Advanced Time Series

Lecture 5:
Time-to-event and PdM

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Logistics

+1 lecture - Mar 22

- **HW 4:** today, deadline is Mar 15
- **HW 5:** Mar 8, deadline is Mar 22
- **transformers** to be added

Today

Time series classification $\longrightarrow$ time-to-event and PdM:

- **InceptionTime** implementation
- **dilated convolutions**
- **other architectures** for t. s. classification
- **predictive maintenance**: setup
- **survival analysis** basics, TTE distributions

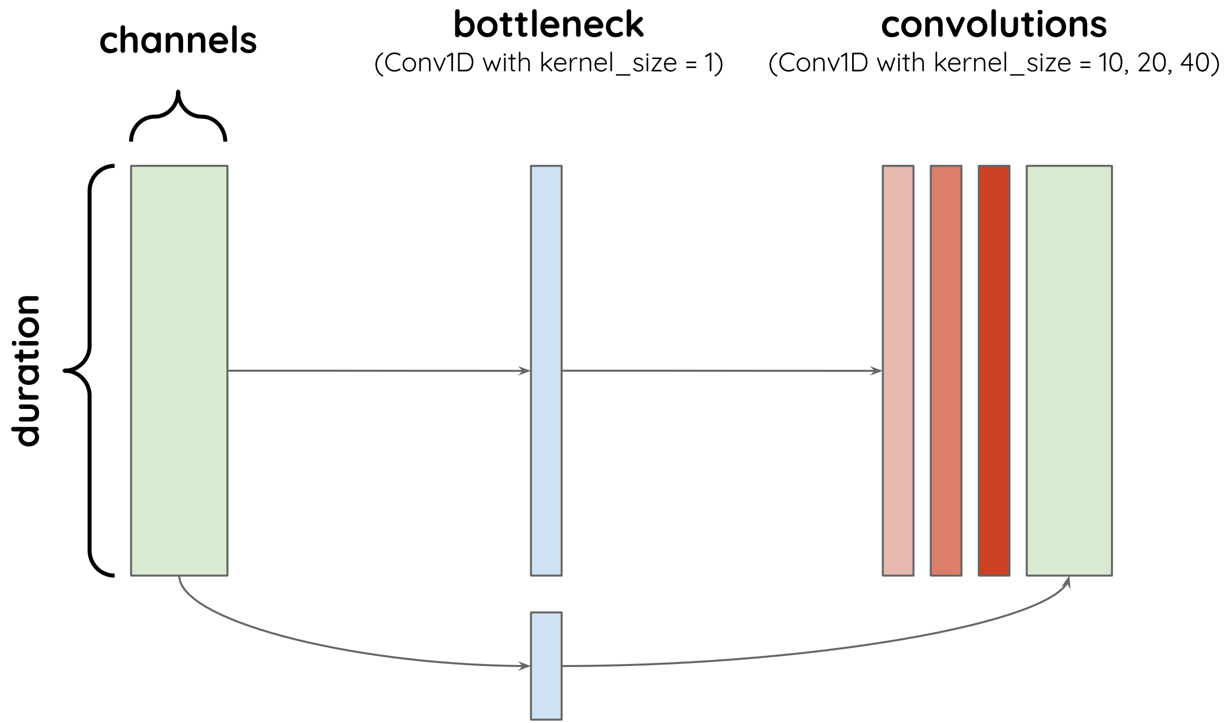
InceptionTime implementation

InceptionTime

Inception blocks:

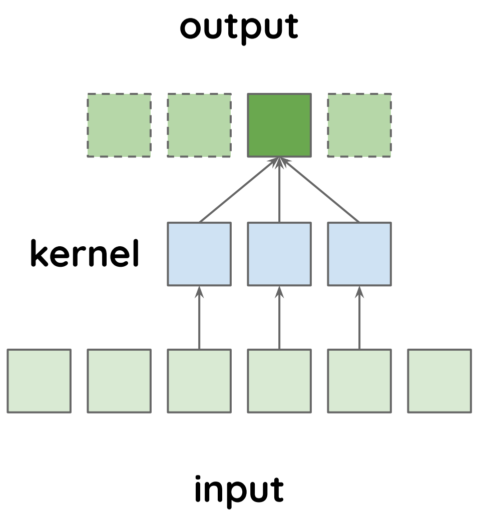
- introduced in Going Deeper with Convolutions
- more efficient computationally
- nicely captures multiple (although close) spatial/time scales

Inception block for t. s.



