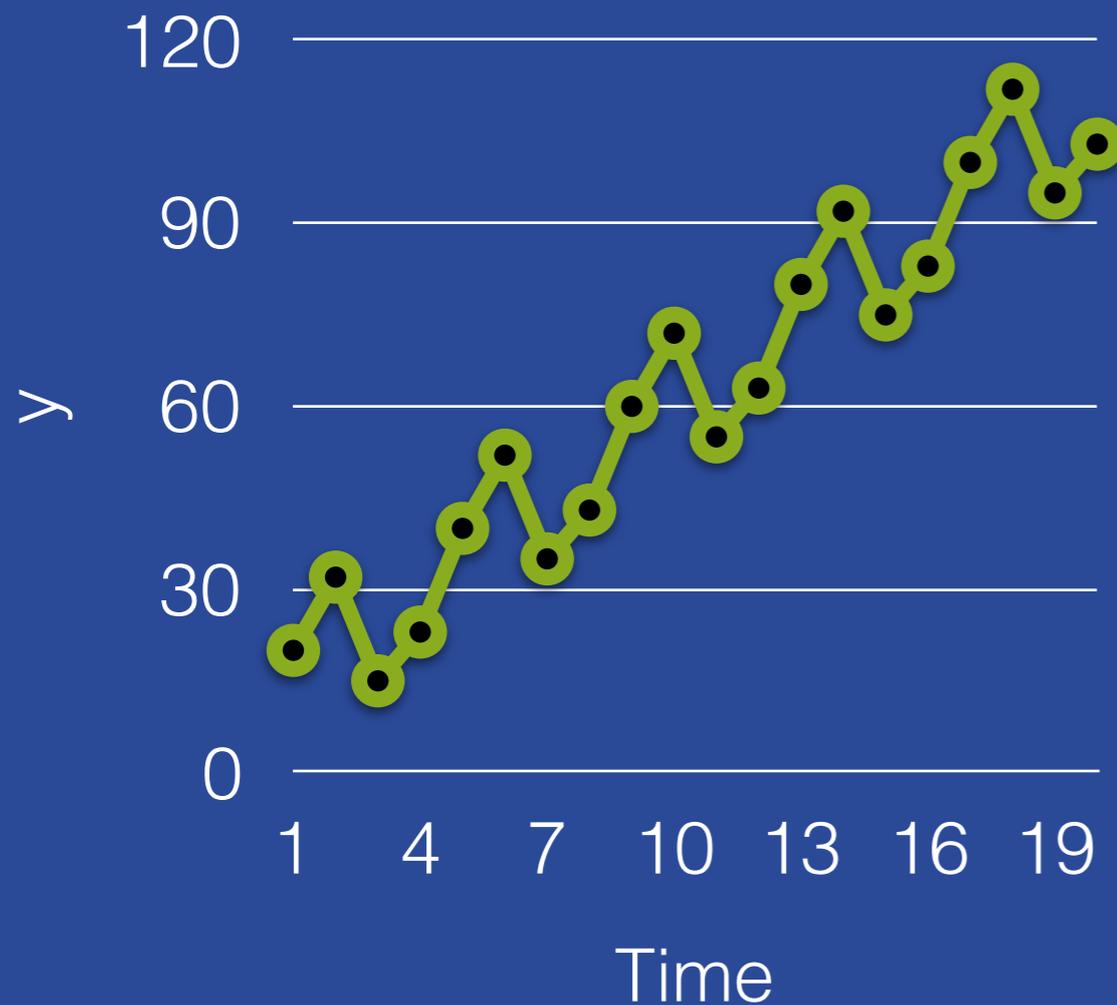
### Multiplicative



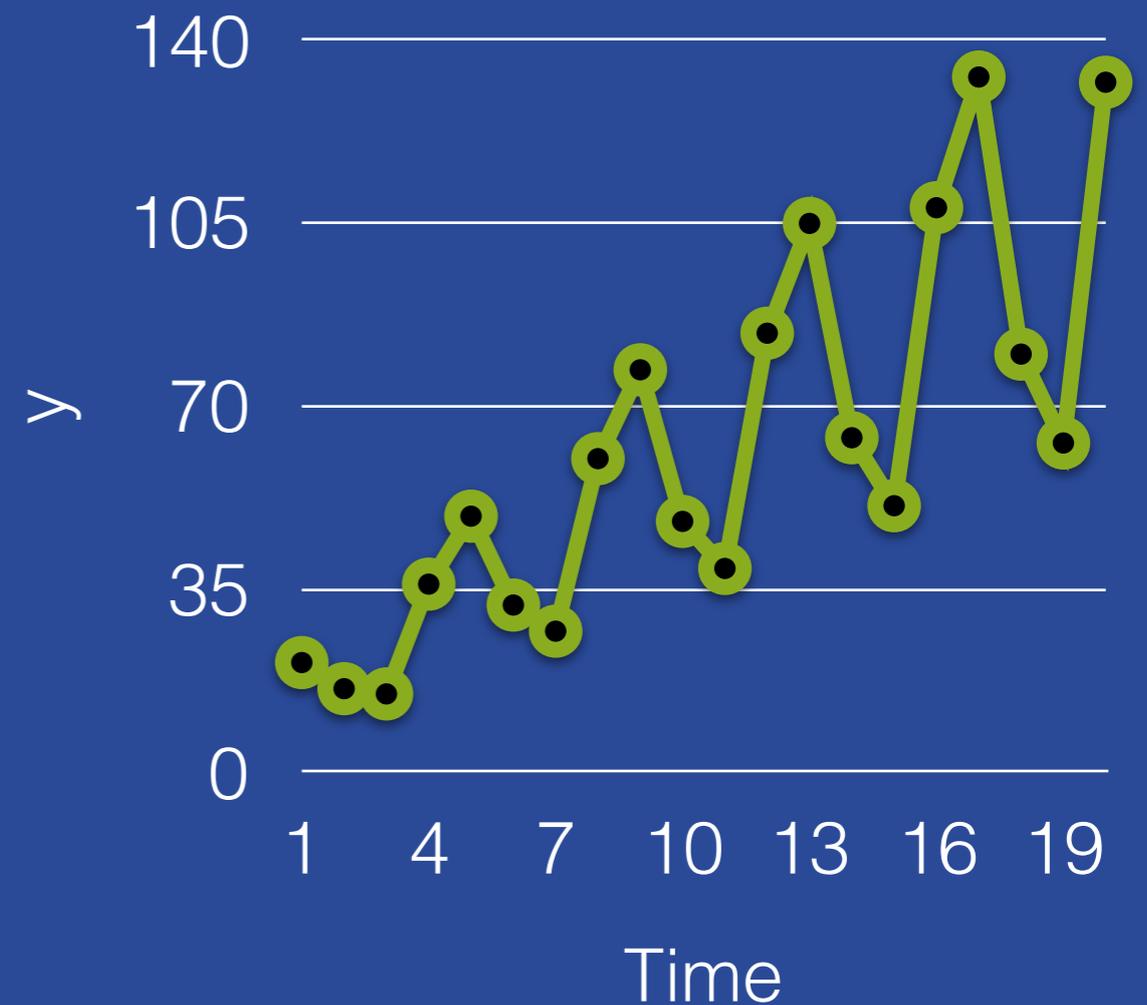
# Seasonality

**Seasonality:** A recurring shorter-term pattern

## Additive

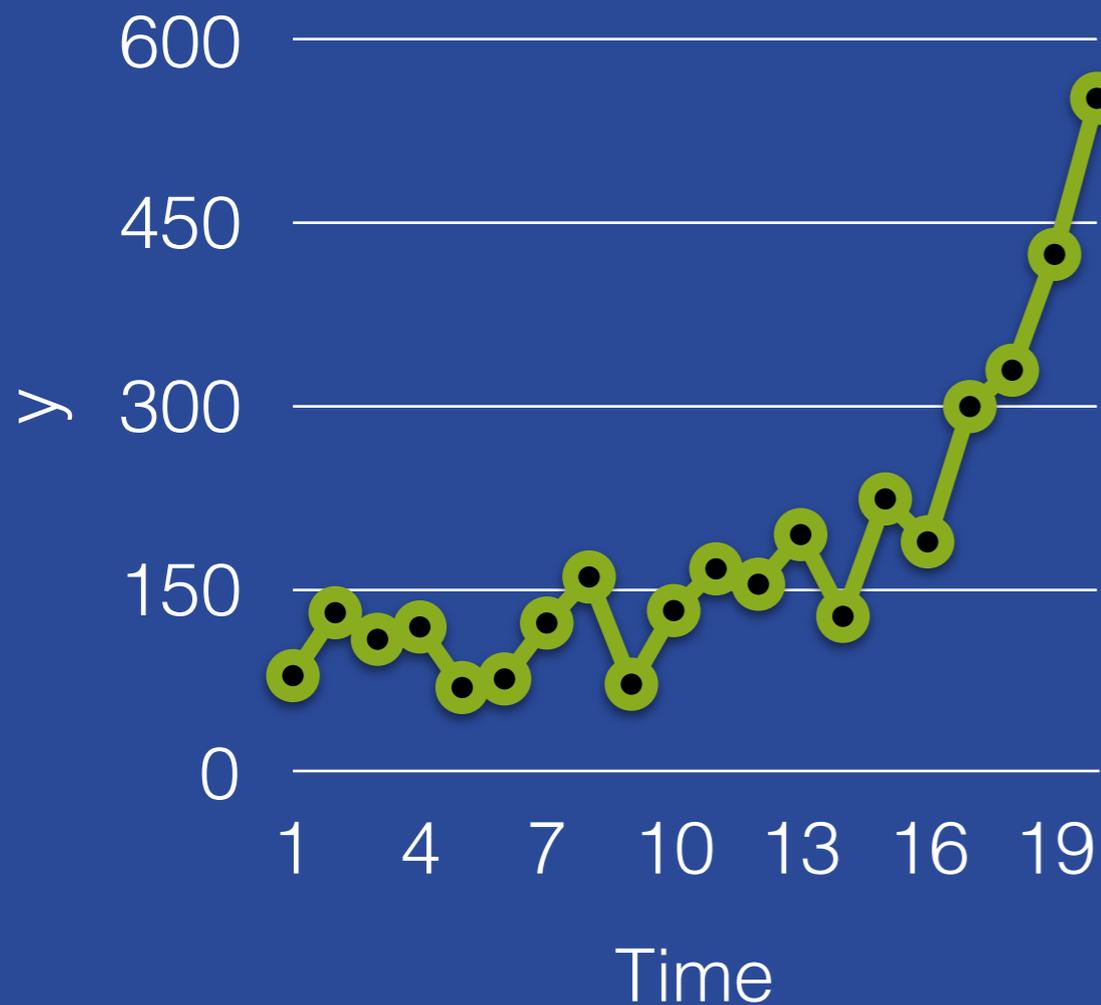


