Time Series Modeling using Neural Networks

Dušan Fedorčák

09/2022

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Background

- Ph.D. in computer science at VŠB-TU Ostrava
  - Neural networks & unsupervised self-organization
- Experienced in simulations
  - flood prediction system for MSK
  - traffic monitoring & prediction systems
- Experienced in computer graphics & scientific visualization
  - GIS related real-time 3D visualizations
- 5+ years in applied ML and artificial intelligence
  - Lead researcher in GoodAI – general artificial intelligence
  - CTO in Neuron Soundware – sound processing via Deep Learning
  - Lead ML in Merlon Intelligence Inc. – natural language processing

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Content

DAY 1

- **Classical time series analysis**
  - *Decomposition of time series*
  - *ARIMA models family*
  - *State space models generalization*
- **Theoretical window**
  - *Neural Networks & Recurrent NNs*
  - *Time series specifics*
- **Practical examples**
  - *Simple regression – toy example*
  - *Rainfall-runoff simulation – regression*

– lunch break –

- **Practical examples**
  - *Trampoline jumping – classification*
  - *Local Weather Forecast – regression*

DAY 2

- **Product Design & ML**
  - *Integration of ML models into products*
  - *Tips & tricks for debuging NNs*
- **Practical Examples** (in random order)
  - *Exoplanets Hunting*
  - *Mobile Motion Sensing*

– lunch break –

  - *Manufacturing Process Modeling*
  - *Financial distress prediction*

- *Google Drive Folder with data*
- *GitHub repository with example sources*
- *this presentation*

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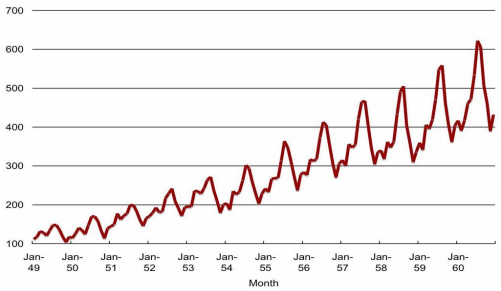
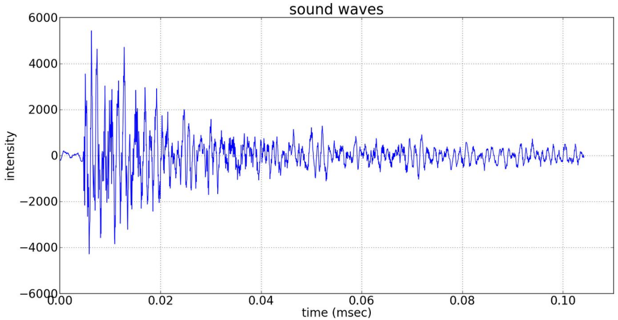
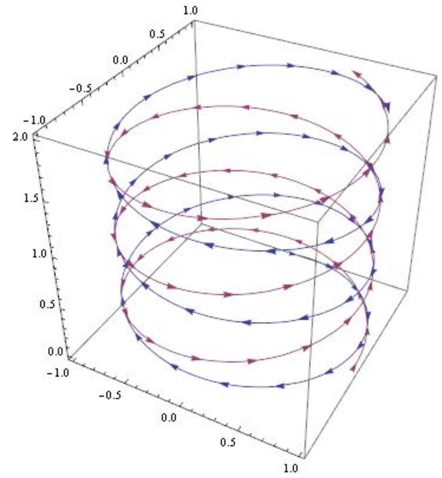
Time series – example data







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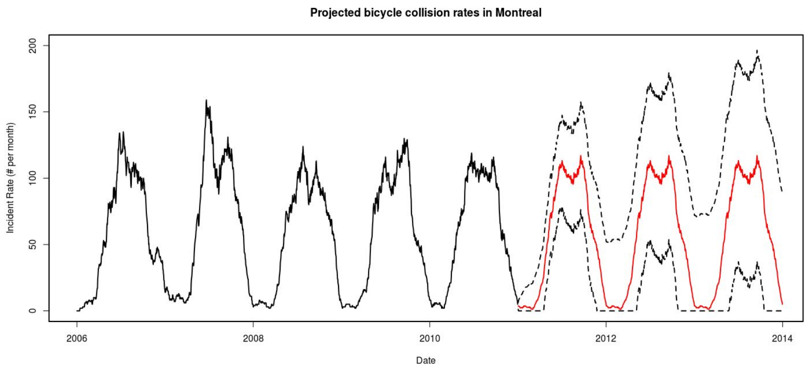
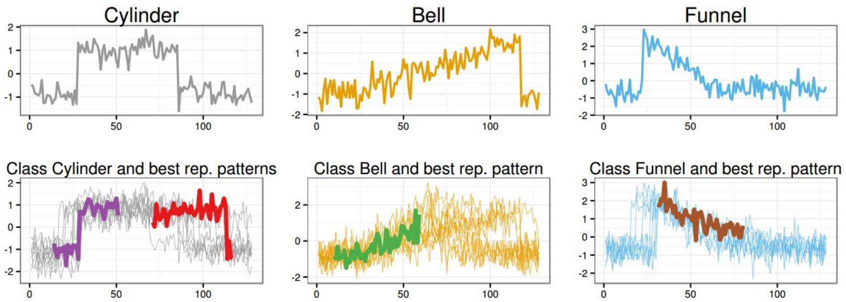
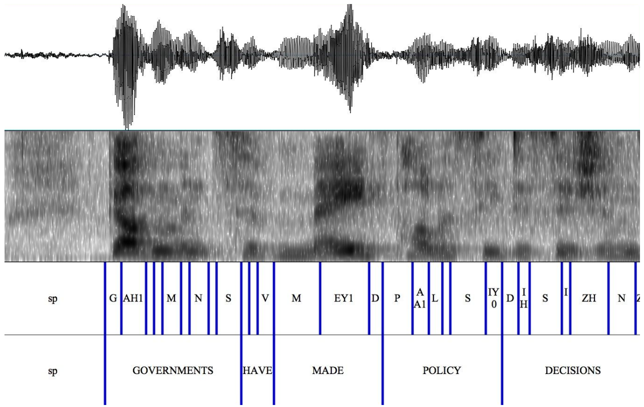
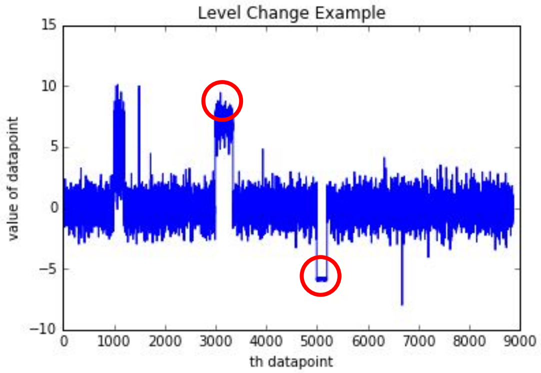
Time series – example tasks



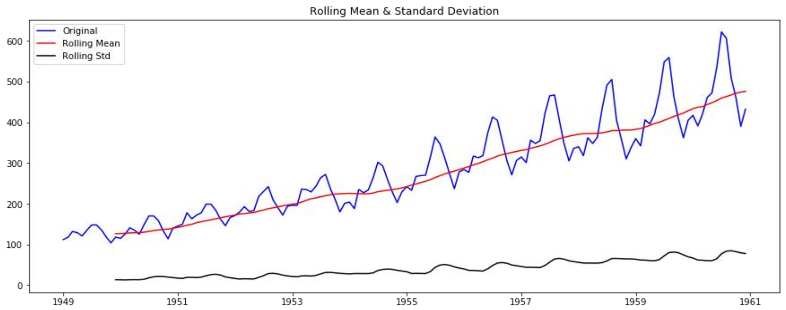


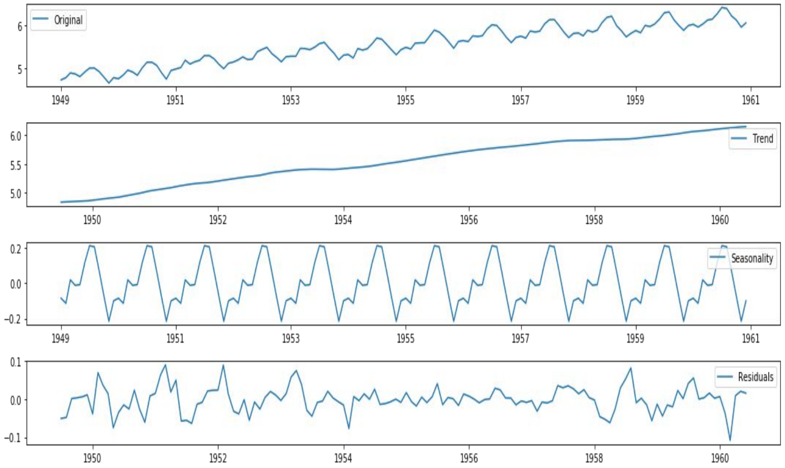


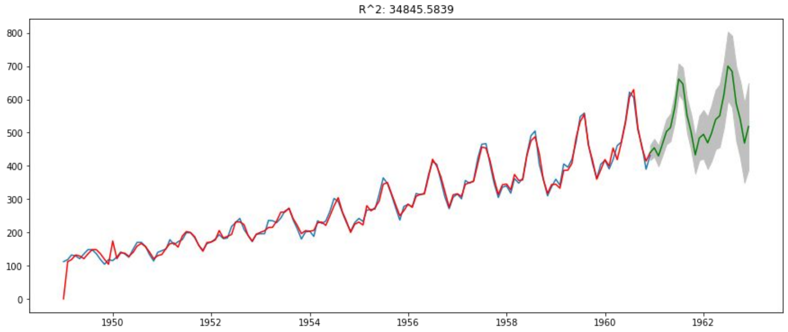


Time Series – classical analysis & modeling

- Time Series Decomposition
  - Inflation, trend, seasonality, differencing
- ARIMA models
  - http://people.duke.edu/~rnau/411home.htm







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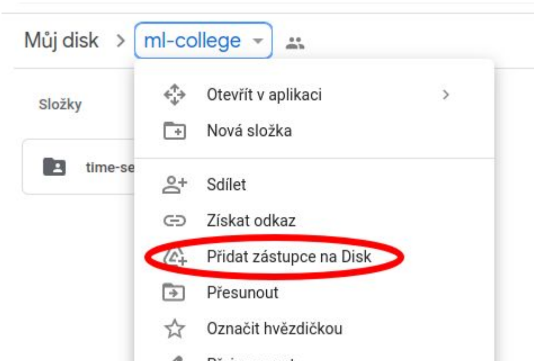
Time Series – classical analysis & modeling

1. Open *this link*

or

1. Open *colab.google.com*
2. In the Open Notebook menu
    a. Navigate to GitHub tab
    b. Enter **mlcollege** into search bar
    c. Select **mlcollege/timeseriesanalysis** repo
    d. Open **arima-complete.ipynb**

Do not forget to add this Google Drive Folder to your drive



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State Space Models

- State Space Models
  - A dynamic system that **evolves over time**
  - Knowing **the current state of the model is enough** to predict the future
  - The true state of the system might **not** be **directly observable**
- Model Description
  - State
    - $\boldsymbol{x}_t \sim N(\boldsymbol{x}_t, \boldsymbol{P}_t)$
  - State Equation
    - $\boldsymbol{x}_t = \boldsymbol{F}\boldsymbol{x}_{t-1} + N(0, \boldsymbol{Q})$ – *sometimes without noise*
  - Observation Equation
    - $\boldsymbol{y}_t = \boldsymbol{H}\boldsymbol{x}_t + N(0, \boldsymbol{R})$

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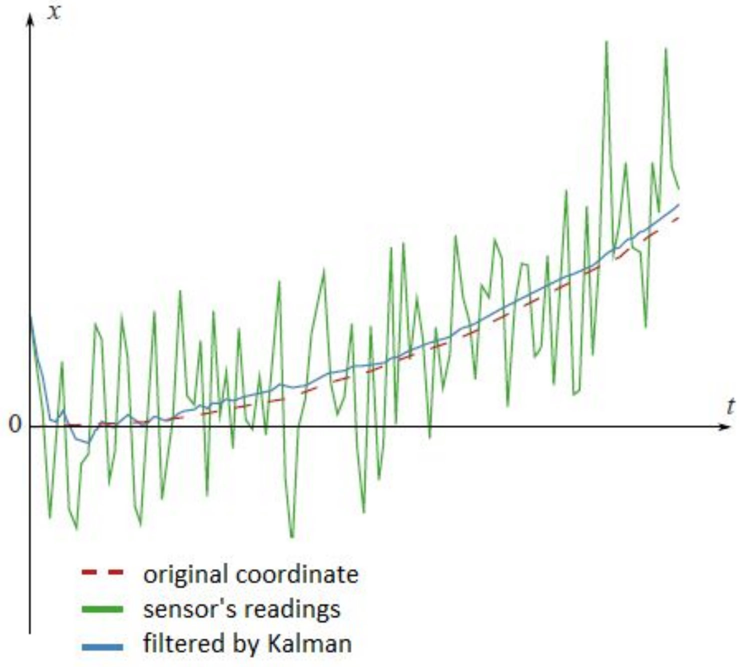
Kalman Filter

- Evolve state
  - $x'_t = Fx_{t-1}$
  - $P'_t = F\,P_{t-1}F^T + Q$
- Integrate observation
  - $x_t = x'_t + K_t(y_t - Hx'_t)$
  - $P_t = (I - K_tH)\,P'_t$
- **Kalman Gain**
  - $K_t = P'_t\,H^T(HP'_tH^T + R)^{-1}$
- ARIMA and Kalman Filter
  - ARIMA can be viewed as a state space model
  - ARIMA can be fitted with MLE via Kalman Filter
  - https://bookdown.org/rdpeng/timeseriesbook/maximum-likelihood-with-the-kalman-filter.html
  - https://towardsdatascience.com/the-kalman-filter-and-maximum-likelihood-9861666f6742



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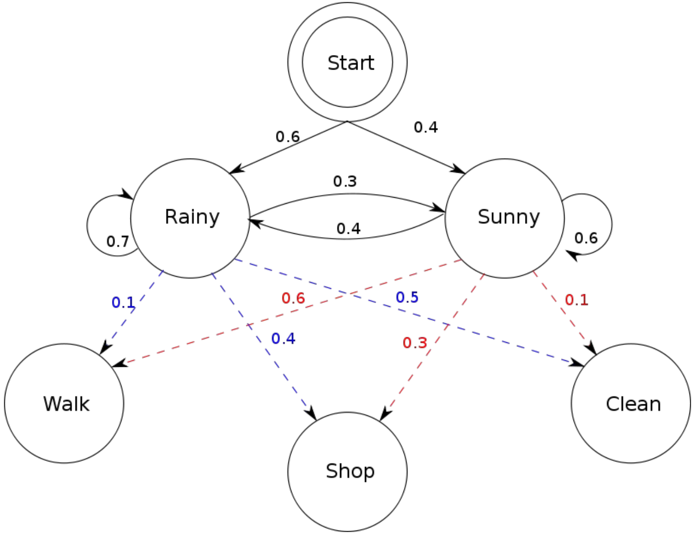
Hidden Markov Model

- Model Description
  - HMM (**λ**) can be viewed as a **state space model**
  - Finite set of hidden states
    - $\mathbf{Q} = \{q_1, q_2, \dots, q_n\}$, $\boldsymbol{\pi} = \{\pi_1, \pi_2, \dots, \pi_n\}$ – init
    - $\boldsymbol{n}$ – number of states (hyperparameter)
  - Set of observations
    - $\mathbf{O}_i = (o^1, o^2, o^3, \dots, o^T)$
  - Transition probability matrix & emissions
    - $\mathbf{A} = (a_{00}, \dots, a_{nn})$, $\mathbf{B} = q_i \rightarrow o$



- Model Capabilities
  - $P(\mathbf{O}|\boldsymbol{\lambda})$ – Give prob. of **O** being produced by **λ** – *forward-backward alg.*
  - $P(\mathbf{q}_1, \dots, \mathbf{q}_t|\mathbf{O}, \boldsymbol{\lambda})$ – Give most likely sequence of states for given **O** – *Viterbi alg.*
  - $\mathbf{O} \Rightarrow \boldsymbol{\lambda}$ – Model must be trainable with **O** – *Baum-Welch alg.*

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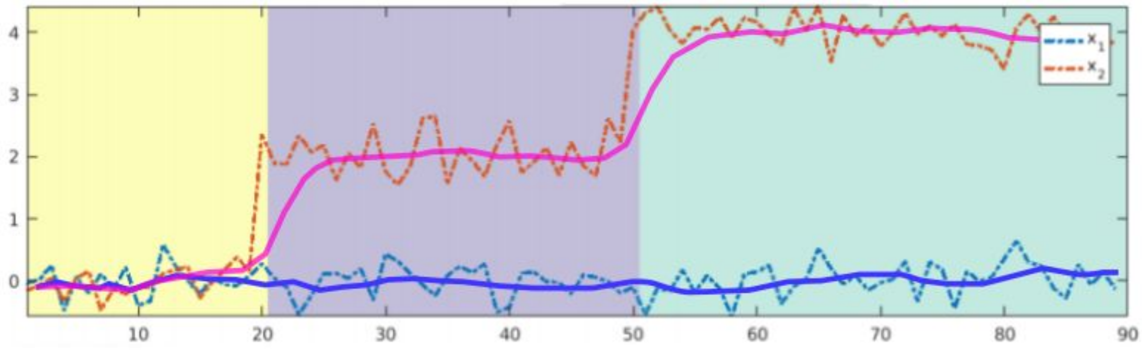
Kalman Filter vs. Hidden Markov Model

- **Kalman Filter**
  - Continuous state
  - Generic state & observation equation
  - Linear dynamic system
  - *Fusion of sensor readings and controls*
  - *ARMA models implementation*
- **Hidden Markov Model**
  - Discrete set of states
  - N-states hyperparameter
  - Emission & Transition tables
  - *Speech recognition*
  - *Time series segmentation*



http://lasa.epfl.ch/teaching/lectures/ML_MSc_Advanced/Slides/Lec_XI_HMM_extensions.pdf

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Time Series – goals in classical terminology

- **Forecasting**
  - Given the past and the present observation, what will the future look like?
- **Time scale analysis**
  - Given the observations, what time scales dominate when observing temporal variation in the data
- **Filtering**
  - Given the past and the present observation, how should I update my estimate of the true state of nature?
- **Smoothing**
  - Given a complete dataset, what can I infer about the true state of nature in the past?
- **Regression**
  - Given a time series of two phenomena, what is the association between them?

https://bookdown.org/rdpeng/timeseriesbook/

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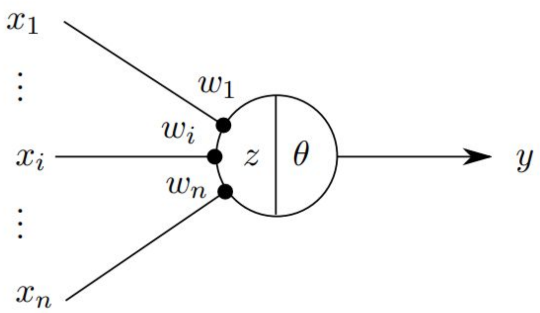
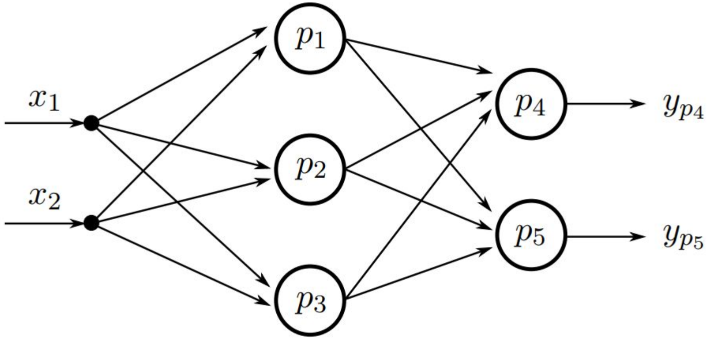
Neural networks