Dilated and causal convolutions

Convolution



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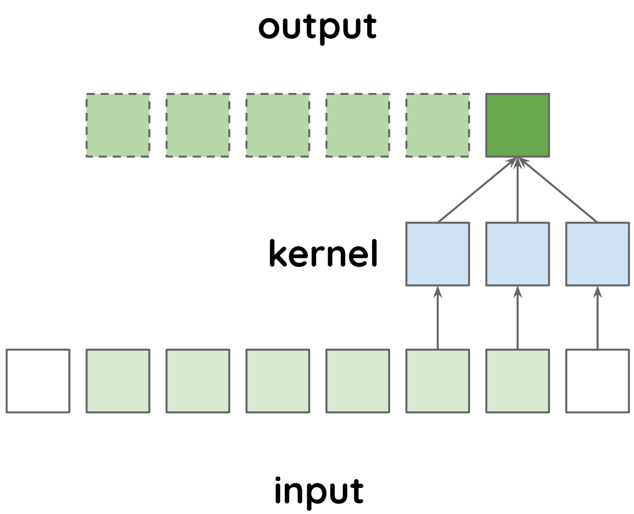

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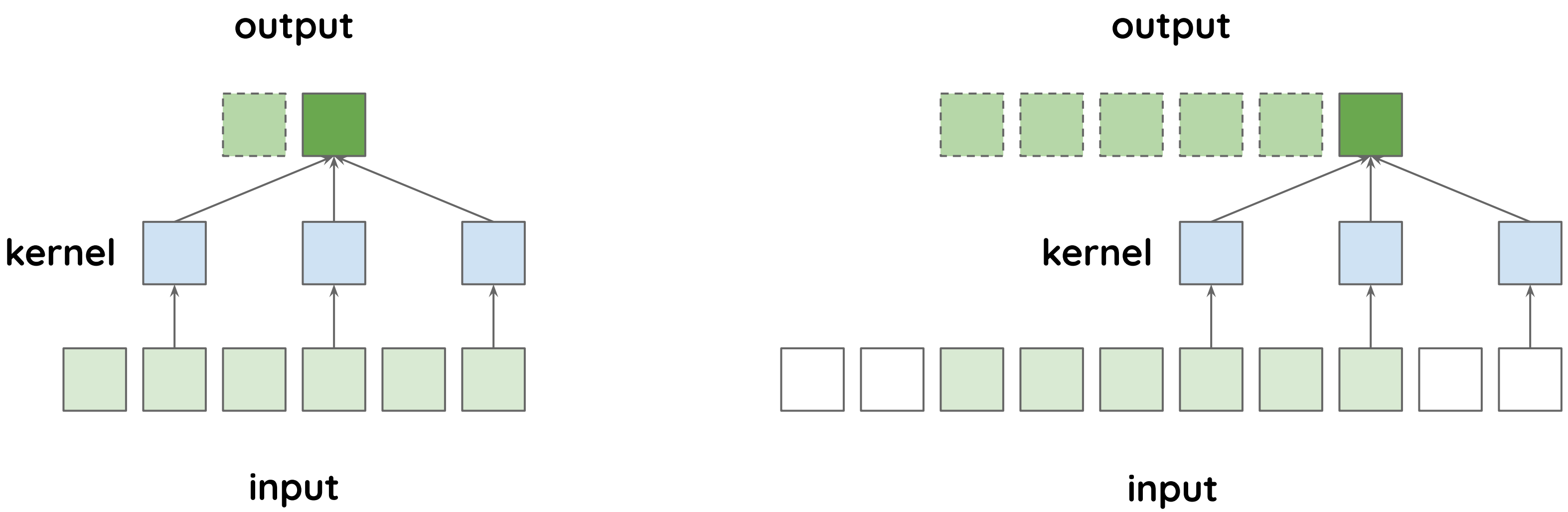
Dilated convolution