## Multiplicative

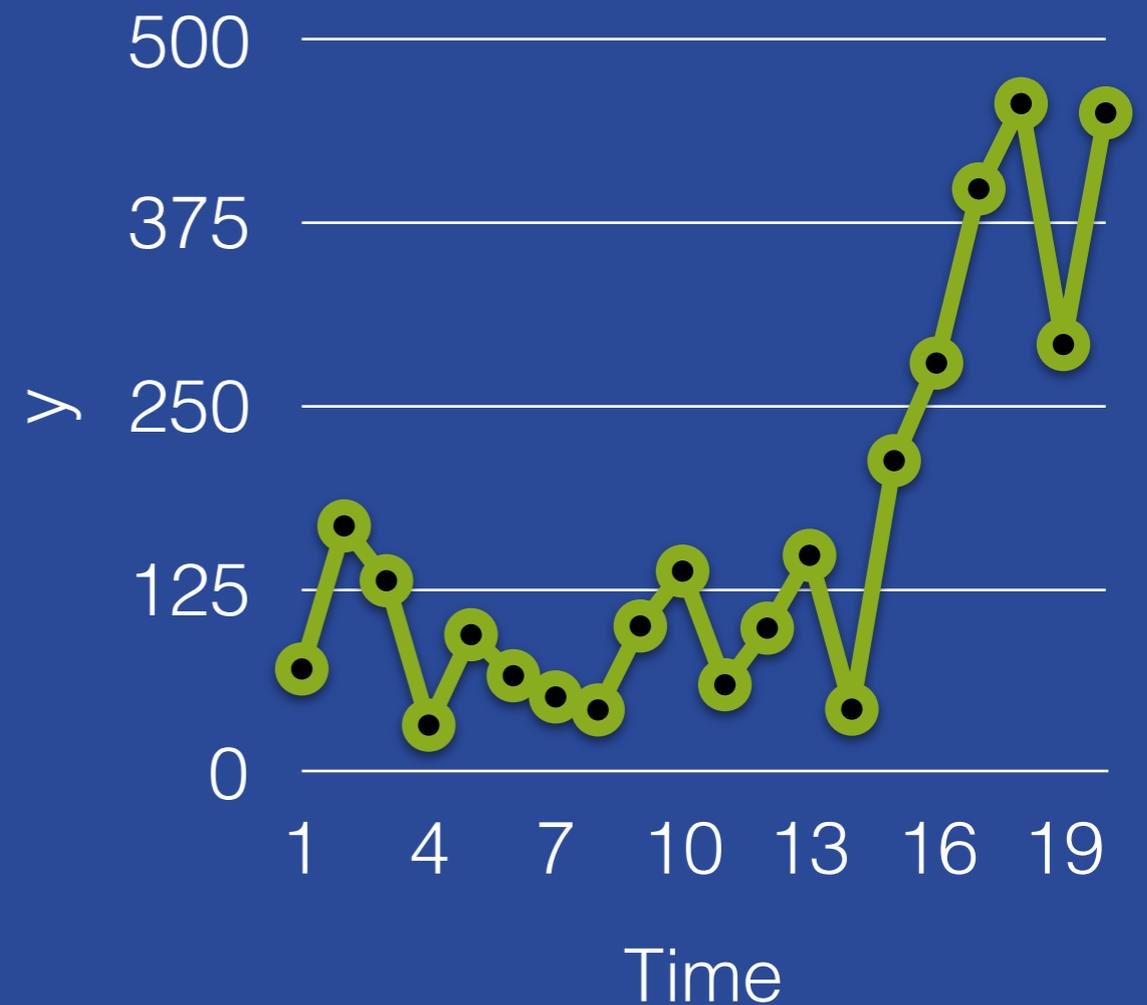


**Error:** Cumulative error from the smoothing

## Additive

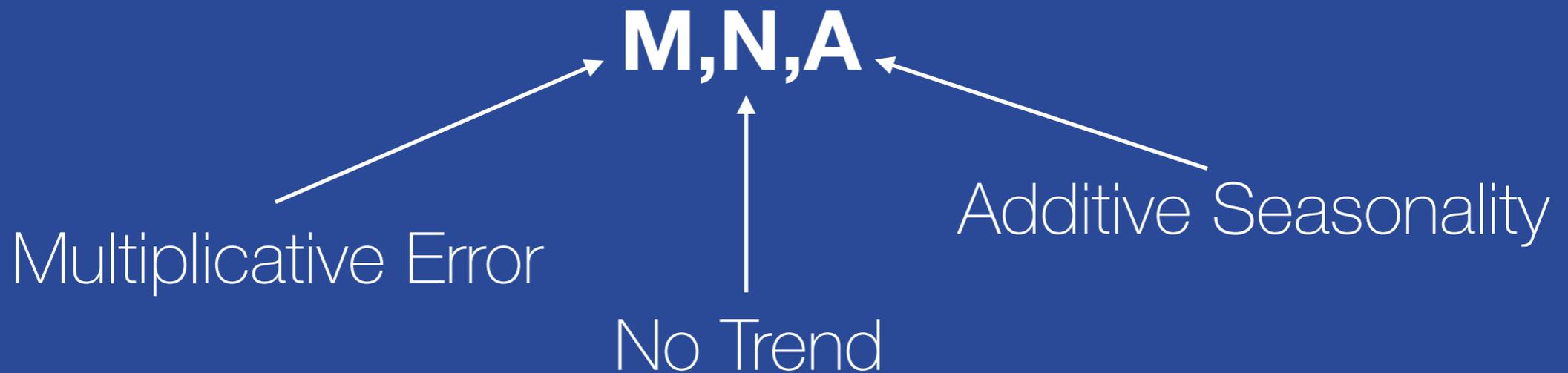


## Multiplicative



# Time Series Model