- Artificial Neural Cells
  - Linear combination of inputs
  - Non-linear activation function
- Connected Neurons
  - Directed graph
  - Layered structure
    - Dense connections
    - Convolutions & pooling
    - Recurrency, signal gates
    - Masking & attention heads
- Universal function approximator
  - Trainable with data
  - Backpropagation
  - Deep vs. shallow architecture

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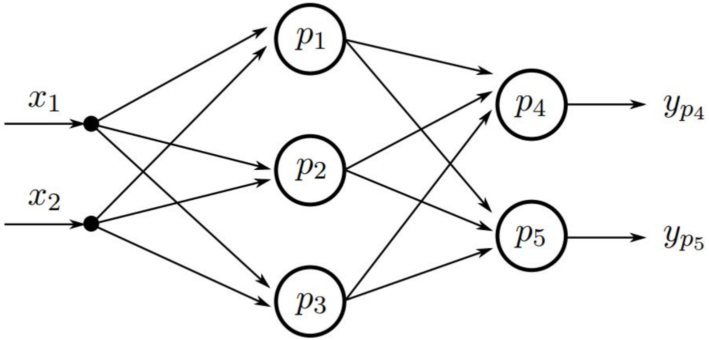
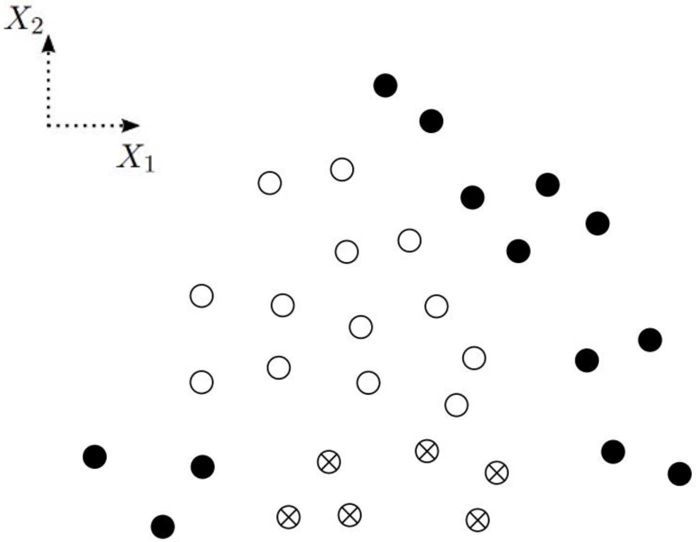
Neural networks – Input space separation





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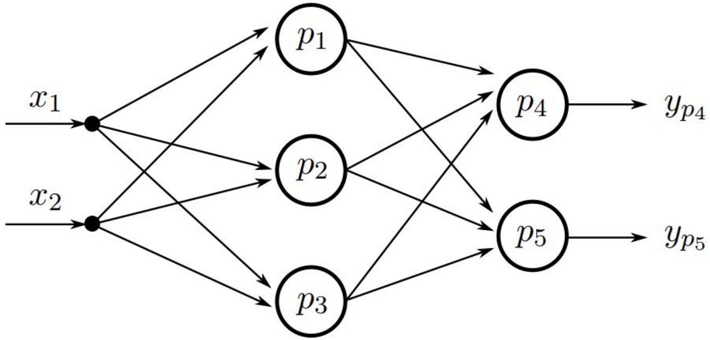
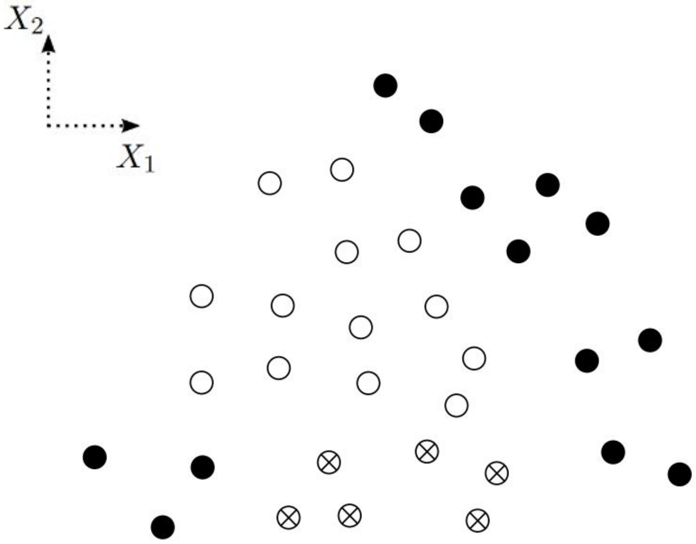
Neural networks – Input space separation





$$y = s(\Sigma\, w_i x_i - \theta)$$

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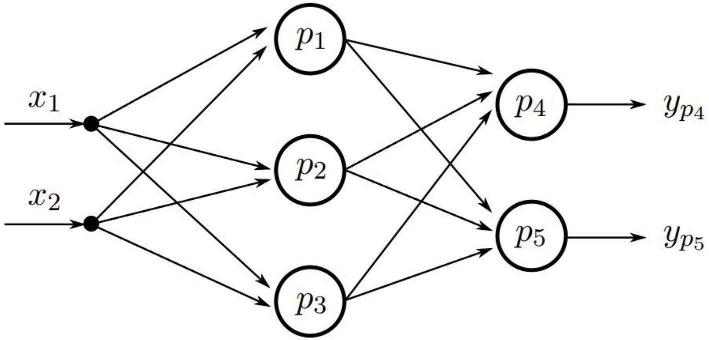
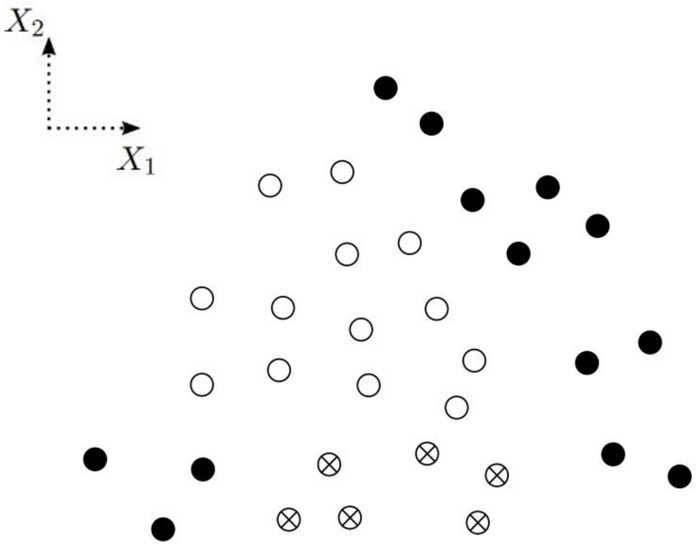
Neural networks – Input space separation





$$y = s(\Sigma\, w_i x_i - \theta) = s(w_1 x_1 + w_2 x_2 - \theta)$$

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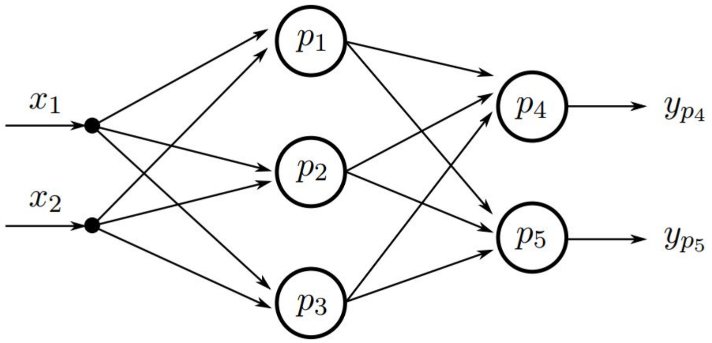
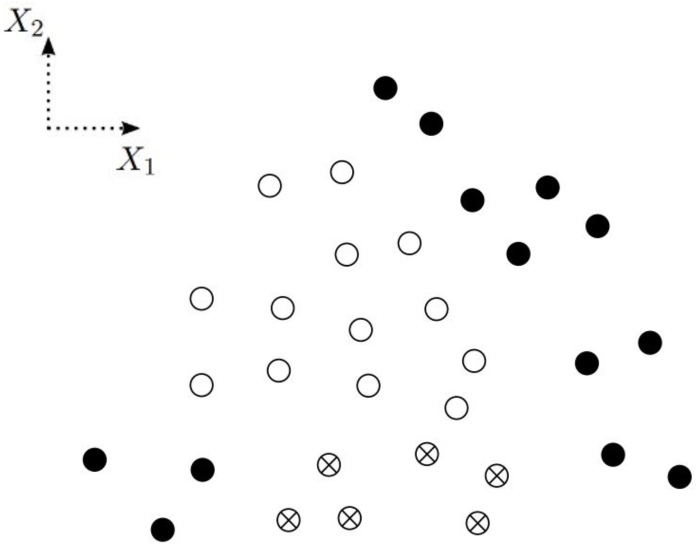
Neural networks – Input space separation





$$ax + by + c = 0$$

$$y = s(\Sigma w_i x_i - \theta) = s(w_1 x_1 + w_2 x_2 - \theta)$$

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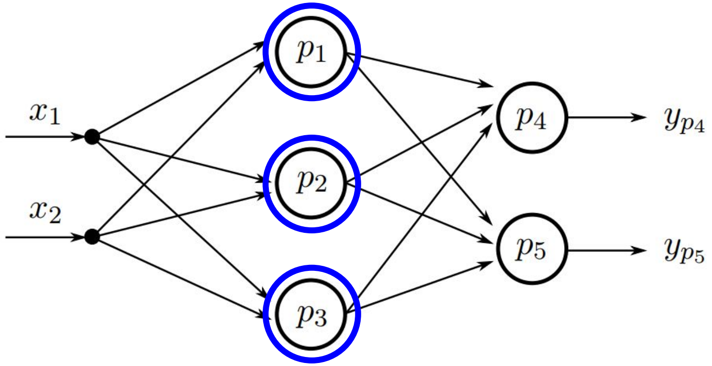
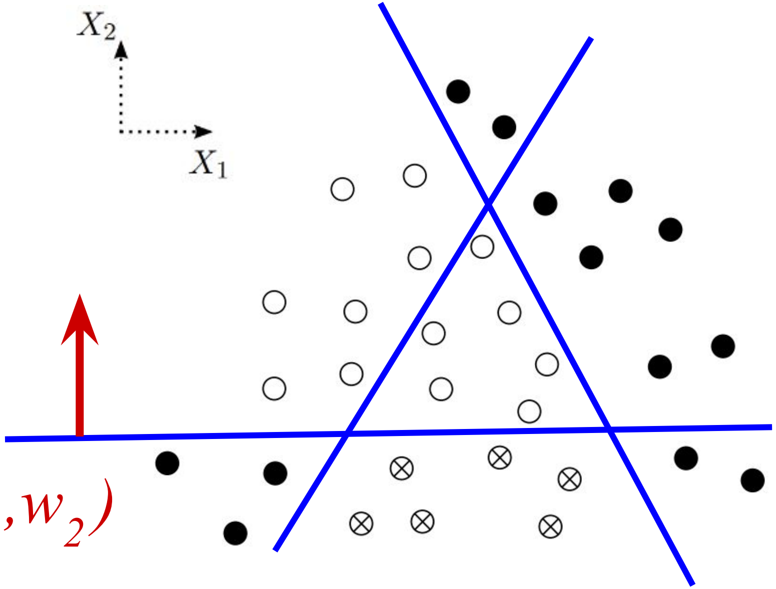
Neural networks – Input space separation





$$(a,b) = (w_1, w_2)$$

$$ax + by + c = 0$$

$$y = s(\Sigma w_i x_i - \theta) = s(w_1 x_1 + w_2 x_2 - \theta)$$

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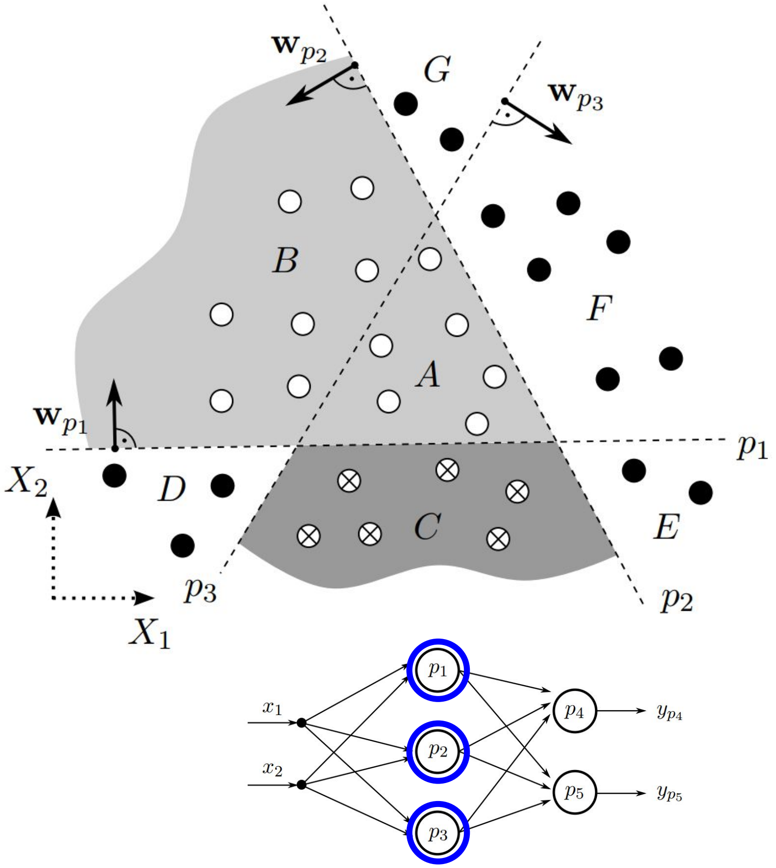
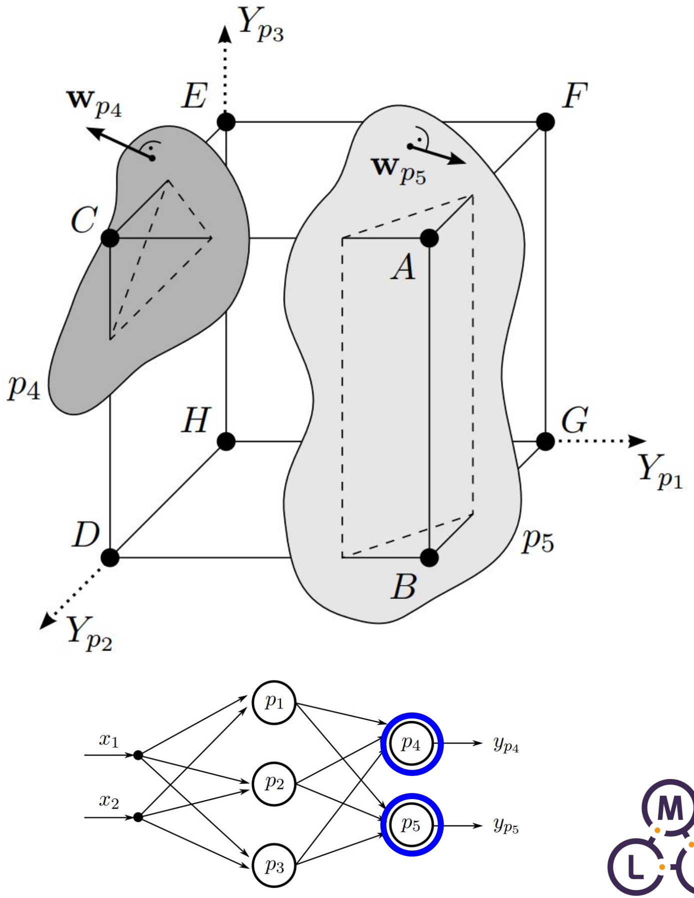
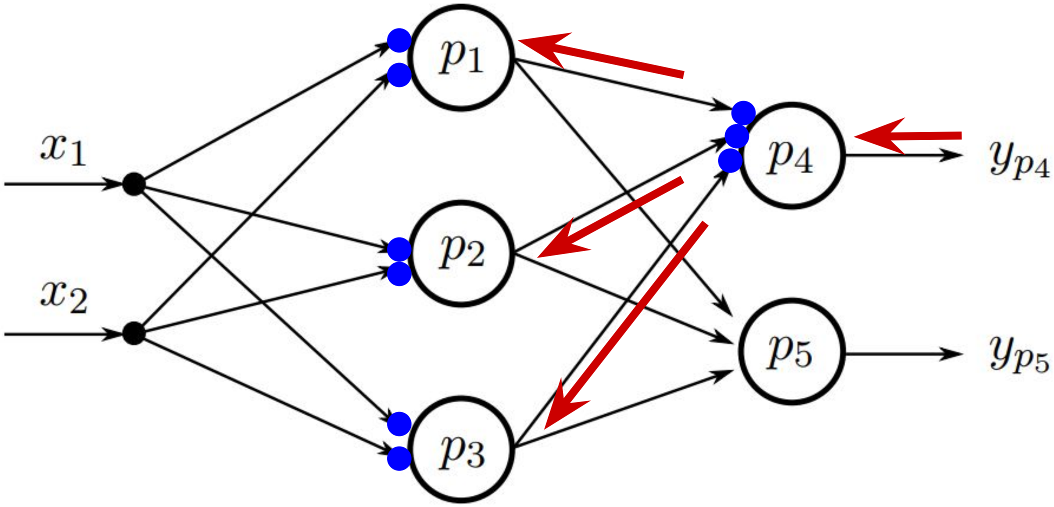
Neural networks – Input space separation





