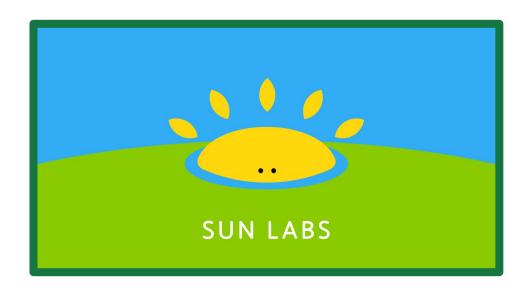
Single and multiple step forecasting of solar power production: applying and evaluating potential models.

**Process data** 

Machine learning

Start-up

#### Sun Labs



Data
visualization
and
real-time
logging for
solar cell
facilities

# Primary research question

Create a solar power forecasting model based on Sun Labs collected data.

Can exogenous variables increase accuracy of the models?

# Sala Facility



Photo from Solel i Sala och Heby

Installed max power: 47 kW

Yearly energy production: 40 MWh

#### **Data Limitation**

One year

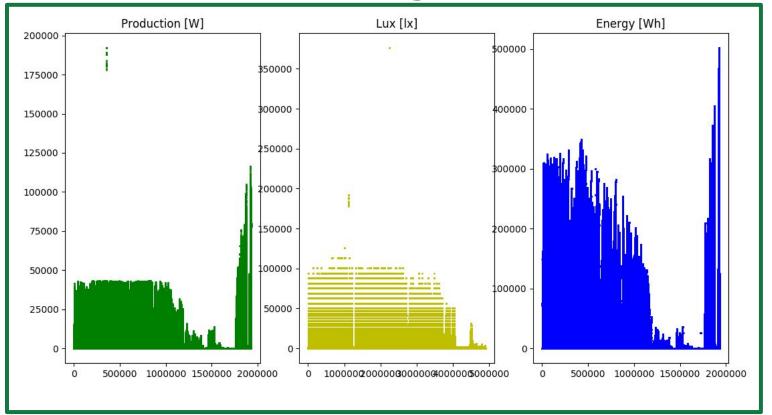
Six months

Three months

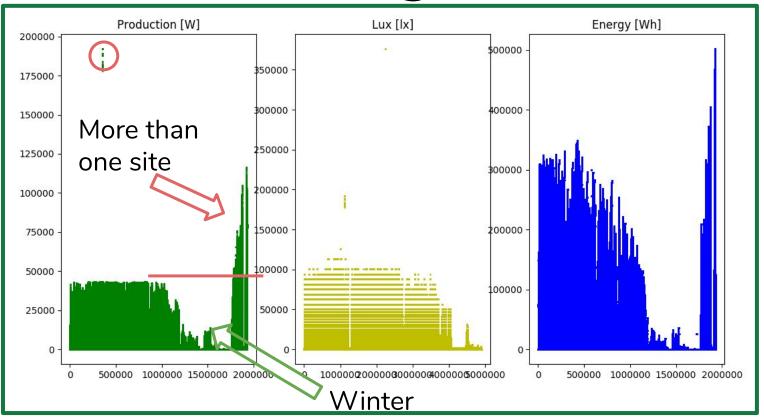
1 month

July, 28 days

# Ex: Data cleaning



# Ex: Data cleaning



# Data Limitation: exogenous predictors

Meteorological conditions

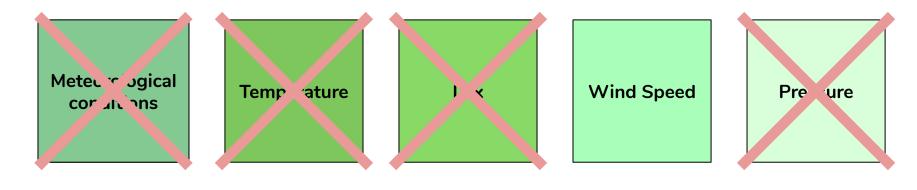