Matrix

These can all be modeled with time series as well!



	None		Additive		Multiplicative	
None	A,N,N	M,N,N	A,N,A	M,N,A	A,N,M	M,N,M
Additive	A,A,N	M,A,N	A,A,A	M,A,A	A,A,M	M,A,M
Additive + Damped	A,Ad,N	M,Ad,N	A,Ad,A	M,Ad,A	A,Ad,M	M,Ad,M
Multiplicative	A,M,N	M,M,N	A,M,A	M,M,A	A,M,M	M,M,M
Multiplicative + Damped	A,Md,N	M,Md,N	A,Md,A	M,Md,A	A,Md,M	M,Md,M

- Question: Which one works best?

# Time Series Forecasts

Use the data from the past to predict the future



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# Time Series Demo #1

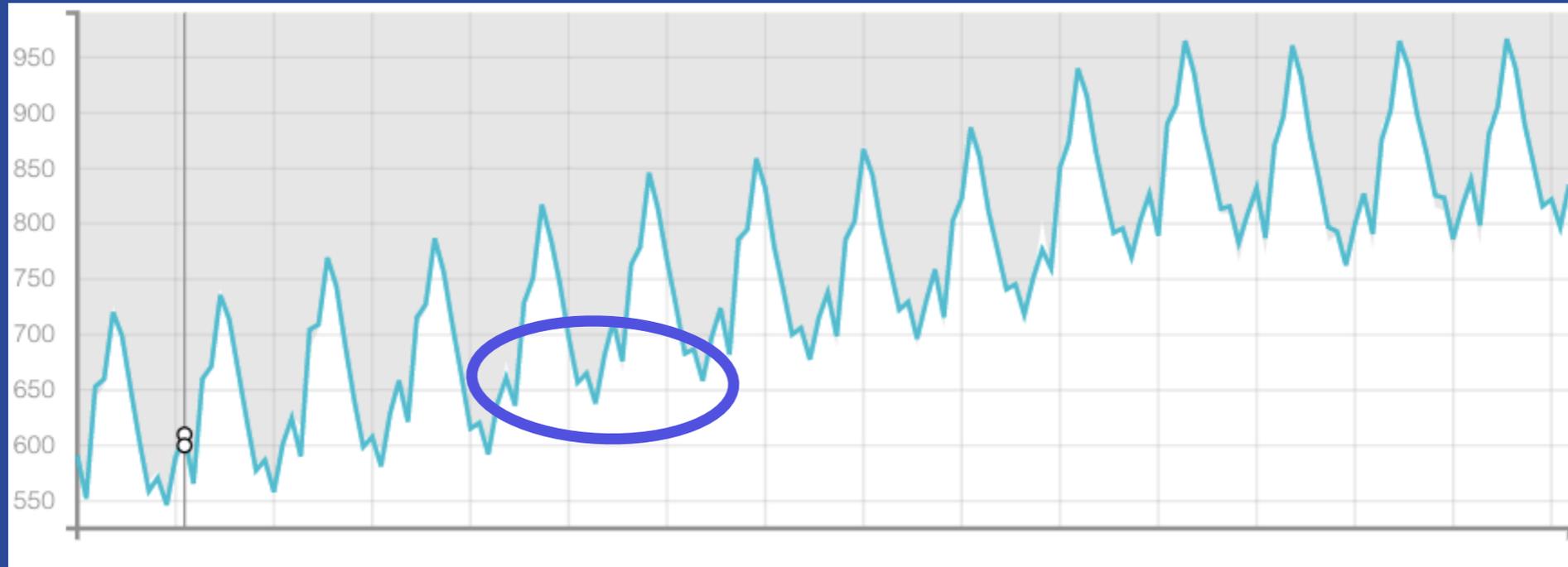
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# Your Turn!