Neural networks – Backpropagation



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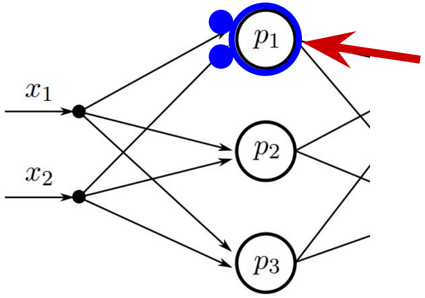
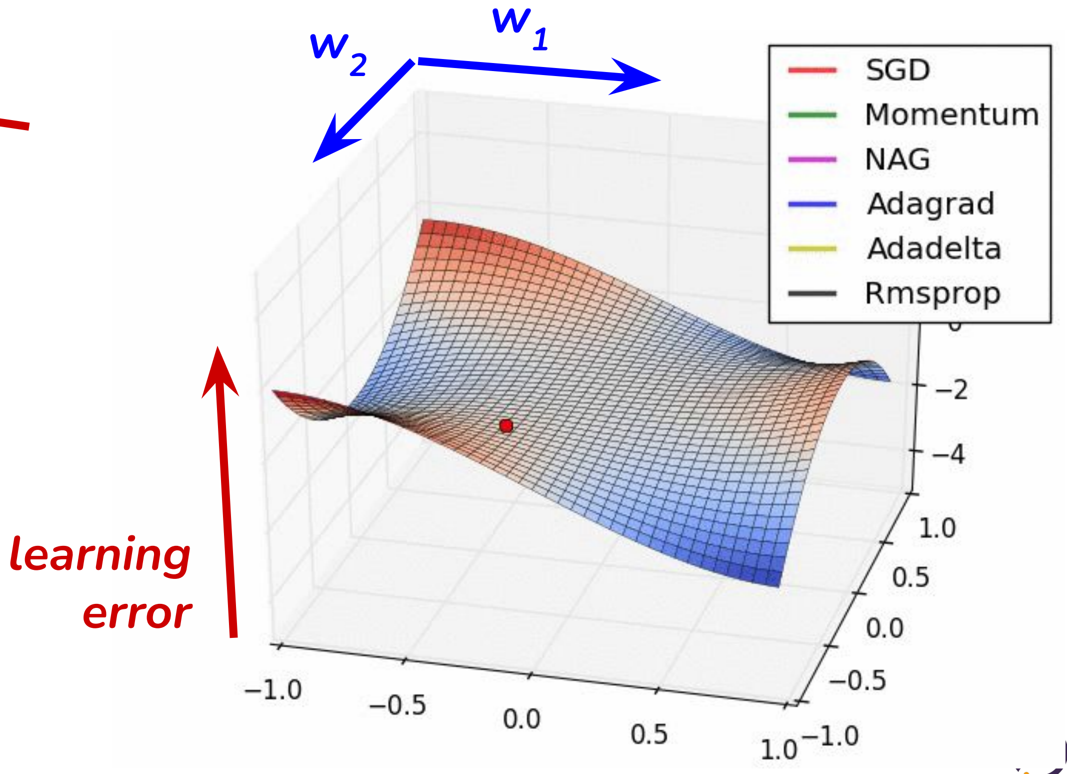
Neural networks - Backpropagation





http://www.denizyuret.com/2015/03/alec-radfords-animations-for.html

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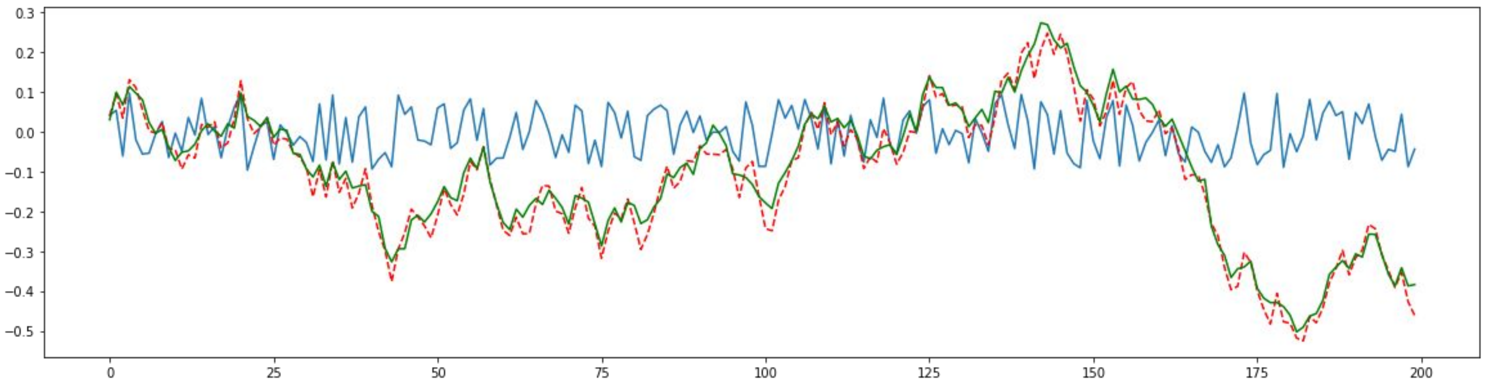
Time Series with Neural Networks



- Neural Networks
  - How to **express time domain**
  - How to **prepare training data**
  - How to **design the model**
  - How to **train & test the model**

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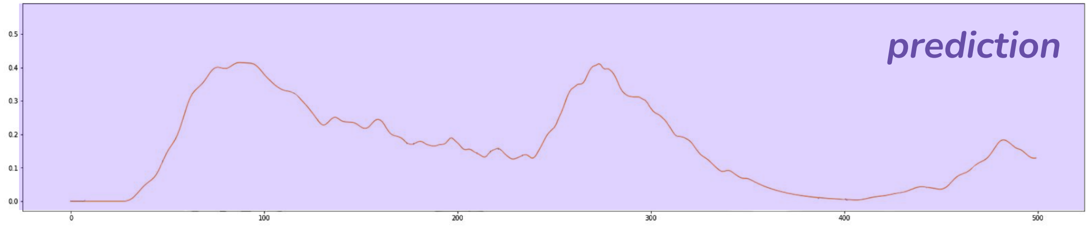
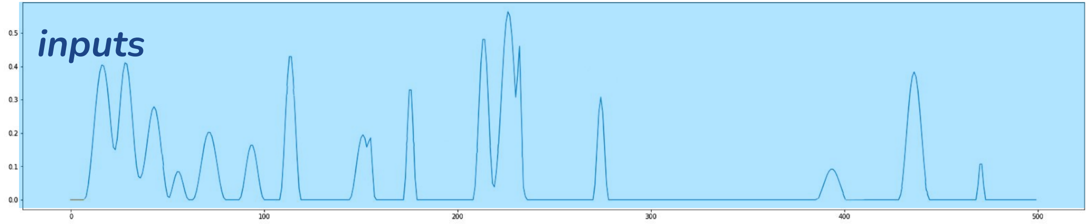
How neural network fits?





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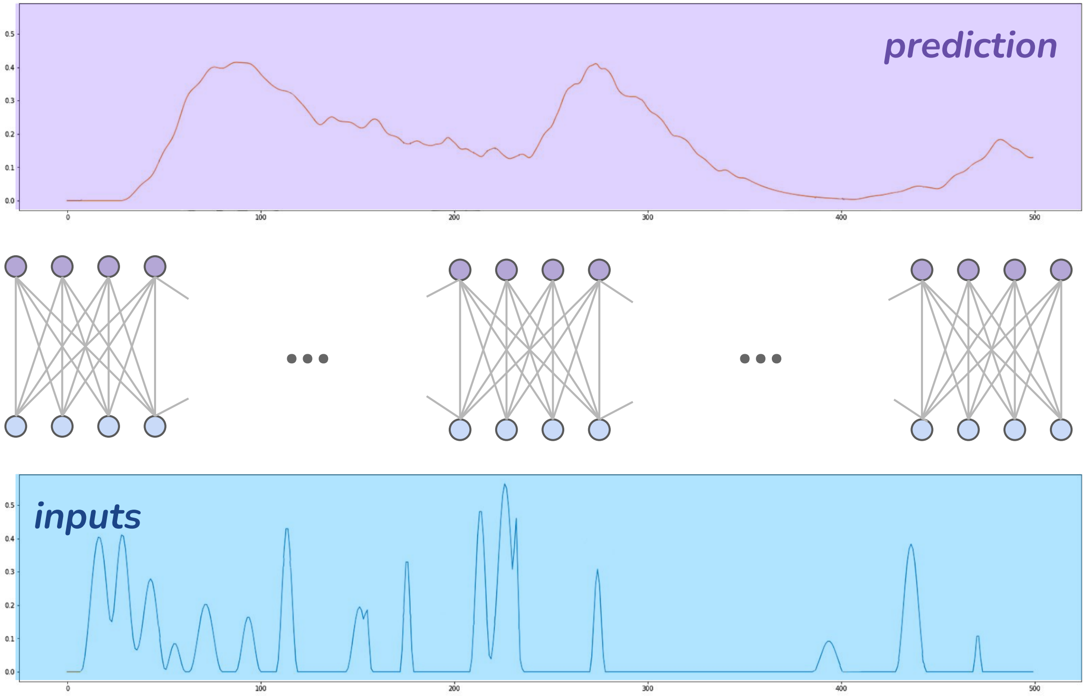
Simple feed-forward network



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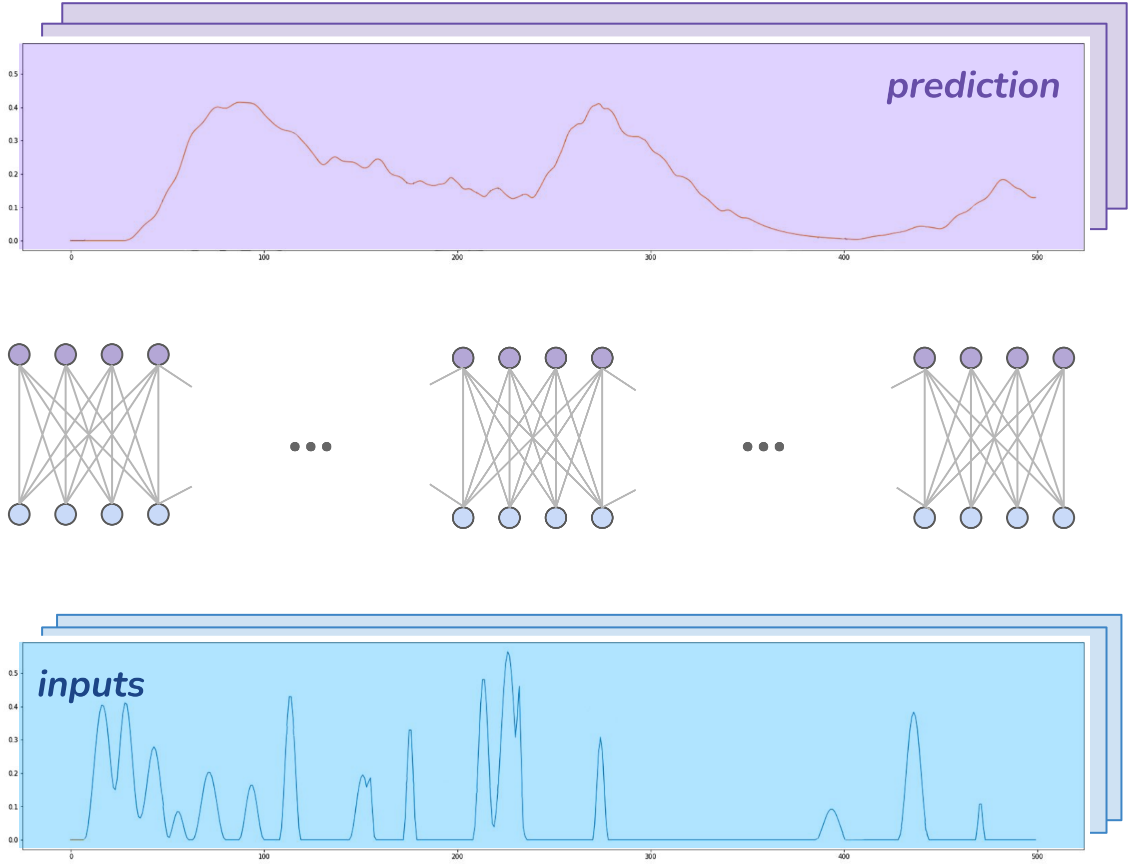

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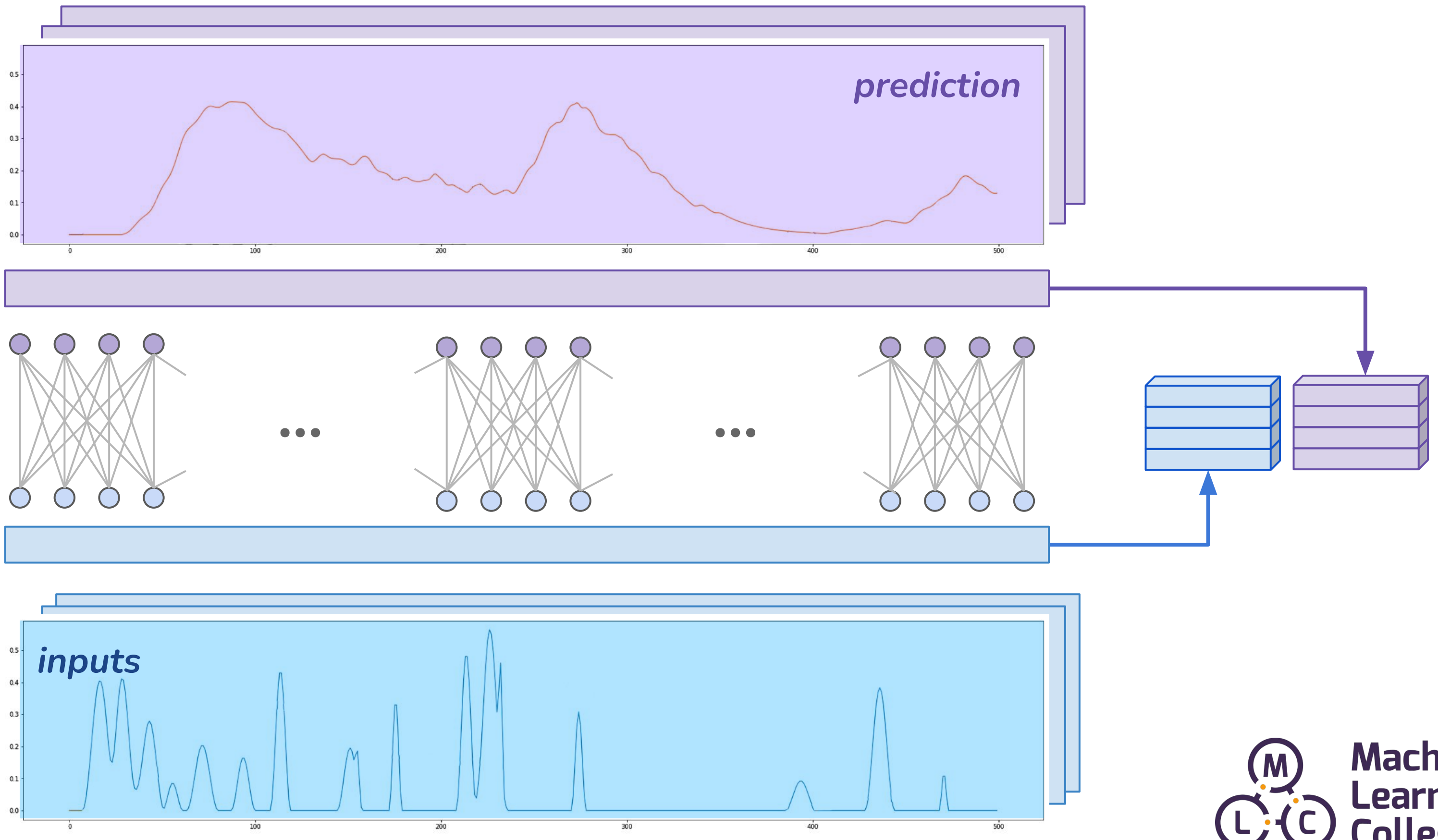

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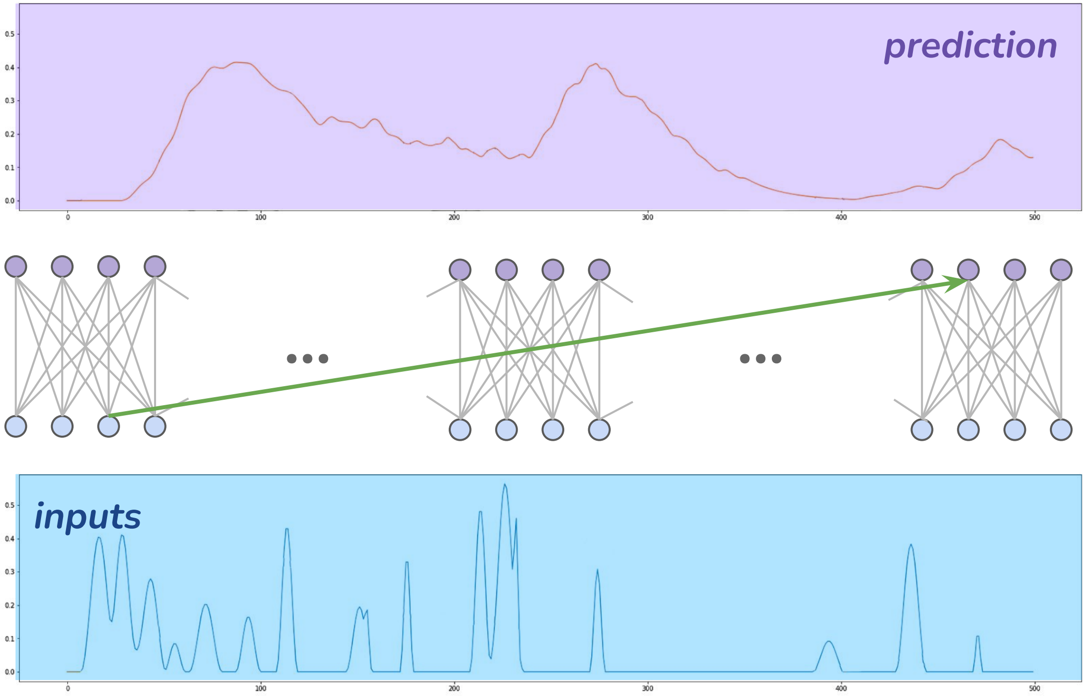

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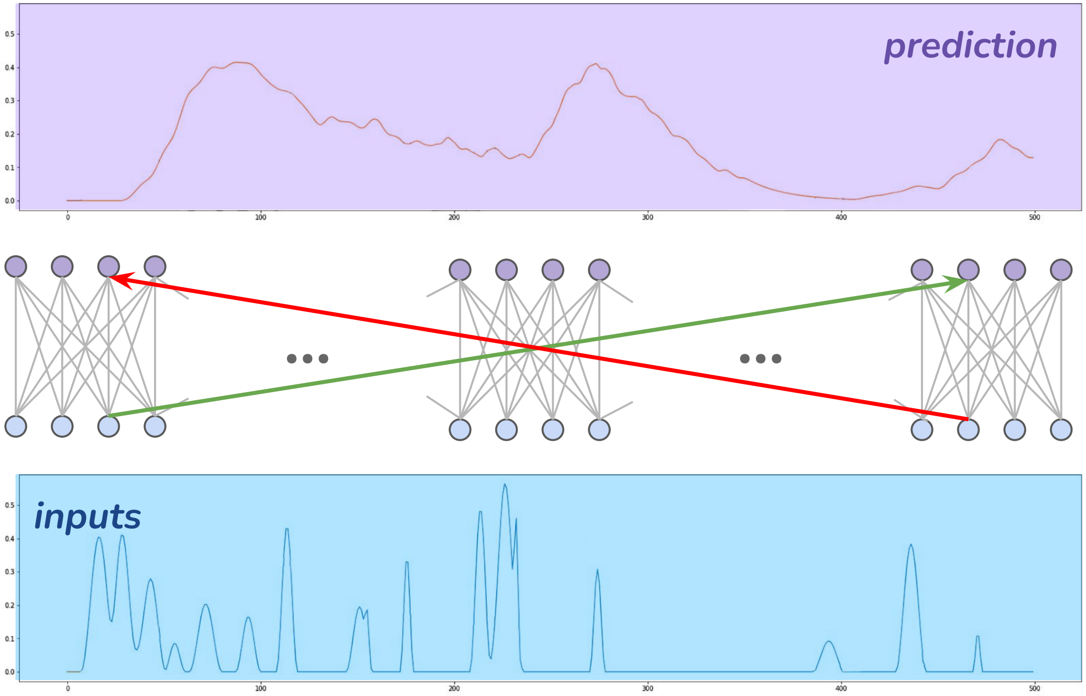

predicting
from future ?