**Temperature** 

Lux

Wind Speed

Pressure

# Data Limitation: exogenous predictors



#### Model choice

1

Linear model: ARIMA and ARIMAX

1

Linear model: ARIMA and ARIMAX -> single step forecast

#### Model choice

1

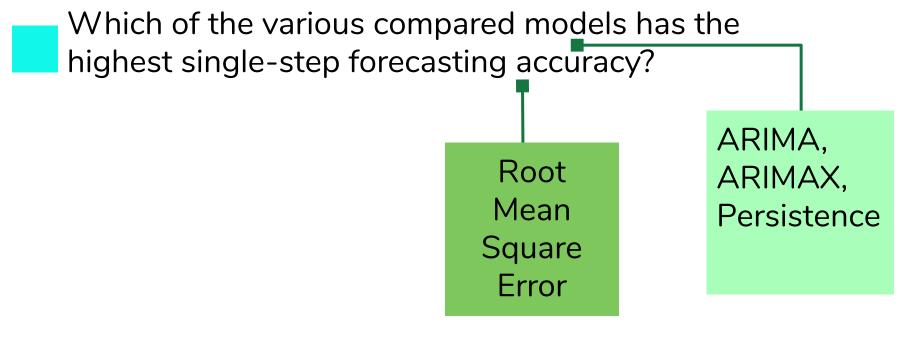
Linear model: ARIMA and

ARIMAX ->

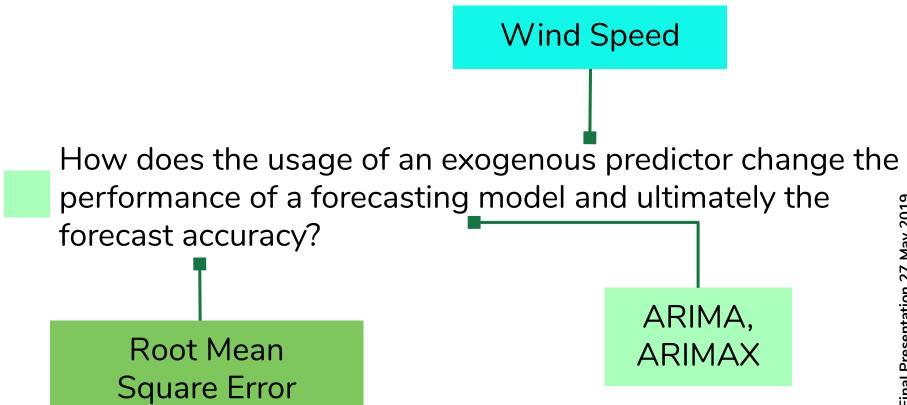
single step forecast

Nonlinear model:
Gaussian process ->
multiple step forecast

- Which of the various compared models has the highest single-step forecasting accuracy?
- How does the usage of an exogenous predictor change the performance of a forecasting model and ultimately the forecast accuracy?
- Which of the two compared models has the highest multiple step forecasting accuracy?



Presentation 27 May 2



Gaussian process, persistence

Root Mean Square Error

Which of the two compared models has the highest

multiple step forecasting accuracy?