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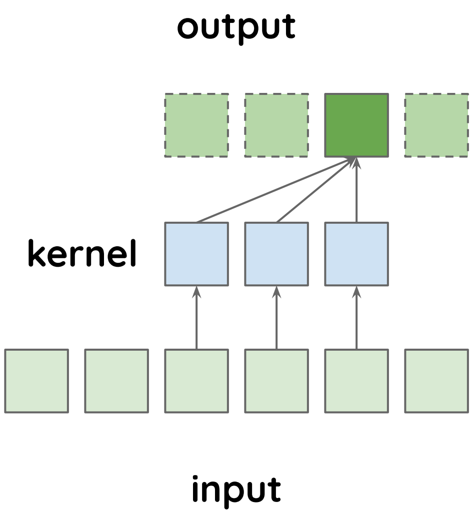
Causal convolution



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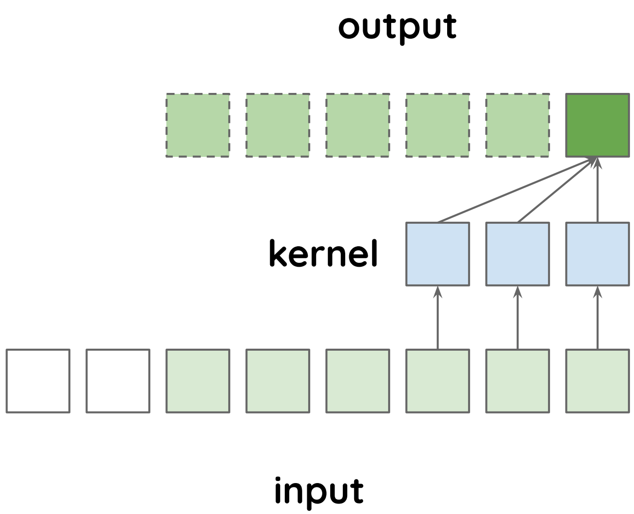

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Why dilated convolutions

- fast extension of receptive field
- no additional computational costs
- high resolution input is manageable (high-frequency t. s.)

Other architectures

ROCKET

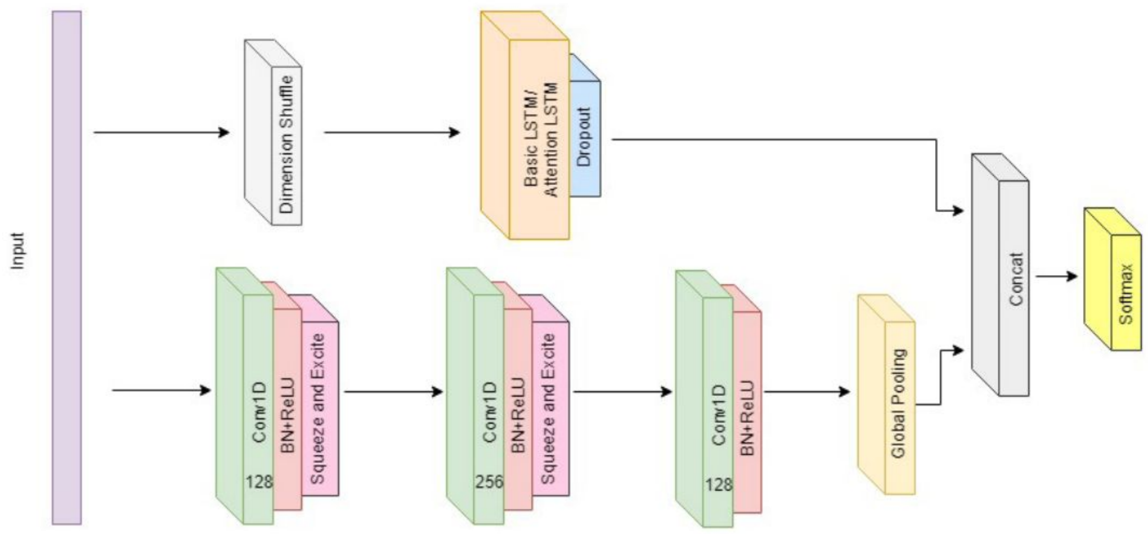
“Single-layer” convolutional network:

- random kernels (size, dilation, etc.)
- linear classifier

ROCKET: Exceptionally fast and accurate time series classification using random convolutional kernels

LSTM-FCN

[Multivariate LSTM-FCNs for Time Series Classification]



TTE and predictive maintenance

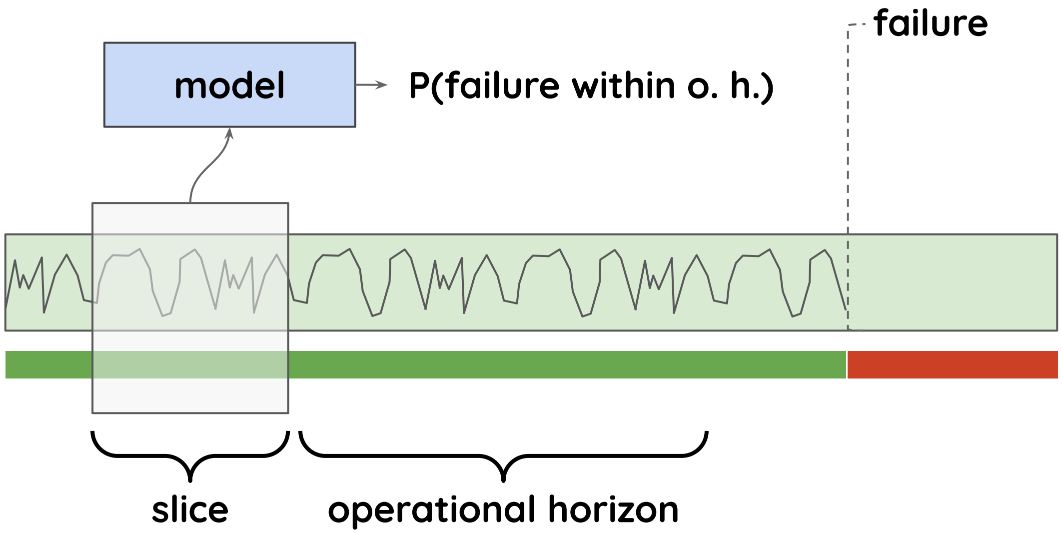
TTE and PdM

Typical scenario:

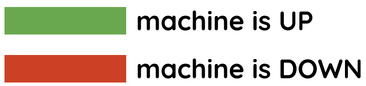
- **equipment,** vehicles, etc. fails from time to time
- **sensors** provide time series data (often used for other reasons)
- **failures data** is collected as well
- can we **predict failures using sensors data?**