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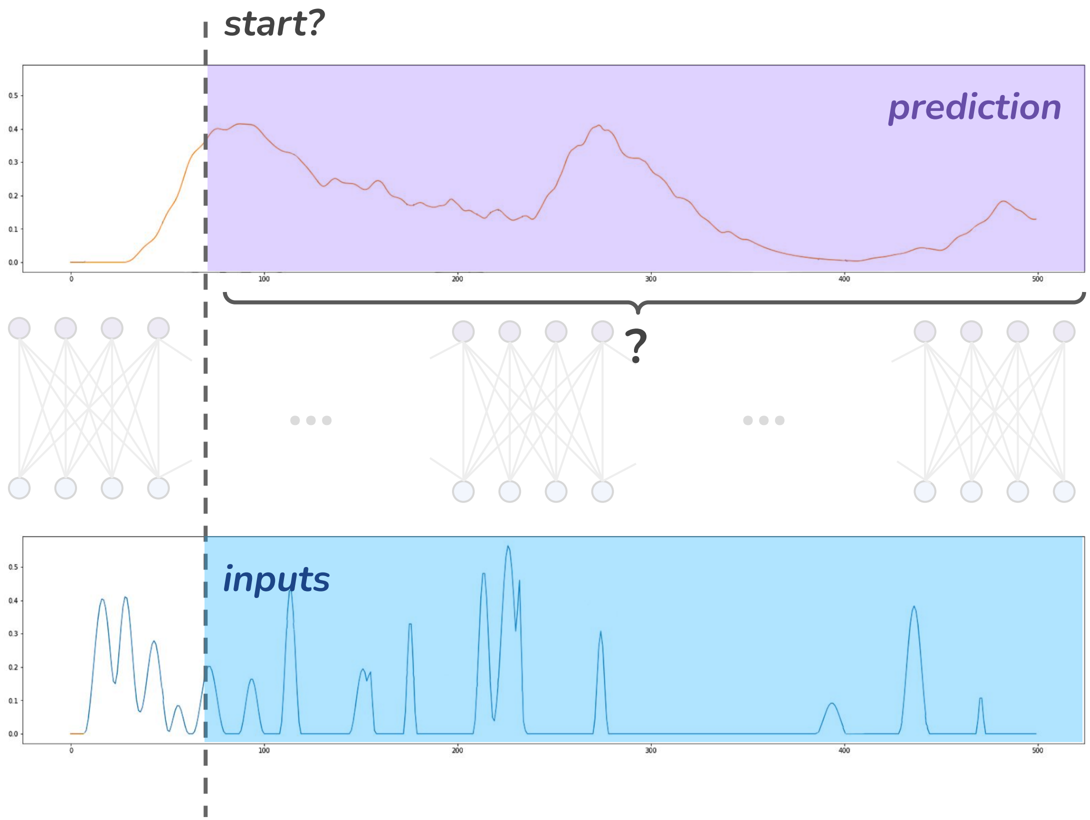
Simple feed-forward network



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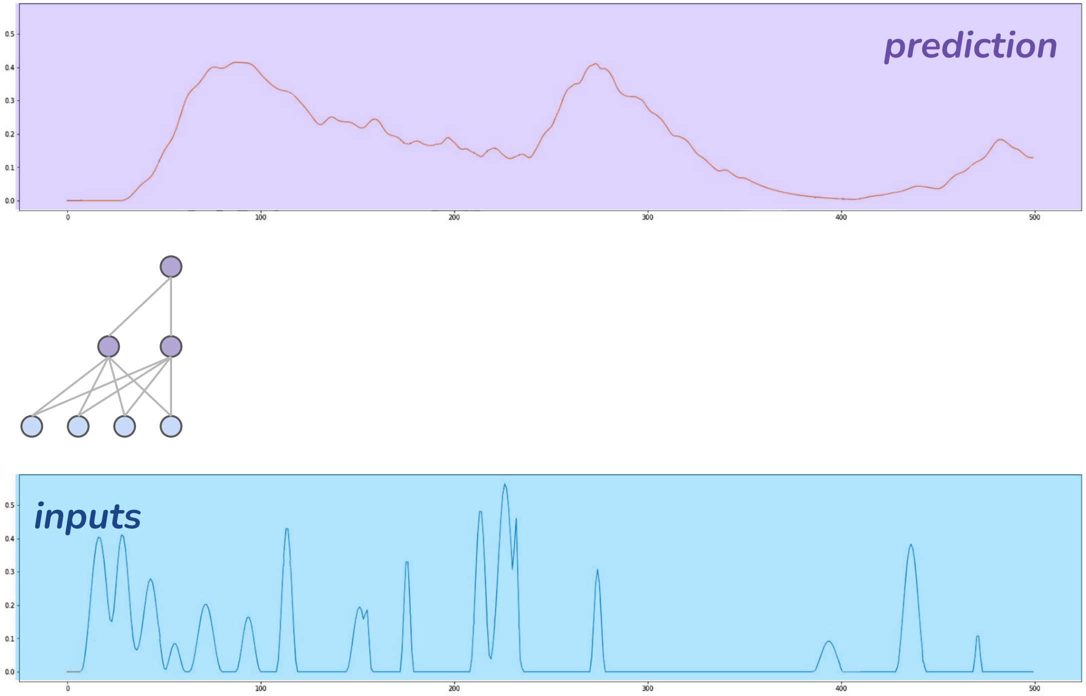
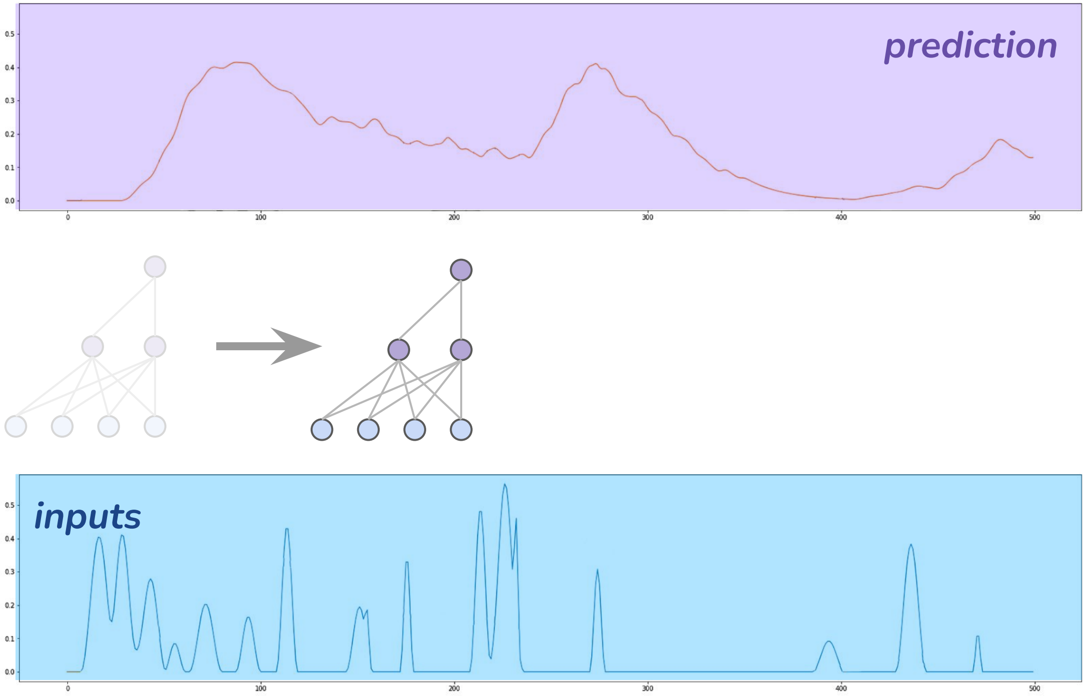
Sliding feed-forward network



Sliding feed-forward network



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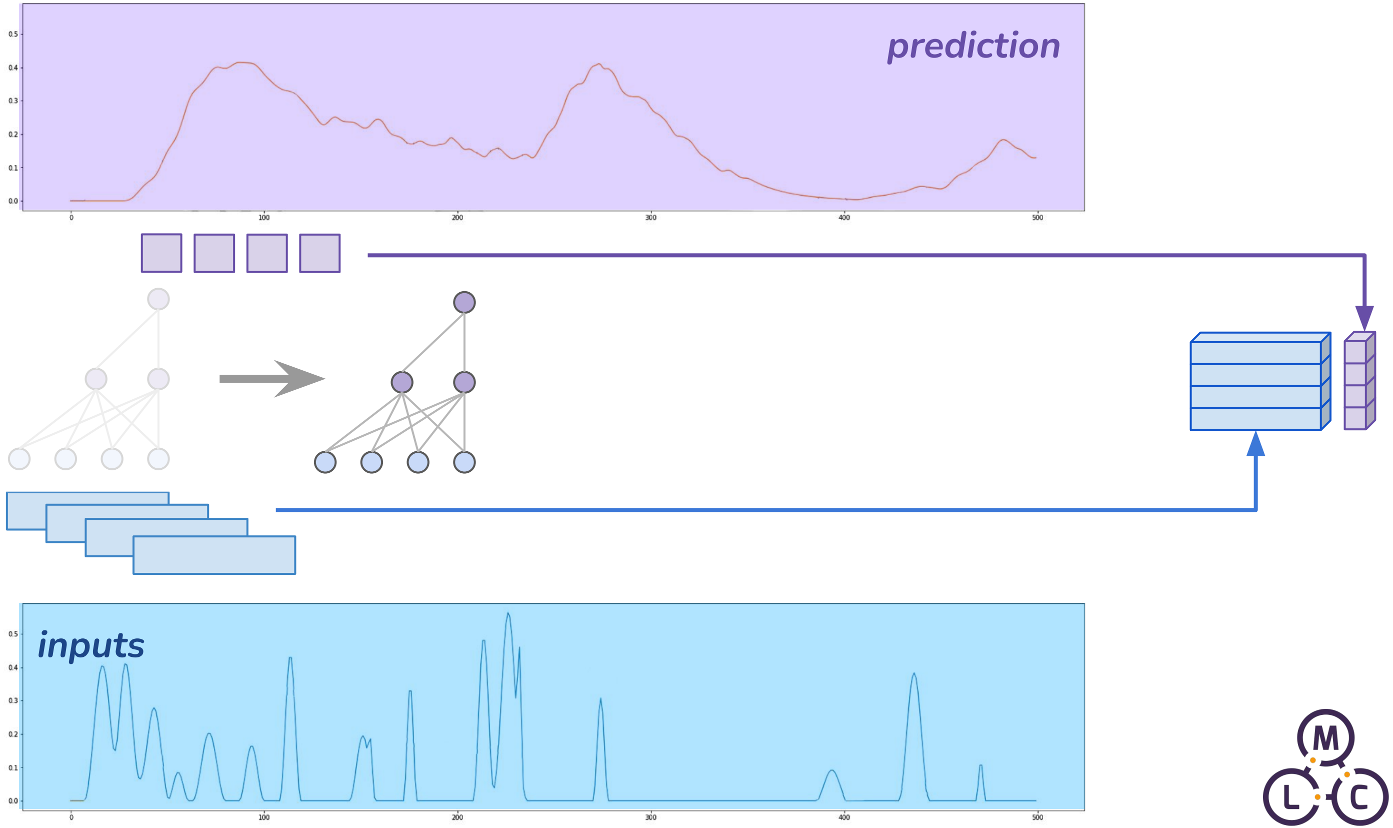

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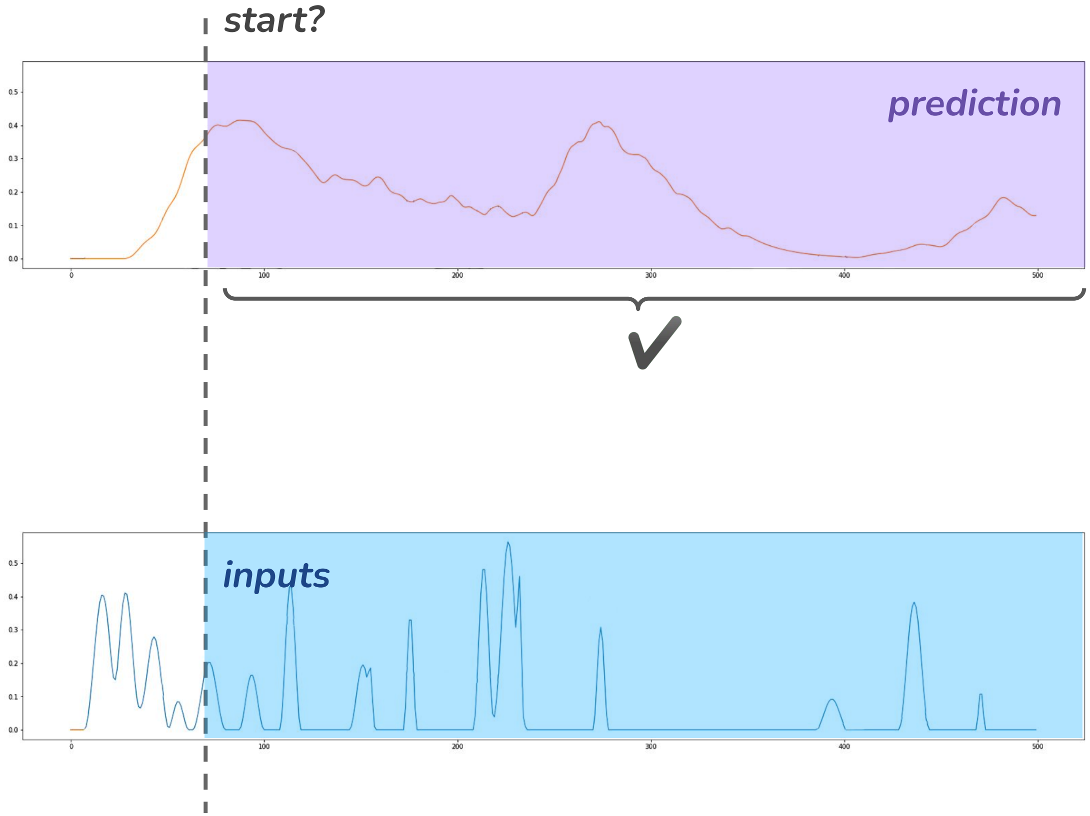

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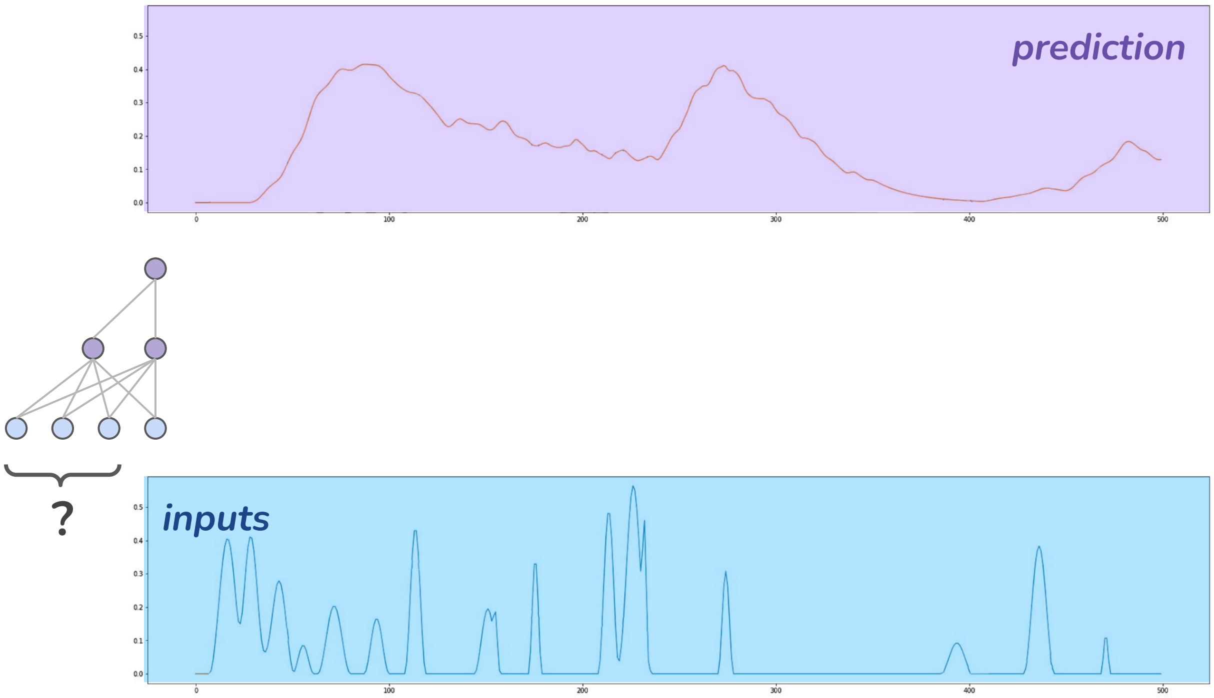

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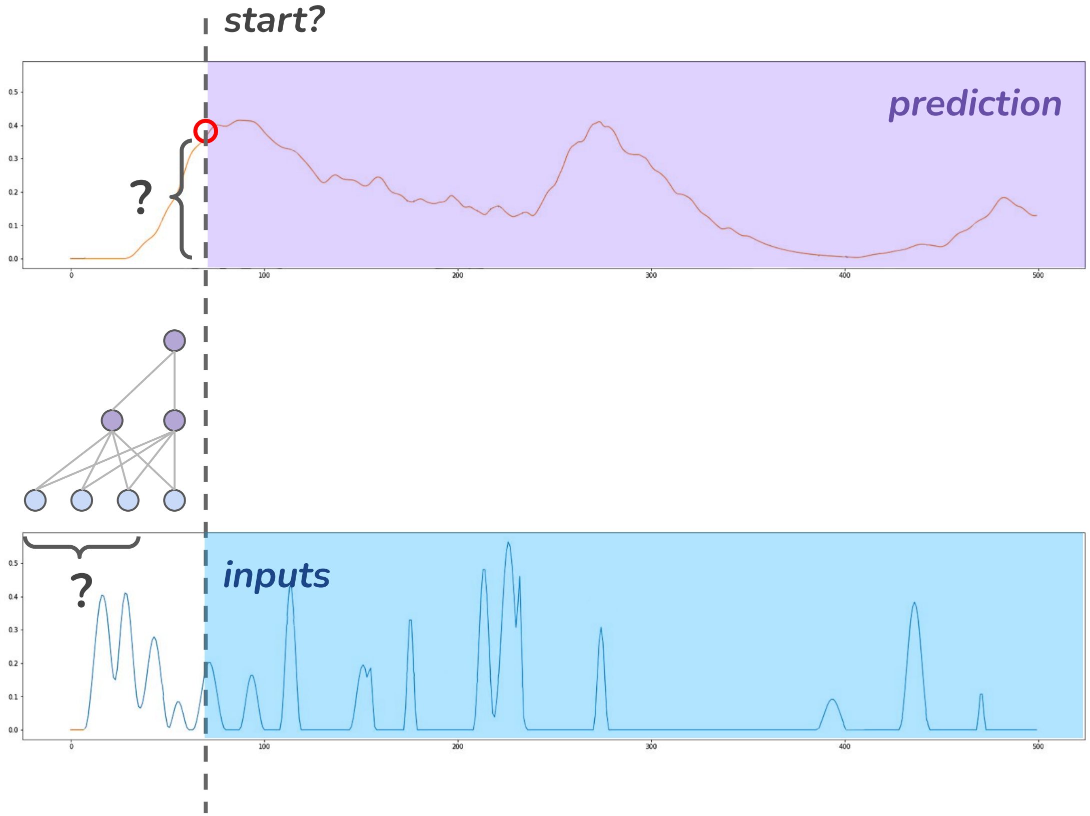
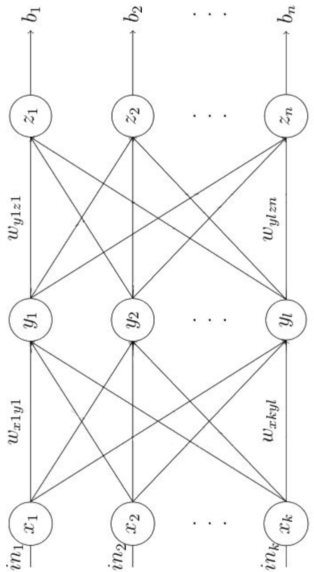
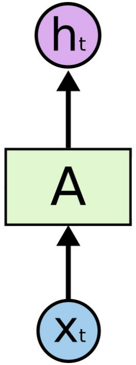
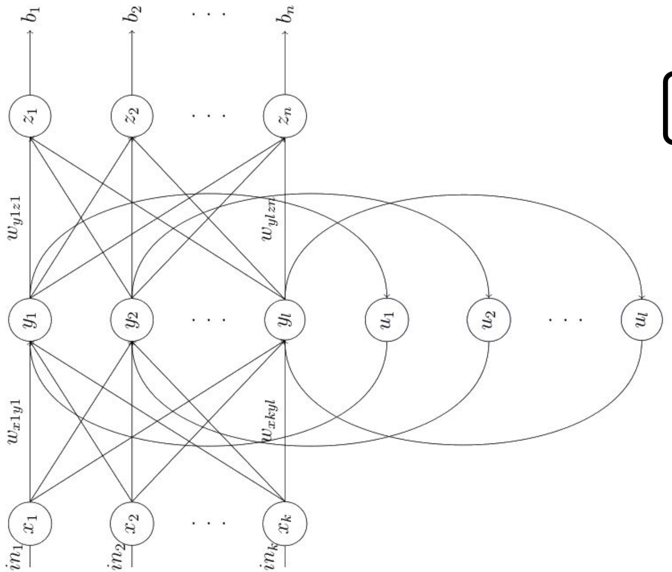
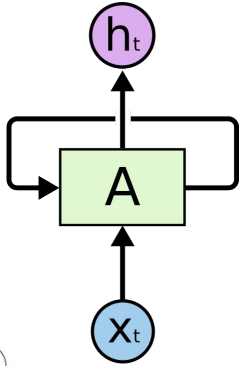