Single step implementation

Persistence

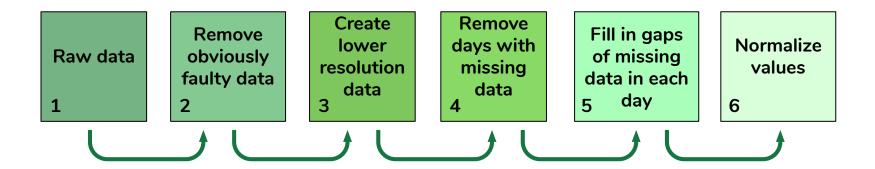
**ARIMA** 

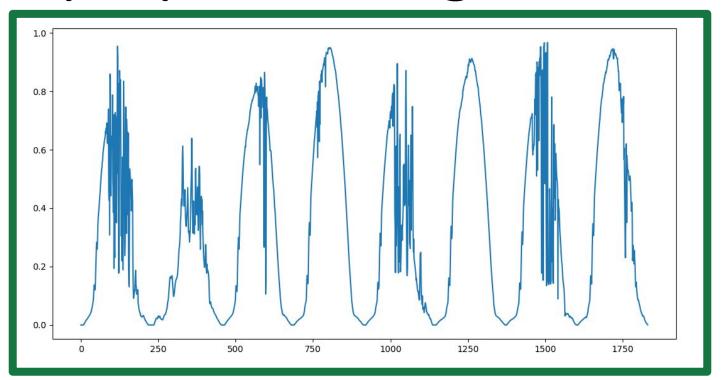
**ARIMAX** 

Multiple step implementation

Persistence

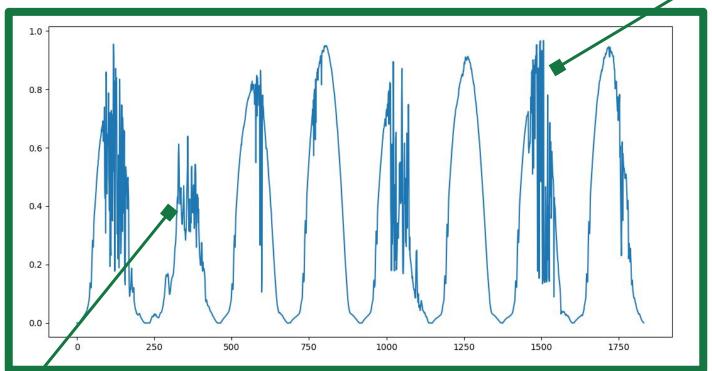
Gaussian process





Example 8 days of July

Cloudiness



"Rainy day"

Example 8 days of July

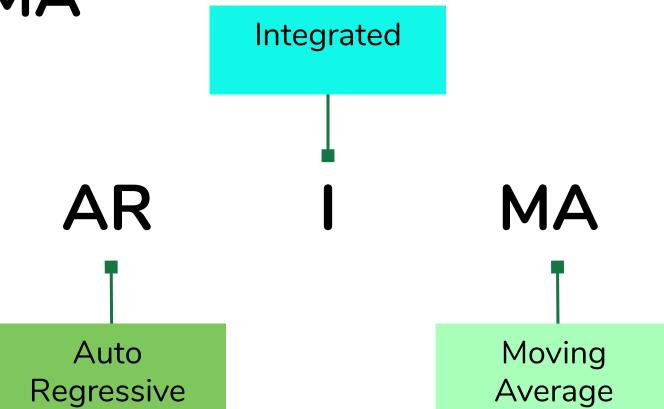
#### Persistence

Forecast value the same as present value

Forecast value the same as present value

$$\hat{y}_t = y_{t-1},$$

## **ARIMA**



### **ARIMA**

#### ARIMA(p,d,q)

$$y'_{t} = c + \varphi_{1}y'_{t-1} + \dots + \varphi_{p}y'_{t-p} + \theta_{1}\varepsilon_{t-1} + \dots + \theta_{q}\varepsilon_{t-q} + \varepsilon_{t} ,$$

p: lags of earlier values

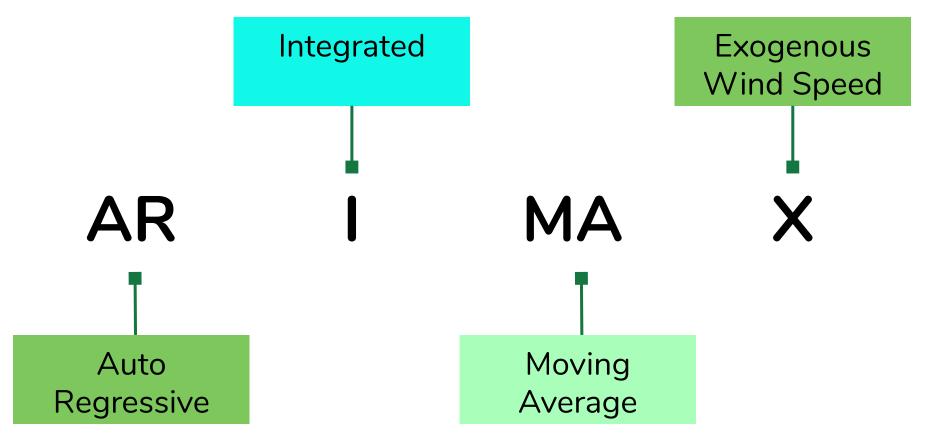
AR

d: order of differencing of y'

linear combination of q lags of forecasted errors.