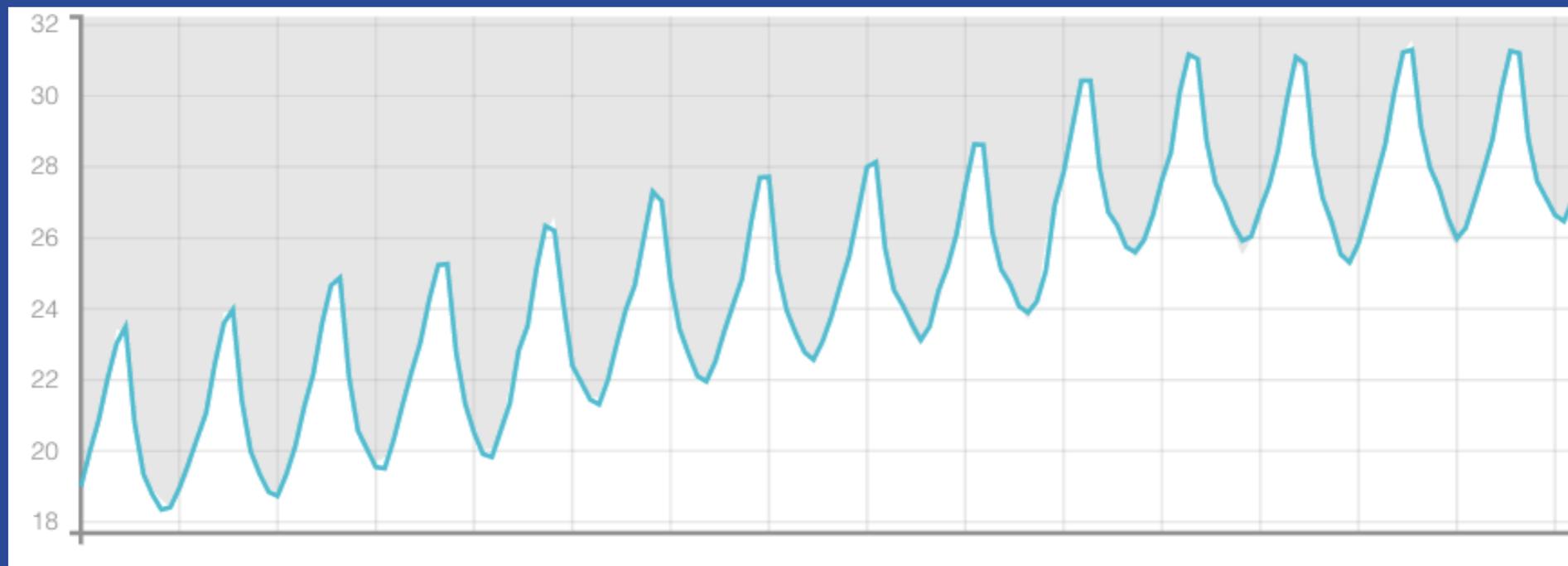


- Upload the Milk Production Source
- Create a Dataset and a 1-click Time Series
- Forecast the monthly milk production for 50 months

# Calendar Correction



- Time Series data can show variations due to aggregation
- For example: “pounds/month” produced
- Transform:  $\text{pounds/month} \div \text{days/month} = \text{pounds/day}$



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# Calendar Correction

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# Multi-Variate TimeSeries

- We built a Time Series that predicted two objectives - but this is not multi-variate time series.
- A "convenience" feature. Results are identical to fitting separate individual time series models
- Planned for a future release!



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