Recurrent Neural Networks









*http://colah.github.io/posts/2015-08-Understanding-LSTMs/

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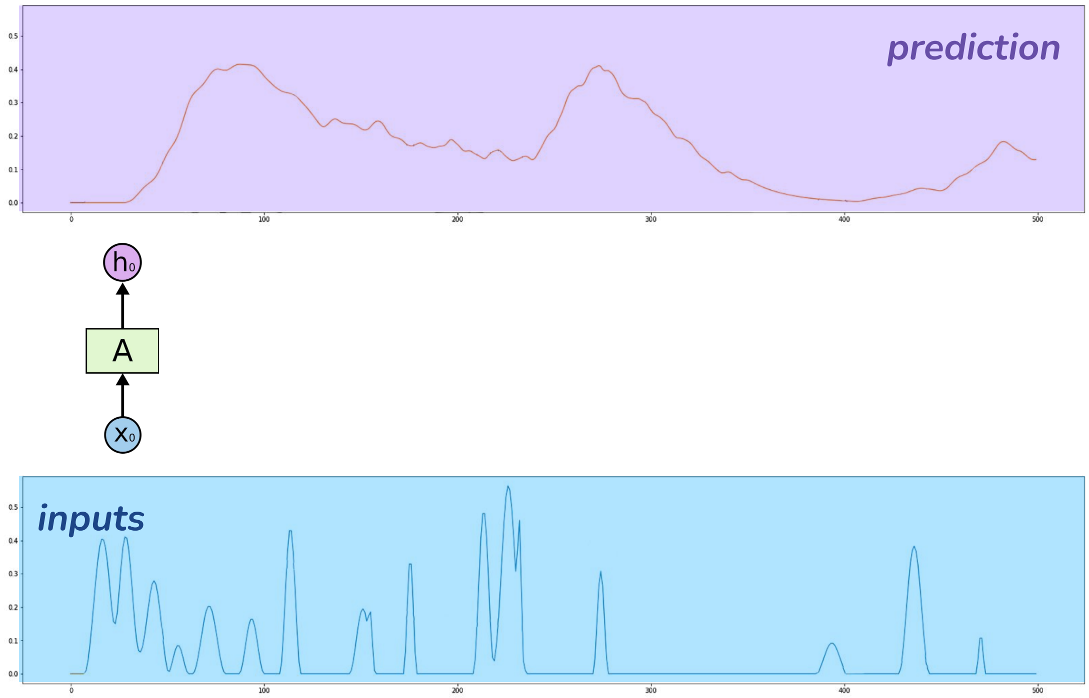
RNN for time series prediction



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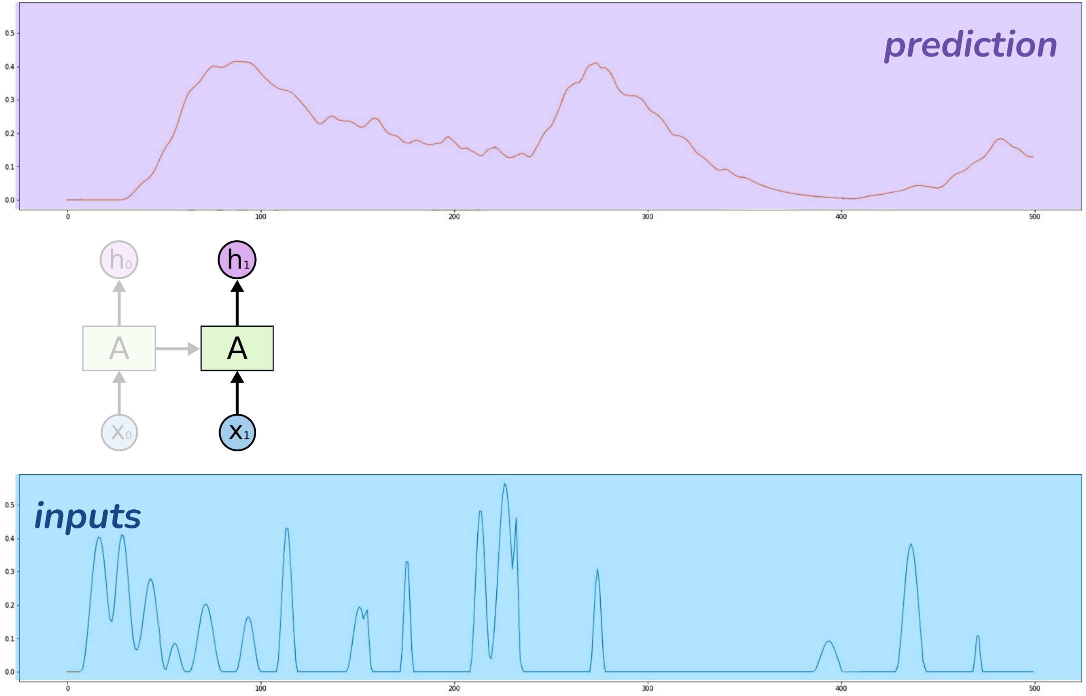
RNN for time series prediction



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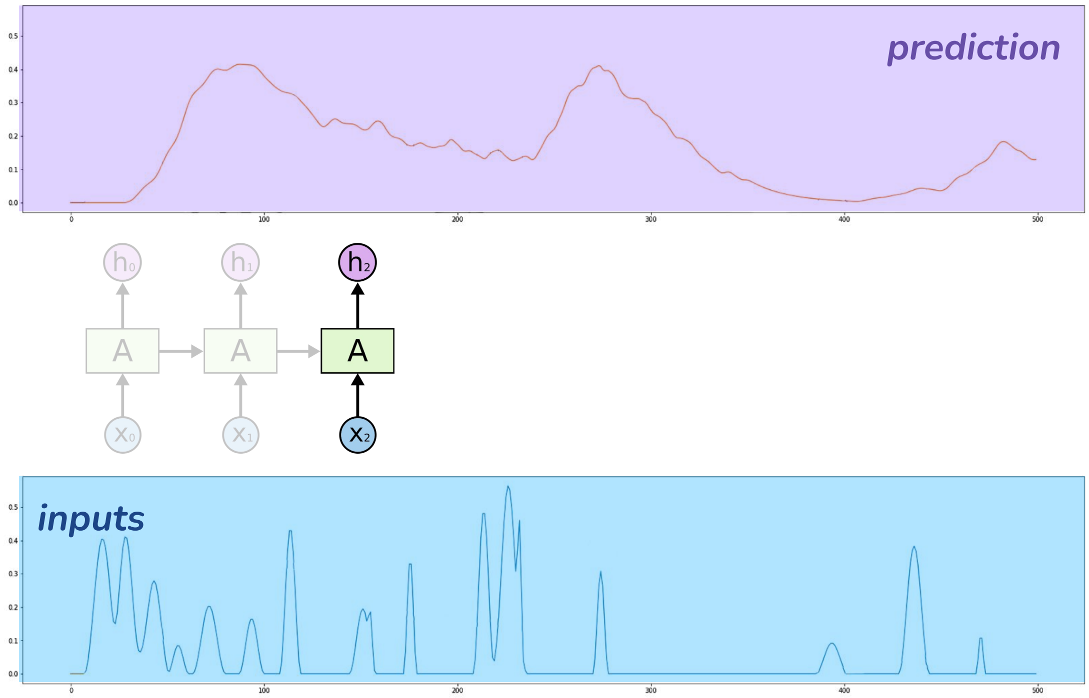
RNN for time series prediction



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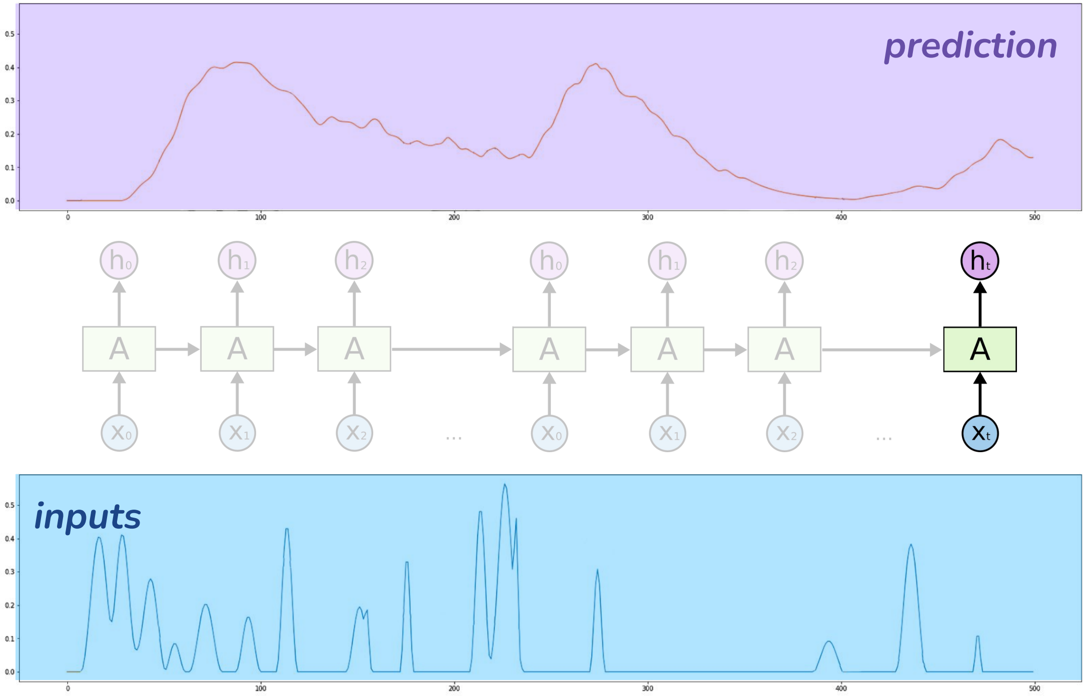
RNN for time series prediction



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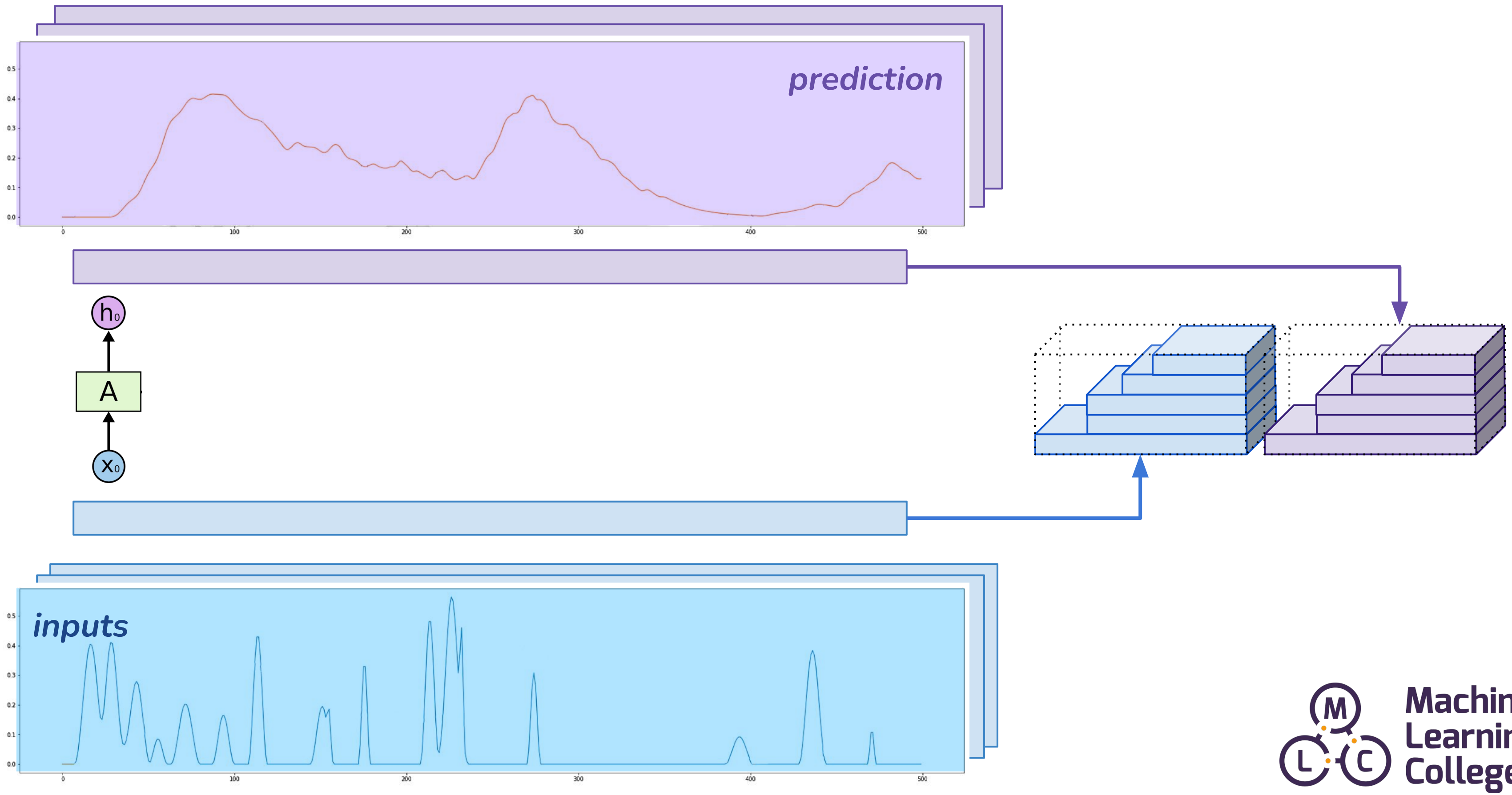
RNN for time series prediction



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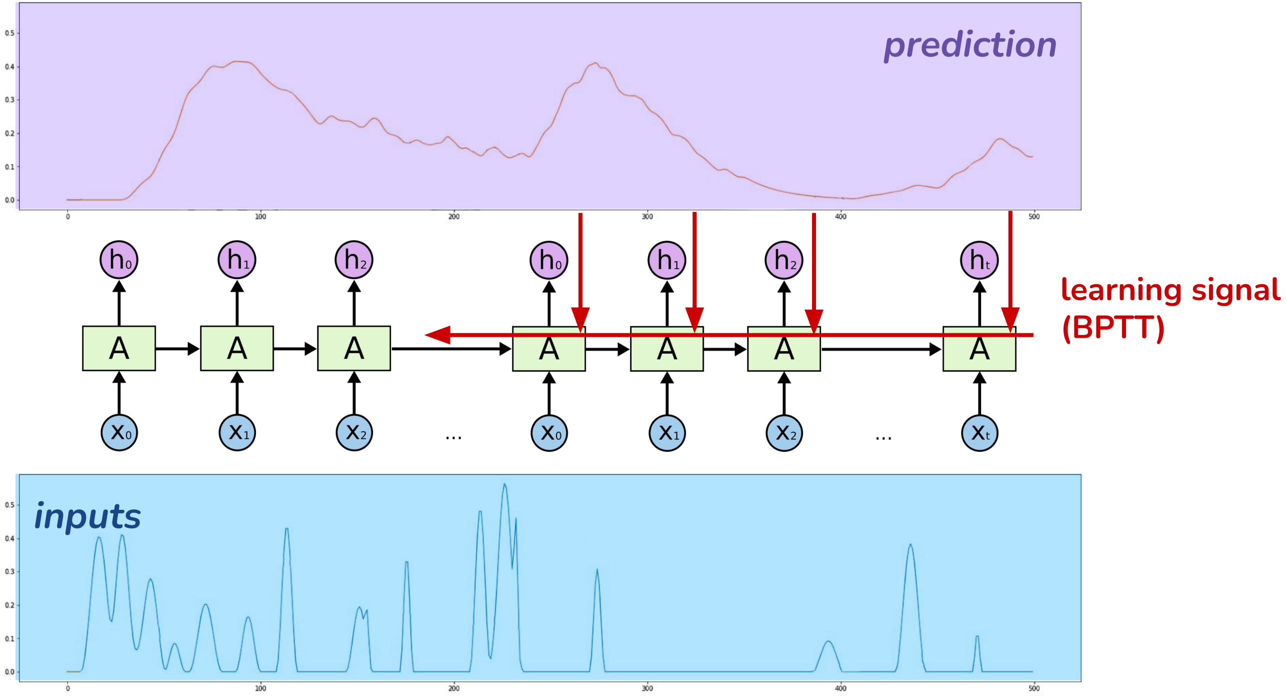

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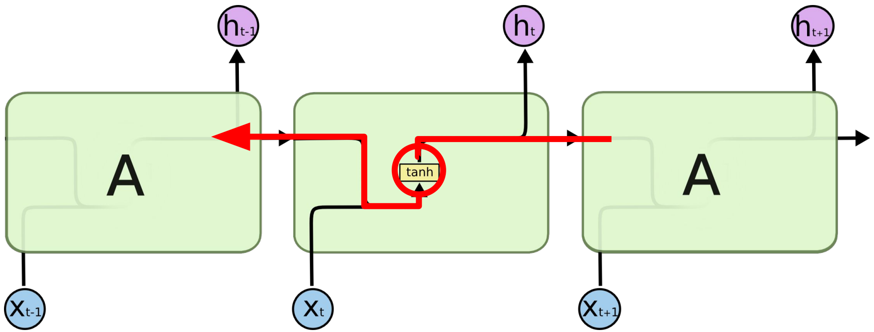
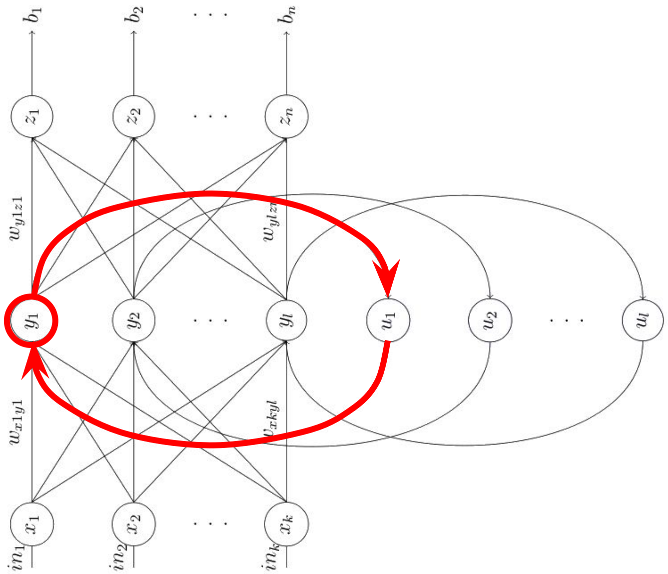
RNN – Vanishing gradients