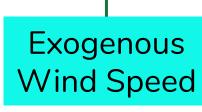
MA

#### **ARIMAX**



#### **ARIMAX**

$$y'_{t} = bx_{t} + \varphi_{1}y'_{t-1} + \dots + \varphi_{p}y'_{t-p} + \theta_{1}\varepsilon_{t-1} + \dots + \theta_{q}\varepsilon_{t-q} + \varepsilon_{t},$$



# Gaussian process

A Gaussian process is a finite collection of random variables, which have a joint distribution.

# Gaussian process

A Gaussian process is a finite collection of random variables, which have a joint distribution.

Different kernel characteristics (assumptions) decide forecast function form

# Final Presentation 27 May 2019

# Gaussian process

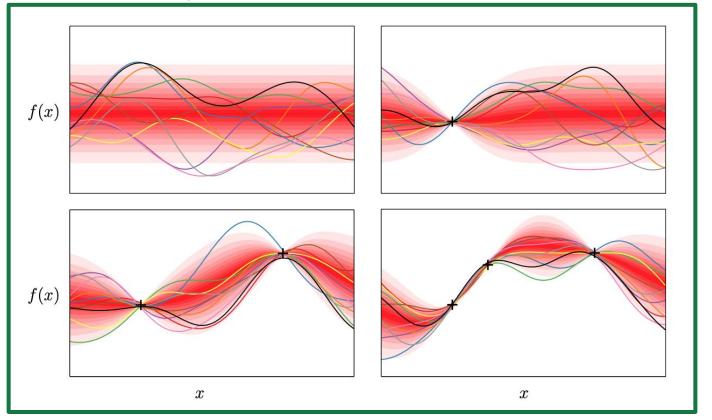


Figure from (Duvenaud, 2014)

**Forecast** 

Actual value

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N} (\hat{y}_n - y_n)^2}{N}}$$

# Single step model implementations

Compared models:
Persistence,
ARIMA,
ARIMAX

Two
different
time steps
5 minutes
and 10
minutes

ARIMA and ARIMAX orders (5,1,0), (5,1,1) and (4,1,2).

Random shuffle days

Trained using the first 24 days (≈86% of dataset) of July

Forecast
next time
step for 4
days
(≈14% of
dataset) of
July

# Result: single step models

DI (GE	(5,1,0)		(5,1,1)		(4,1,2)	
RMSE	5 minutes	10 minutes	5 minutes	10 minutes	5 minutes	10 minutes
Persistence	7.65%	8.89%	7.65%	8.89%	7.65%	8.89%
ARIMA	7.49%	8.72%	7.52%	8.73%	7.54%	8.69%
ARIMAX	7.47%	8.68%	7.49%	8.70%	7.52%	8.66%

# Result: single step models

ARIMA, ARIMAX order

RMSE	(5,1,0)		(5,1,1)		(4,1,2)	
	5 minutes	10 minutes	5 minutes	10 minutes	5 minutes	10 minutes
Persistence	7.65%	8.89%	7.65%	8.89%	7.65%	8.89%
ARIMA	7.49%	8.72%	7.52%	8.73%	7.54%	8.69%
ARIMAX	7.47%	8.68%	7.49%	8.70%	7.52%	8.66%