Value: improved **operational efficiency**

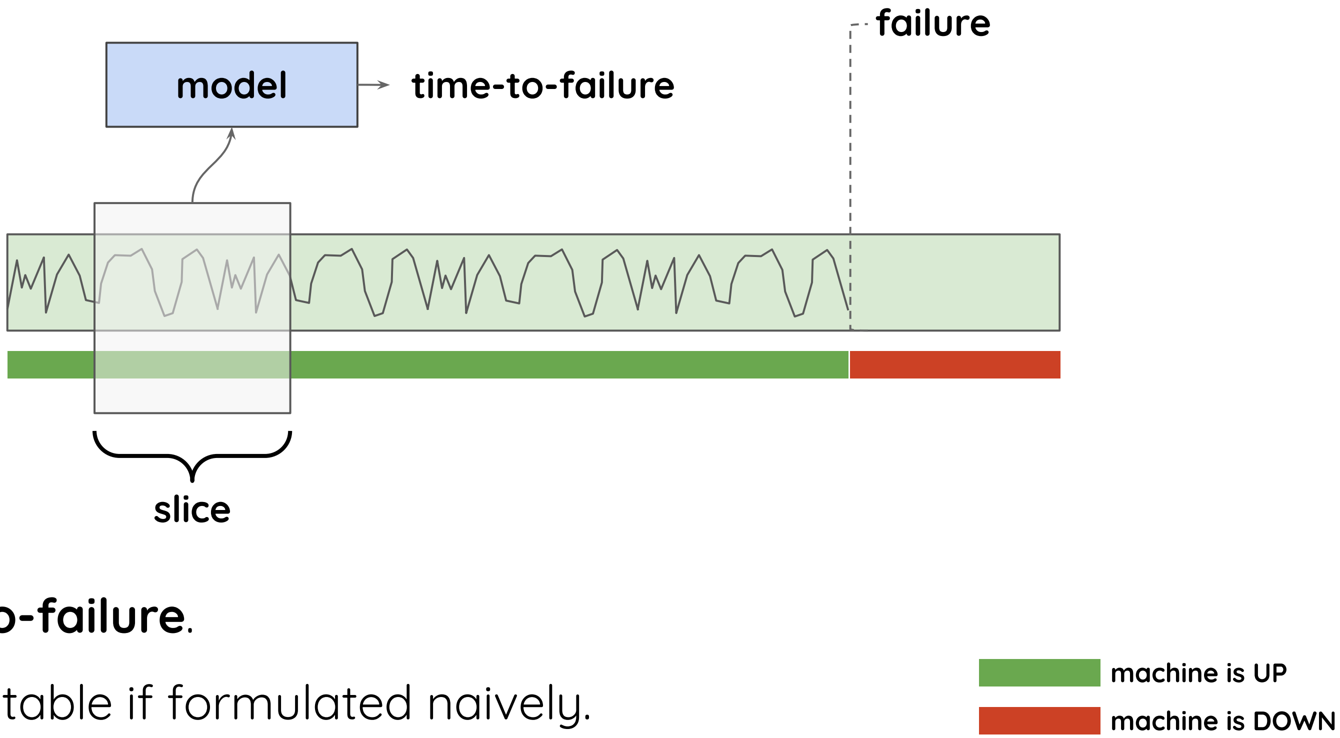
Setup: probability



Predict **probability of failure** within operational horizon.



Setup: TTE



Predict **time-to-failure**.

Way more unstable if formulated naively.

TTE and PdM

Naive formulation:

- create some windowed features/use deep learning model
- train a classification model
- rolling predictions

TTE and PdM

When formulated naively:

- failure probability over a **single** o. h. may be **not enough**: no planning beyond o. h.
- **hard to communicate**
- no intrinsic **risk** concept

TTE and PdM

Solution:

- **survival analysis**
- well known in medicine and other domains
- has intrinsic **risk** concept
- can be married with **deep learning**

Survival analysis

Concept 1:

- **survival function:** probability of surviving past t

$$S(t) = P(\underbrace{T}_{\text{time of failure}} > t)$$

Survival analysis

Concept 2:

- **hazard function:** conditioned event rate

$$\lambda(t) = -\frac{S'(t)}{S(t)}$$

Hazard function deciphered

Concept 2:

- **hazard function:** conditioned event rate

$$\lambda(t) = -\frac{P(T>t+dt)-P(T>t)}{S(t)dt}$$

Hazard function deciphered

Concept 2:

- **hazard function:** conditioned event rate

$$\lambda(t) = -\frac{P(T>t+dt)-P(T>t)}{S(t)dt}$$

Hazard function deciphered

Concept 3:

- **proportional** hazards model (Cox regression)

$$\lambda(t) = \lambda_0(t) \exp(a_i X_i)$$

covariates

TTE and PdM

Given the model:

- get **entire** survival function
- quantify how covariates influence the risk
- extend **beyond** linear model

TTE distributions

When doing PdM model:

- look at distribution of between/to event times

Weibull distribution:

scale

$$P(\tau) = \frac{k}{\lambda}\left(\frac{\tau}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^{k}}, \tau \geq 0$$

TTE distributions

Weibull distribution:

- $k < 1$: failure decreases over time
- $k > 1$: failure increases over time
- **$k = 1$:** failure is constant over time - exponential distribution

Turbofan dataset

NASA dataset for engine tests:

- well known
- download at NASA Prognostics Center of Excellence

Next time

- extension of survival analysis for deep learning
- transformers

questions?