*http://colah.github.io/posts/2015-08-Understanding-LSTMs/

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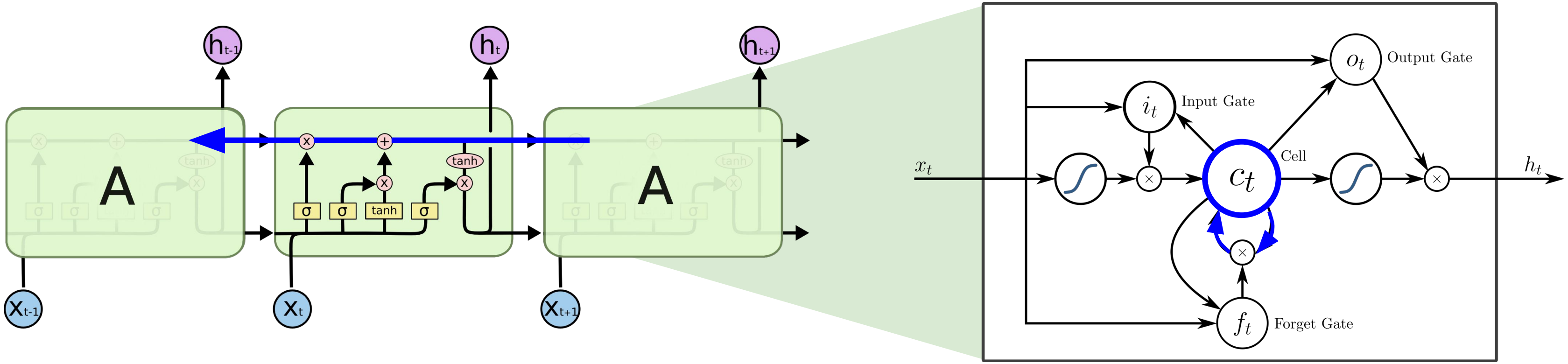
Long short-term memory – LSTM



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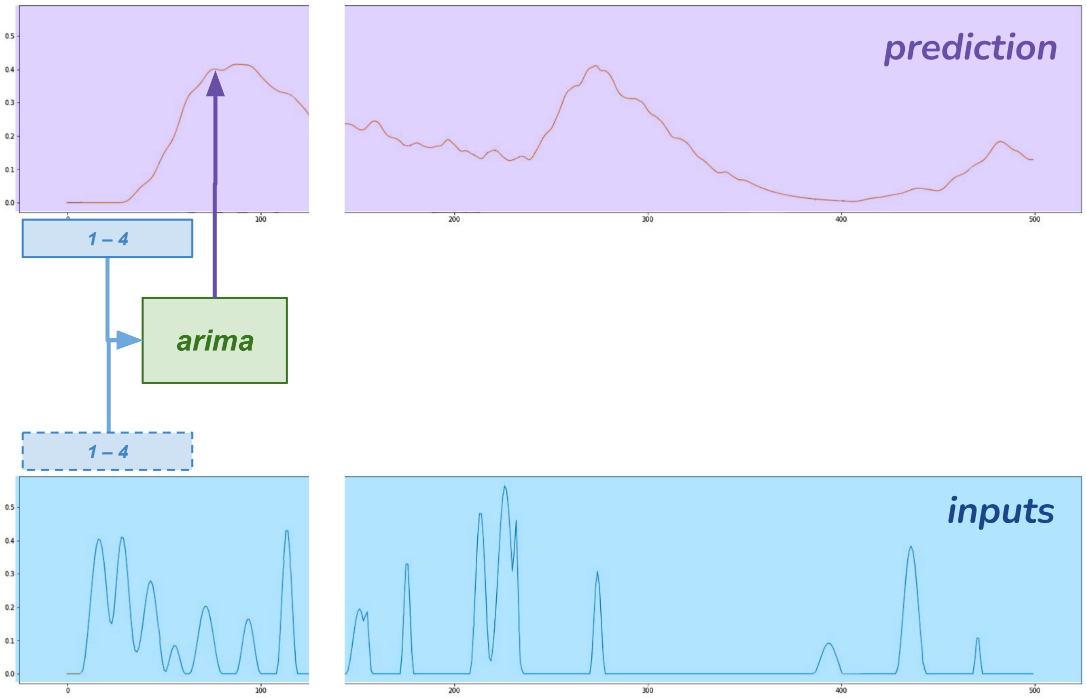
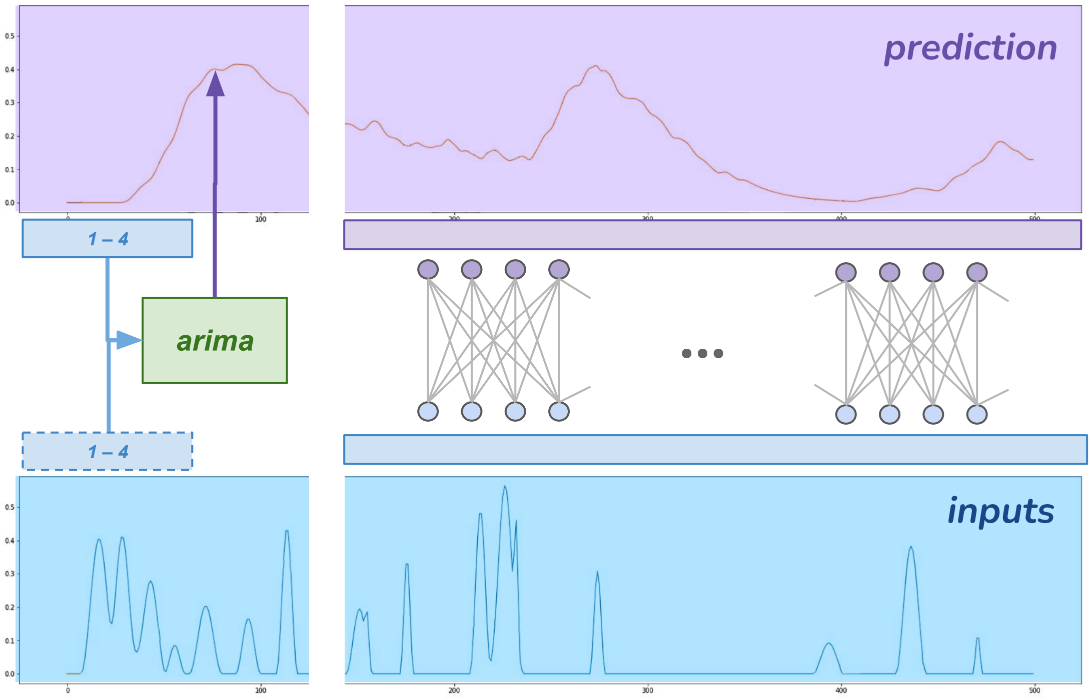
Classical model vs. neural network



Classical model vs. neural network



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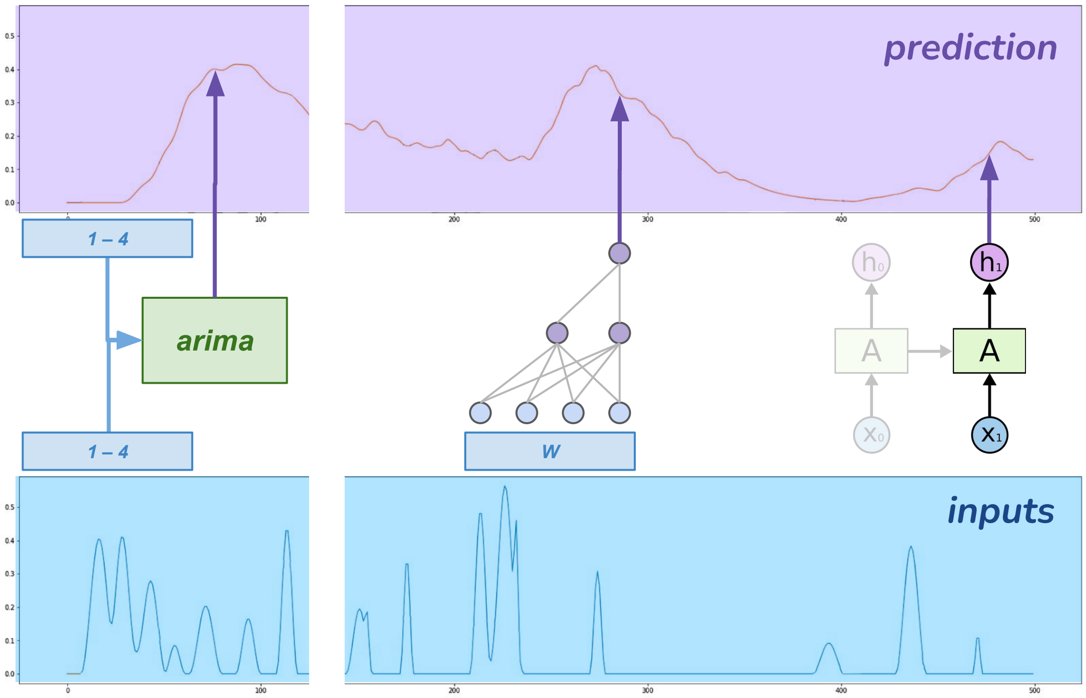
Classical model vs. neural network



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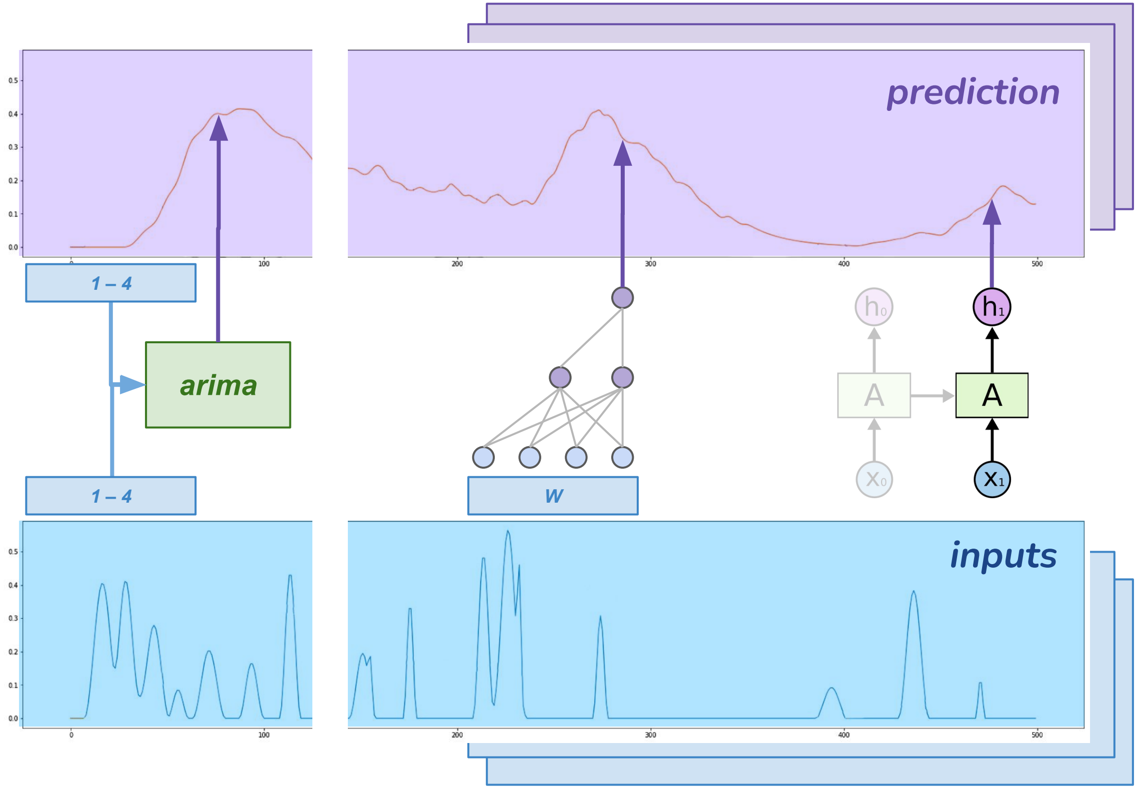
Classical model vs. neural network



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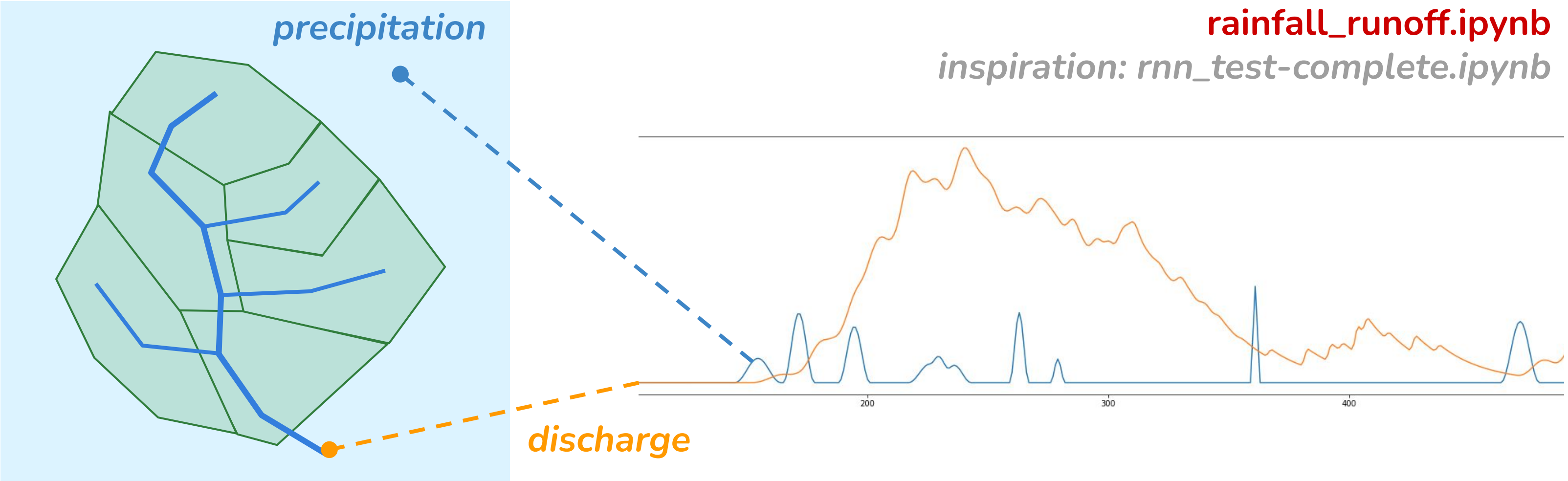
Rainfall-runoff example



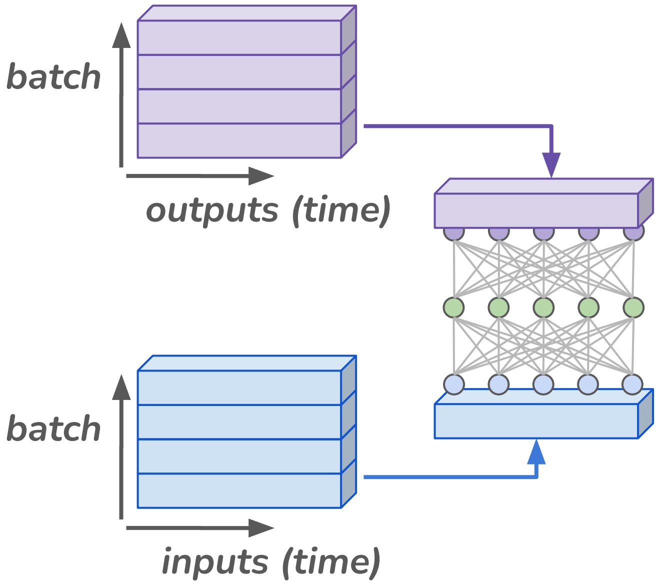
rainfall_runoff.ipynb

inspiration: rnn_test-complete.ipynb

- Test out neural networks on simple **generated rainfall-runoff dataset**
  - Simulated **long-time dependencies** in data
  - Test various neural network architectures
    - Flat feed-forward network
    - LSTM

Tensors & dimentions – univariate regression

Flat NN = 2D training data



$(B, T) \longrightarrow (B, T)$

Tensors & dimentions – univariate regression

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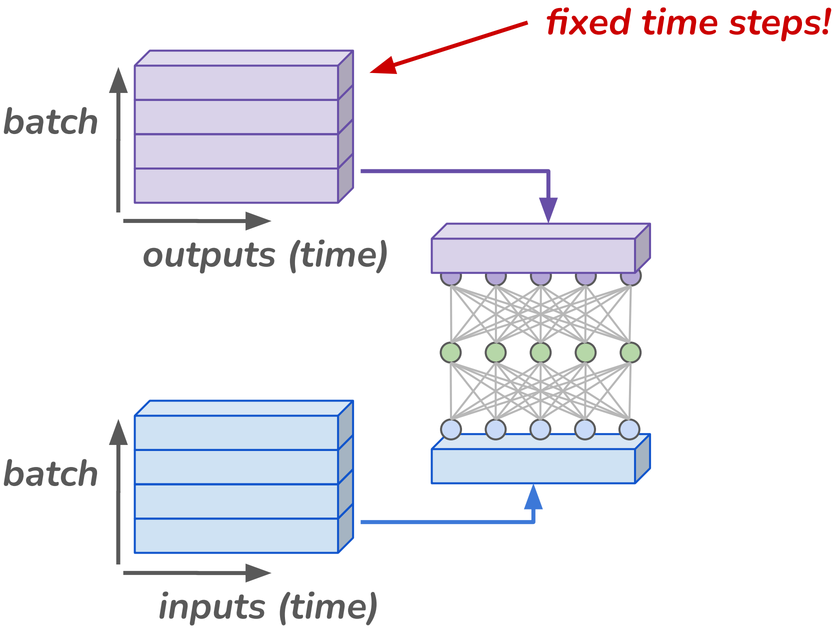