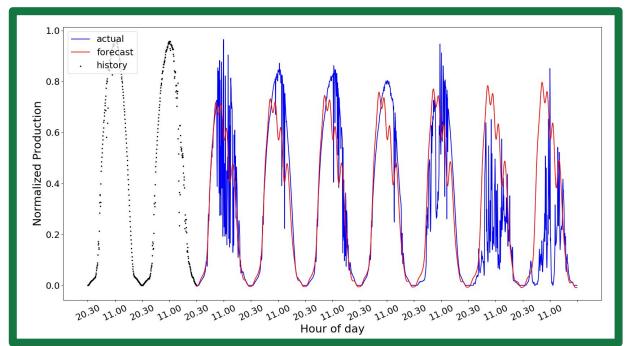
# Result: single step models

ARIMA, ARIMAX order

RMSE (5,1,0)  5 10	(5,1,1) 5 10	(4,1,2) 5 10
<i>RMSE</i> 5 10	5 10	5 10
5 10		
minutes minutes m	ninutes minutes	minutes minutes
Persistence 7.65% 8.89% 7	7.65% 8.89%	7.65% 8.89%
ARIMA 7.49% 8.72% 7	7.52% 8.73%	7.54% 8.69%
ARIMAX 7.47% 8.68% 7	7.49% 8.70%	7.52% 8.66%

#### implementations Only **Forecast** Compared observing According **Trained** models: all time to (Dahl, using the Time step days steps for 7 One week of 5 between 2017) first 21 persistence, days (25% minutes production days (75% Gaussian of dataset) of dataset) start and of July process end 1.30 of July 20.30

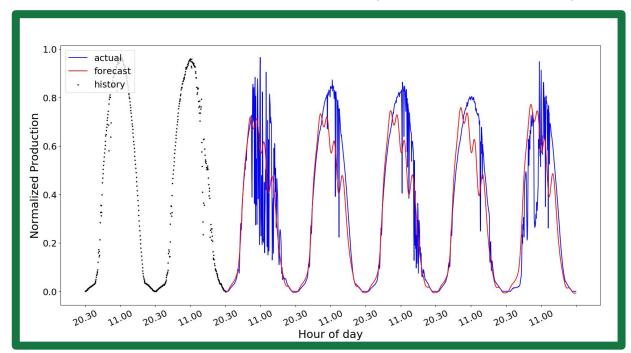
Multiple step model



Persistence RMSE: 22.61%

Gaussian process RMSE: 19.64%

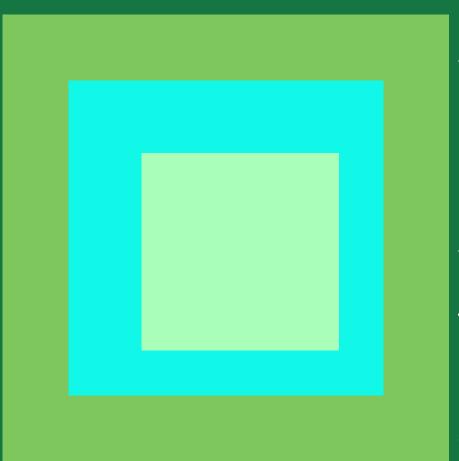
7 days



Persistence RMSE: 20.0%

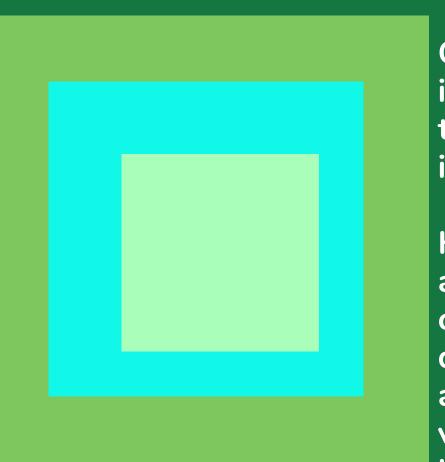
Gaussian process RMSE: 13.7%

5 days



ARIMA is more accurate than persistence in applied model

Adding an exogenous variable did not help improve accuracy significantly



Gaussian process is more accurate than persistence in applied model

However, the applied model can be further developed by adding exog. variable or more history

nal Presentation 27 May 201

# **Computational** time

& time...