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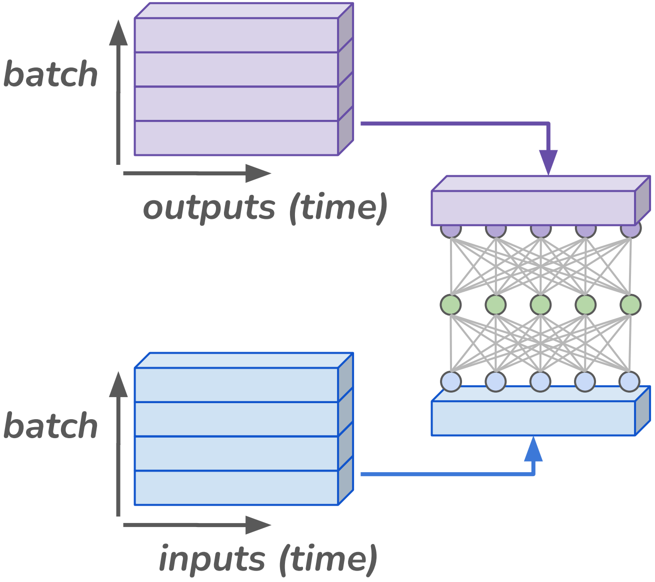
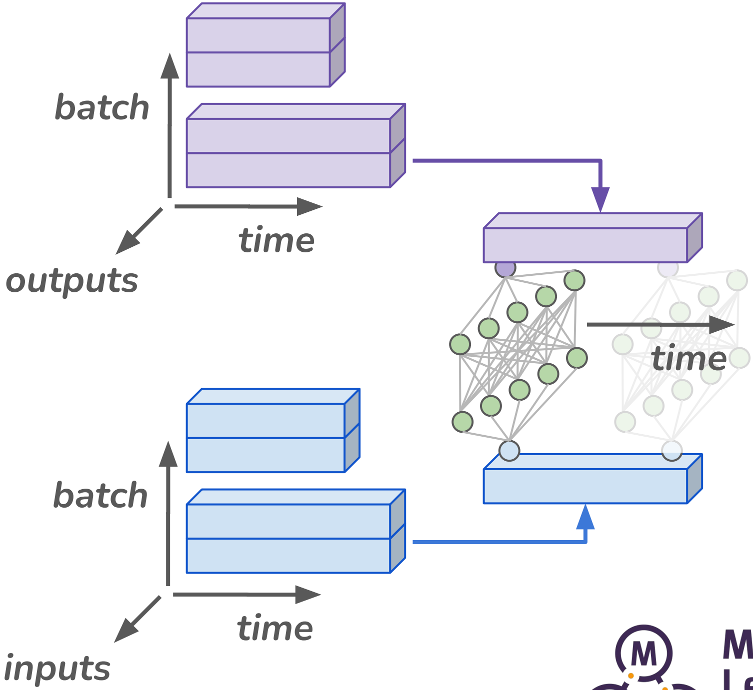


(B, T)⟶(B, T)

Recurrent NN = 3D training data



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Tensors & dimentions – univariate regression

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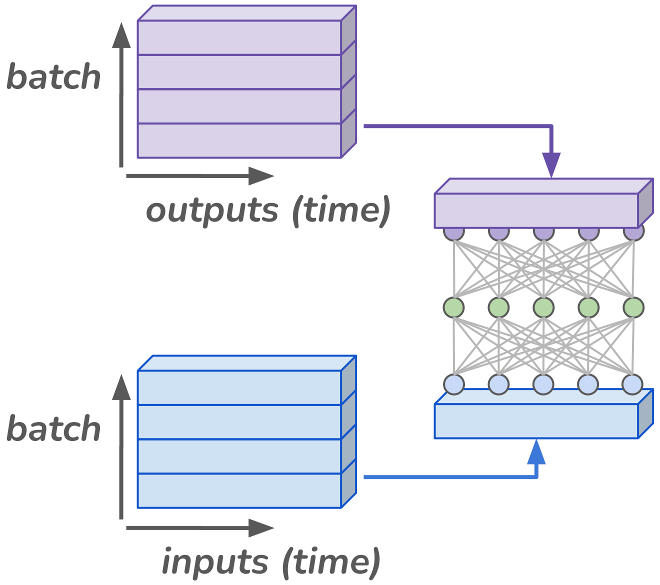

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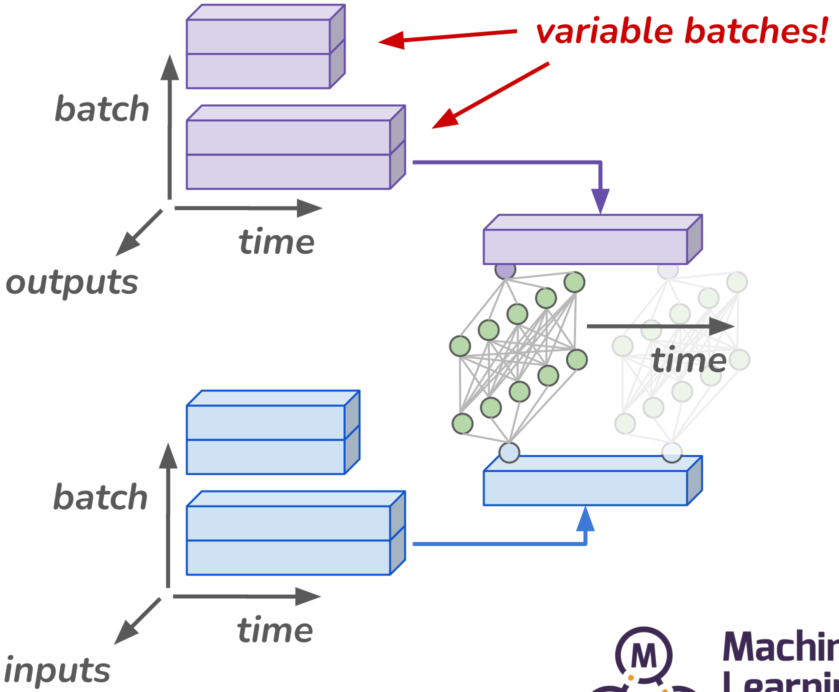

(B, T, 1)⟶(B, T, 1)

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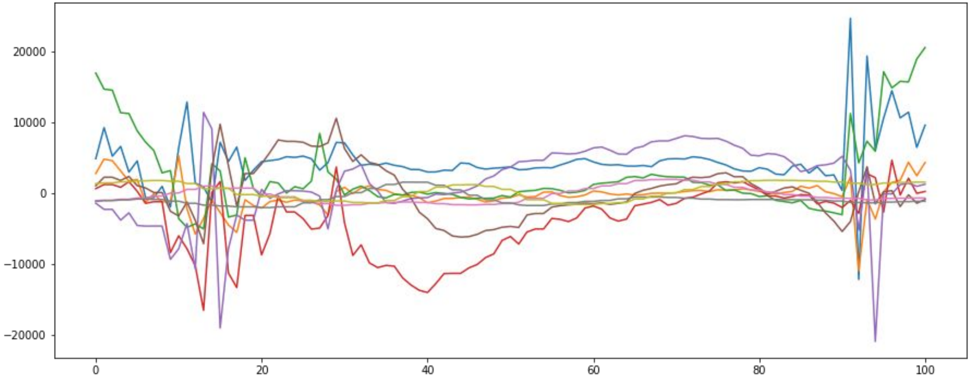
Trampoline jumping example

- Data preparation
  - Dataset normalization
  - Sequence padding
- Binary classification task
  - Target values & dimensions
  - Loss functions
- Training & evaluation
  - Inference visualization
  - Evaluation metrics



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Tensors & dimentions – binary classification

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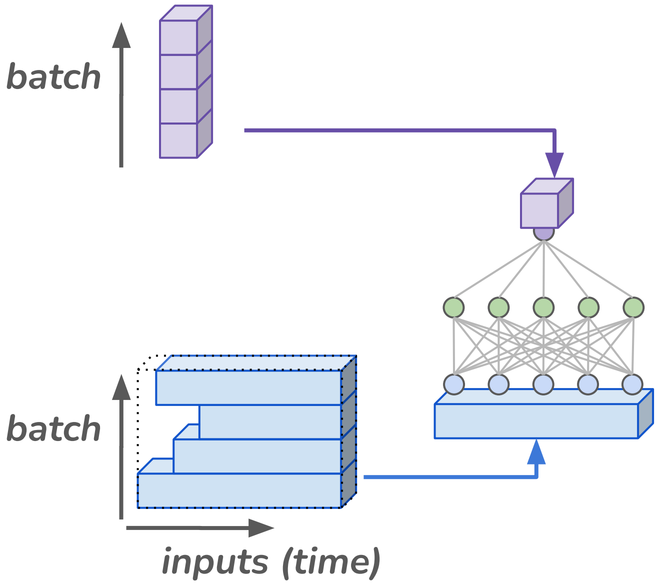

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Tensors & dimentions – binary classification

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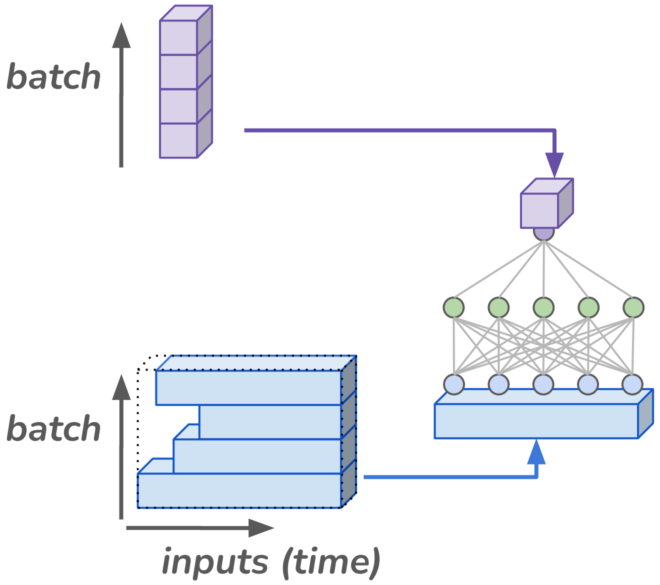

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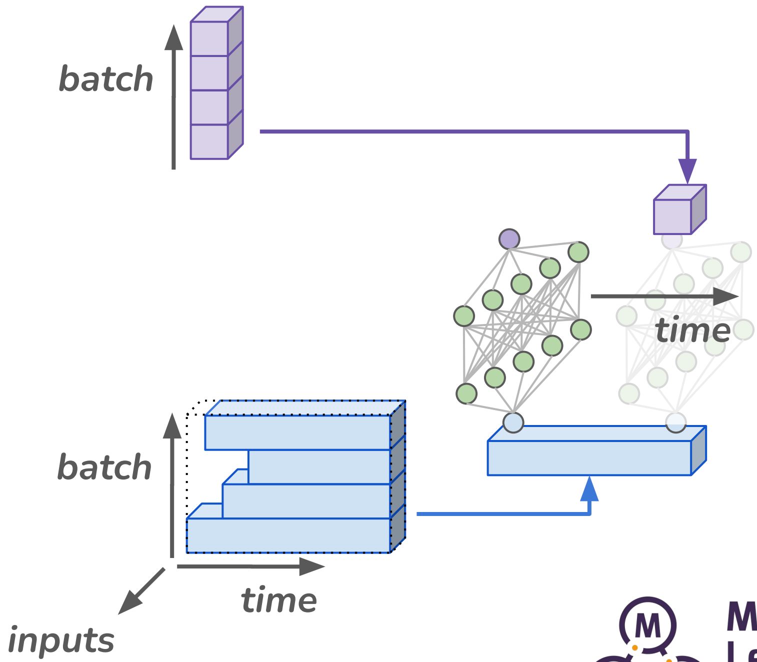

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Tensors & dimentions – binary classification

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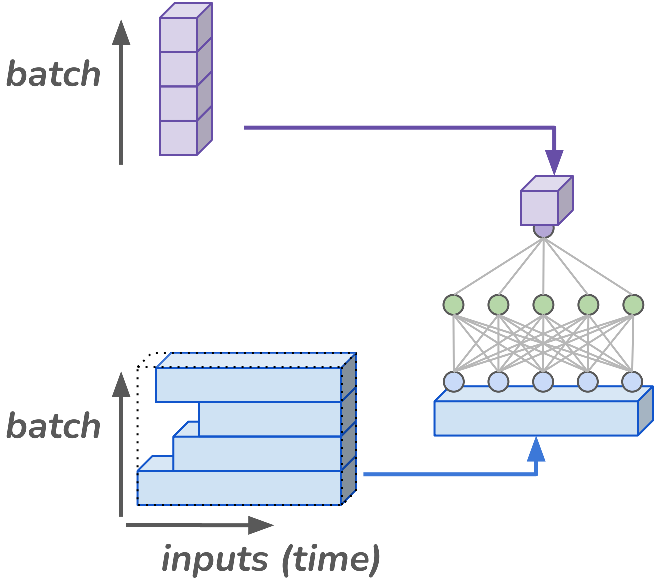

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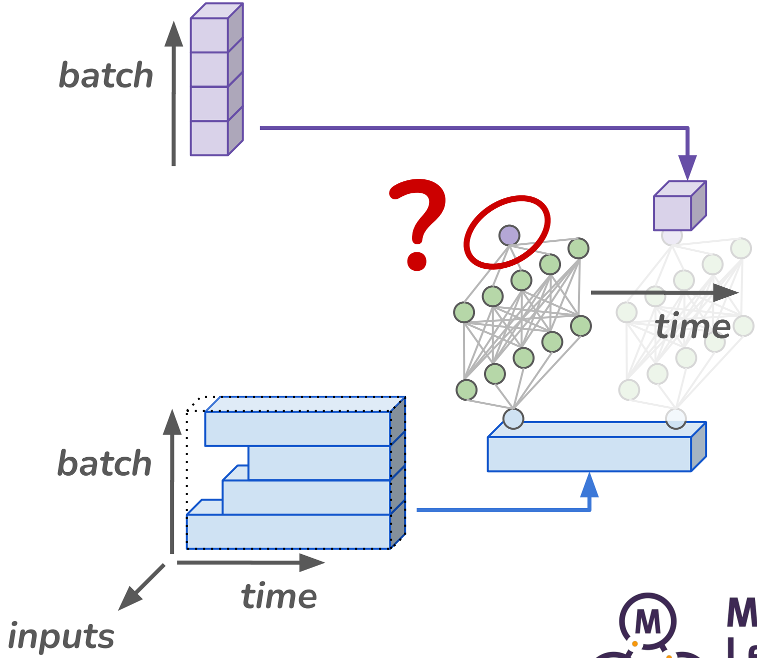

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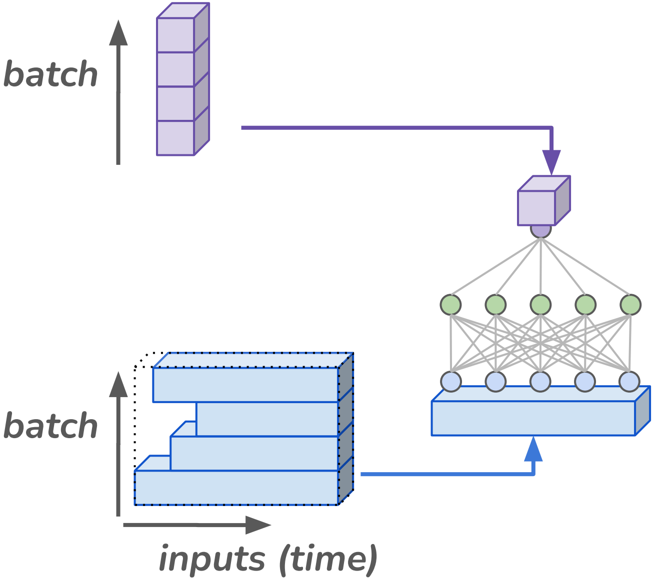

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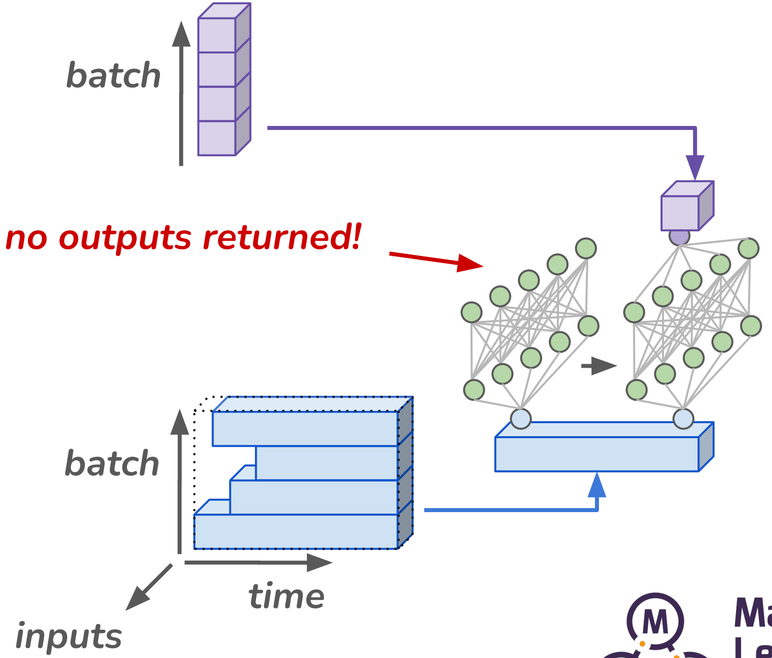

$(B, T, 1) \longrightarrow (B, 1)$

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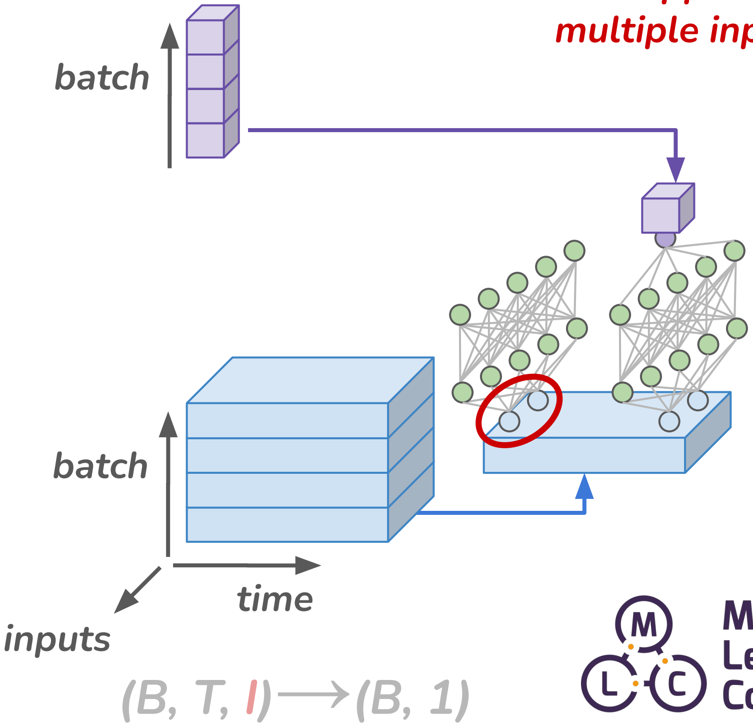
Tensors & dimentions – multivariate b. classification

Flat NN = 2D training data

?

Recurrent NN = 3D training data

natural support for multiple inputs



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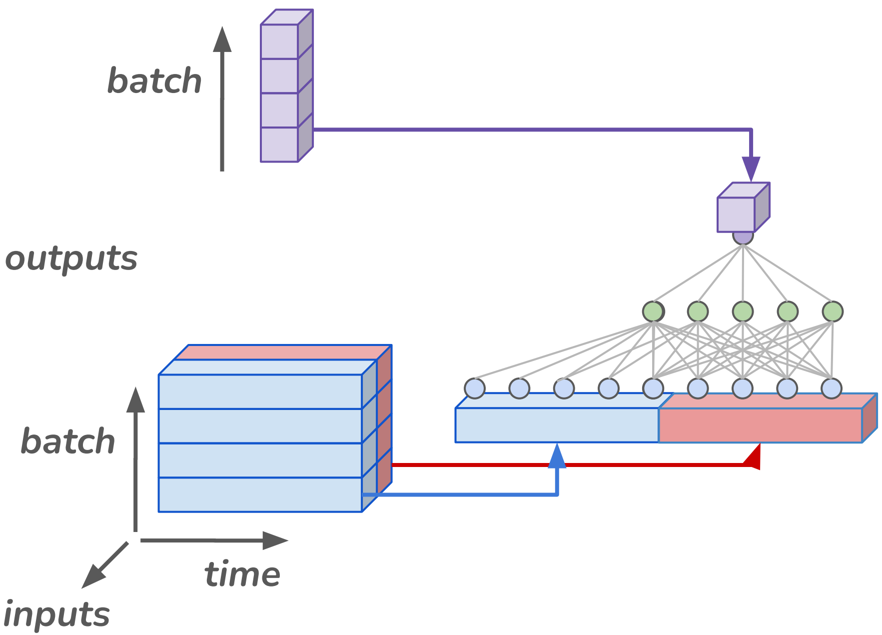
Tensors & dimentions – multivariate b. classification

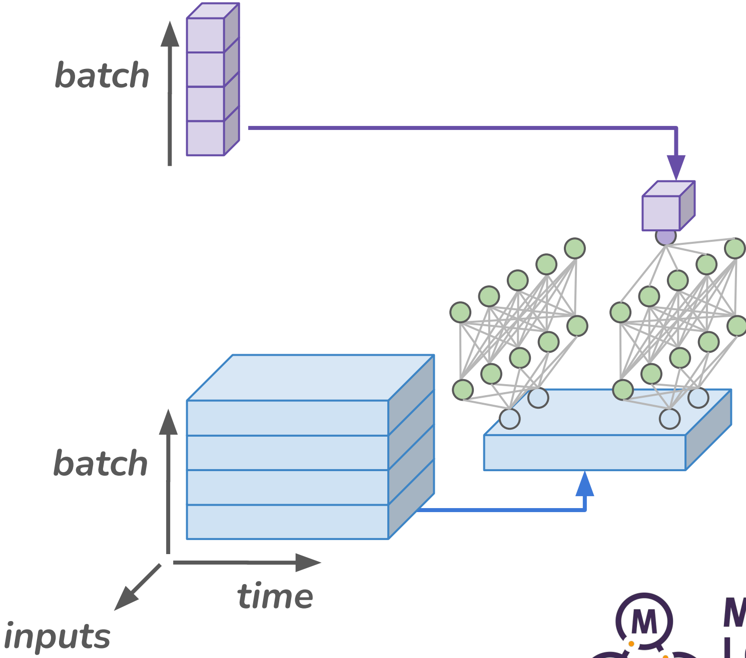
Flat NN = 3D⟶2D training data

flattening / interleaving



(B, T×I)⟶(B, T×O)

Recurrent NN = 3D training data



(B, T, I)⟶(B, 1)

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Binary classification – confusion matrix

		Predicted condition			Sources: [20][21][22][23][24][25][26][27] view · talk · edit
	Total population $= P + N$	**Positive (PP)**	**Negative (PN)**	Informedness, bookmaker informedness (BM) $= TPR + TNR - 1$	Prevalence threshold (PT) $= \frac{\sqrt{TPR \times FPR} - FPR}{TPR - FPR}$
Actual condition	**Positive (P)**	**True positive (TP),** **hit**	**False negative (FN),** **type II error, miss,** **underestimation**	True positive rate (TPR), recall, sensitivity (SEN), probability of detection, hit rate, power $= \frac{TP}{P} = 1 - FNR$	False negative rate (FNR), miss rate $= \frac{FN}{P} = 1 - TPR$
	Negative (N)	**False positive (FP),** **type I error, false alarm,** **overestimation**	**True negative (TN),** **correct rejection**	False positive rate (FPR), probability of false alarm, fall-out $= \frac{FP}{N} = 1 - TNR$	True negative rate (TNR), specificity (SPC), selectivity $= \frac{TN}{N} = 1 - FPR$
	Prevalence $= \frac{P}{P + N}$	Positive predictive value (PPV), precision $= \frac{TP}{PP} = 1 - FDR$	False omission rate (FOR) $= \frac{FN}{PN} = 1 - NPV$	Positive likelihood ratio (LR+) $= \frac{TPR}{FPR}$	Negative likelihood ratio (LR−) $= \frac{FNR}{TNR}$
	Accuracy (ACC) $= \frac{TP + TN}{P + N}$	False discovery rate (FDR) $= \frac{FP}{PP} = 1 - PPV$	Negative predictive value (NPV) $= \frac{TN}{PN} = 1 - FOR$	Markedness (MK), deltaP (Δp) $= PPV + NPV - 1$	Diagnostic odds ratio (DOR) $= \frac{LR+}{LR-}$
	Balanced accuracy (BA) $= \frac{TPR + TNR}{2}$	F_1 score $= \frac{2 PPV \times TPR}{PPV + TPR} = \frac{2TP}{2TP + FP + FN}$	Fowlkes–Mallows index (FM) $= \sqrt{PPV \times TPR}$	Matthews correlation coefficient (MCC) $= \sqrt{TPR \times TNR \times PPV \times NPV} - \sqrt{FNR \times FPR \times FOR \times FDR}$	Threat score (TS), critical success index (CSI), Jaccard index $= \frac{TP}{TP + FN + FP}$

https://en.wikipedia.org/wiki/Confusion_matrix

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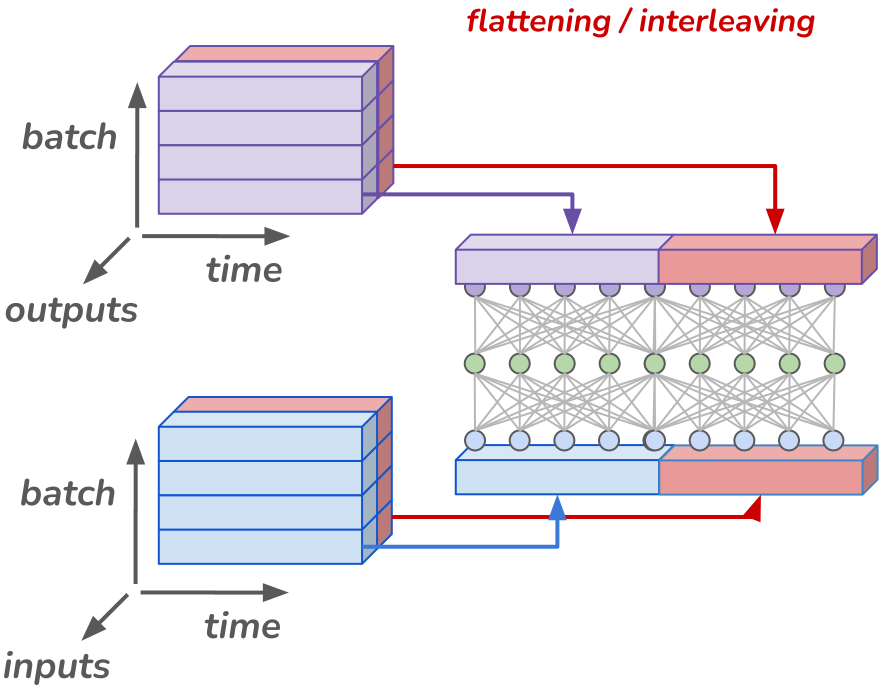
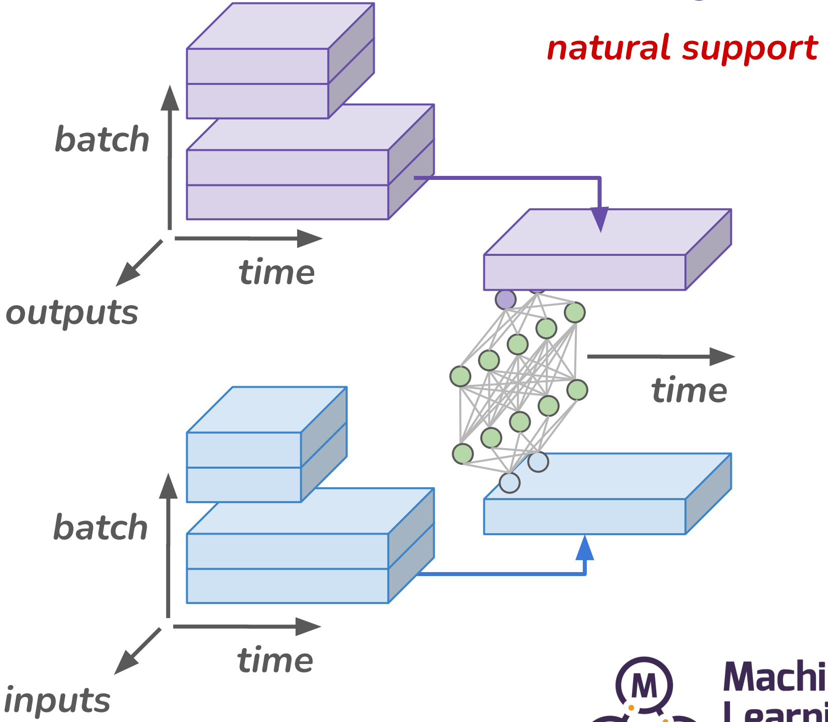
Tensors & dimentions – multivariate regression

Flat NN = 3D⟶2D training data



(B, T×I)⟶(B, T×O)

Recurrent NN = 3D training data



(B, T, I)⟶(B, T, O)

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Time Series Modeling using Neural Networks – DAY 2

Dušan Fedorčák

02/2022 – O2

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Content

DAY 1

- **Classical time series analysis**
  - *Decomposition of time series*
  - *ARIMA models family*
  - *State space models generalization*
- **Theoretical window**
  - *Neural Networks & Recurrent NNs*
  - *Time series specifics*
- **Practical examples**
  - *Simple regression – toy example*
  - *Rainfall-runoff simulation – regression*

– lunch break –

- **Practical examples**
  - *Trampoline jumping – classification*
  - *Local Weather Forecast – regression*

DAY 2

- **Product Design & ML**
  - *Integration of ML models into products*
- **Practical Examples** (in random order)
  - *Exoplanets Hunting*
  - *Mobile Motion Sensing*

– lunch break –

- **Tips & tricks for debuging NNs**
- **Practical Examples**
  - *Manufacturing Process Modeling*
  - *Financial distress prediction*

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ML & Product Design – problems & decisions

- ML should solve **problems**
  - AI is cool ⇒ let's use it in the product! ✖
  - We need to solve this problem ⇒ can we apply ML? ✔
  - *Q: What other means of solving the problem are available?*

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  - *Q: What other means of solving the problem are available?*
- Problems vary in **difficulty**
  - Easily solvable by human ⇒ ML helps to scale up & automate
    - spam filter, face recognition, driving a car
  - Not easily solvable by human ⇒ ML can bring some solution
    - weather forecast, stock market prediction
  - *Q: What are we optimizing for? (costs, risk reduction, better service, …)*

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    - weather forecast, stock market prediction
  - *Q: What are we optimizing for? (costs, risk reduction, better service, …)*
- Problems boils down to **decisions**
  - ML can **assist** with decisions
  - ML can **automate** decisions
  - *Q: Could assistance model work for us or full automation is needed?*

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ML & Product Design – automation

- ML solutions are **imperfect**
  - Expectation control & automation bias ⇒ trust issues
  - Scaling up implerfect models ⇒ quality issues
  - Right evaluation metrics – model evaluation vs. UX evaluation
  - *Q: Do all involved parties understand the problem & solution?*
  - *Q: Is there an evaluation metric everybody understands and agrees with?*

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ML & Product Design – automation

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  - Scaling up imperfect models ⇒ quality issues
  - Right evaluation metrics – model evaluation vs. UX evaluation
  - *Q: Do all involved parties understand the problem & solution?*
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- **Black-box** models are tricky
  - Black-box model + automation ⇒ trust issues
  - Expensive configurability & finetuning
  - *Q: Can we build an understandable stress-test evaluation dataset?*
  - *Q: What tools or probes are available for analysis of our learned black-box model?*

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- Assistance ⇔ Automation – there is a **spectrum**
  1. No automation
  2. Scored set of possible decisions
  3. Narrowed set of decision to approve
  4. Veto before automatic execution
  5. Full automation
  - *Q: What is the lowest level of automation that brings value*

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ML & Product Design – data analysis

- ML solutions **depends on data**
  - More complex models ⇒ more data required
  - Constant battle agaings overfitting
  - Distributions shift over time
  - *Q: What data is available and will be available in the future*

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ML & Product Design – data analysis

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  - *Q: What data is available and will be available in the future*
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  - Base rates can have unintuitive effects on the product
  - Sampling reality often produces imbalanced data
  - *Q: What would be the performace of near-perfect model given the base rates*

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ML & Product Design – data analysis

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  - Sampling reality often produces imbalanced data
  - *Q: What would be the performace of near-perfect model given the base rates*
- All datasets are **biased**
  - Inconsistency between data sampling and model goals
  - Biased evaluation sets
  - *Q: Does our historical data reliably capture the goal of the model*

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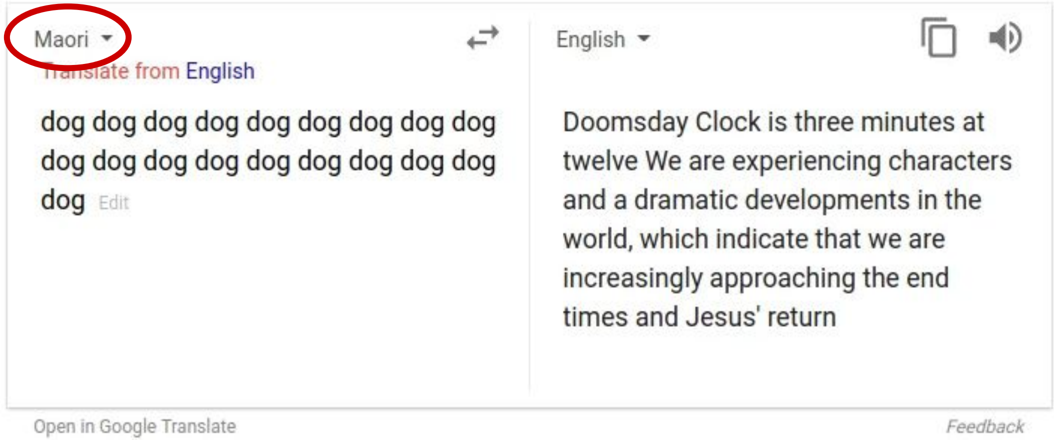
Dataset issues – insufficient number of samples

Dataset issues – insufficient number of samples



https://www.skynettoday.com/briefs/google-nmt-prophecies

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Dataset issues – biased training set

TECHNOLOGY NEWS OCTOBER 10, 2018 / 5:43 AM / UPDATED 2 YEARS AGO

Insight - Amazon scraps secret AI recruiting tool that showed bias against women

By Jeffrey Dastin

8 MIN READ

SAN FRANCISCO (Reuters) - Amazon.com Inc's AMZN.O machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G

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Dataset issues – biased training set

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https://www.aclu.org/blog/privacy-technology/surveillance-technologies/amazons-face-recognition-falsely-matched-28

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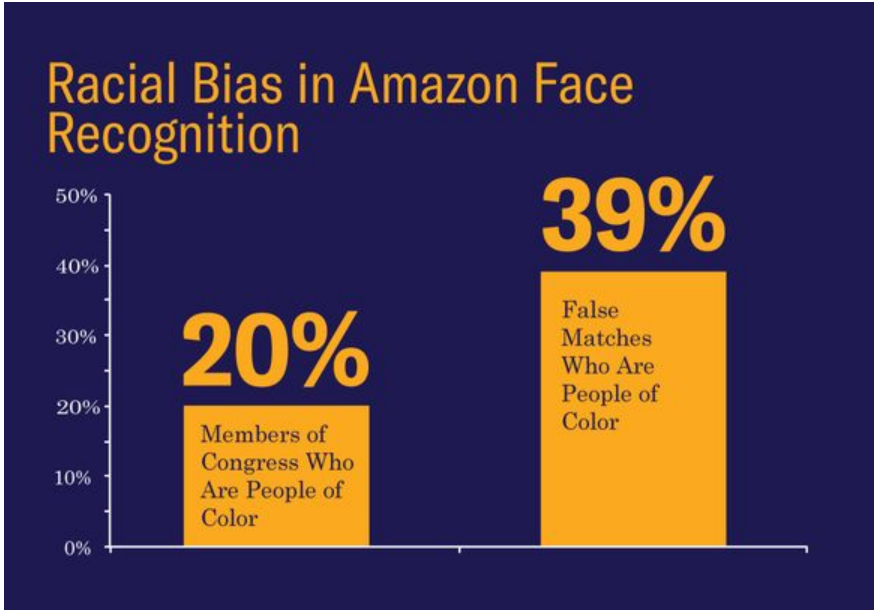

https://www.aclu.org/blog/privacy-technology/surveillance-technologies/amazons-face-recognition-falsely-matched-28

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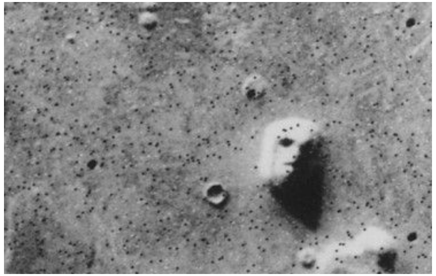
Human perception – overfitted to faces



https://en.wikipedia.org/wiki/Pareidolia

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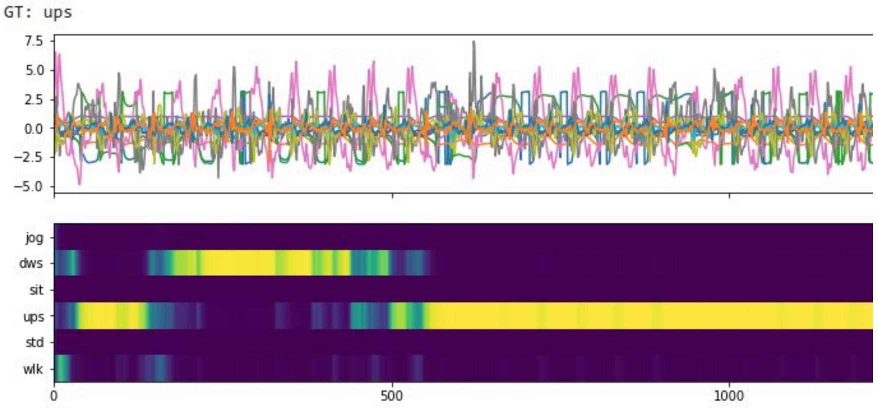
Motion sensing example

- Data preparation
  - Dataset normalization
  - Slicing long sequences
- Categorical classification task
  - Predict activity type
  - Use correct activation & loss function
- Training & evaluation
  - Try different architectures
  - Evaluate resuslt with standard metrics
- Secondary task
  - Subject identification



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ML Tips & Tricks

http://karpathy.github.io/2019/04/25/recipe/

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ML Tips & Tricks

- **Known your data**
  - Visualize everything you can
  - Try to find patterns ⇒ *become the model yourself*
  - Look for noisy labels / missing data
  - Make sure your preprocessing is correct (especially vectorized code)

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- **Simple models first**
  - Build training & evaluation loop
  - Choose simple architectures first ⇒ *less room for errors*
  - Build baseline models for comparison ⇒ *even simple heuristics are useful*

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- **Train iteratively**
  - Train without inputs ⇒ *yields another baseline model*
  - Overfit one batch ⇒ *something is off if you can't get zero loss*
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  - Overfit one batch ⇒ *something is off if you can't get zero loss*
  - Overfit the training set as far as you can
- **Regularize**
  - Early stopping ⇒ *best evaluation loss*
  - Make the model smaller ⇒ *less space for overfitting*
  - Get more training data ⇒ *more labels, data augmentation, pre-training*

http://karpathy.github.io/2019/04/25/recipe/

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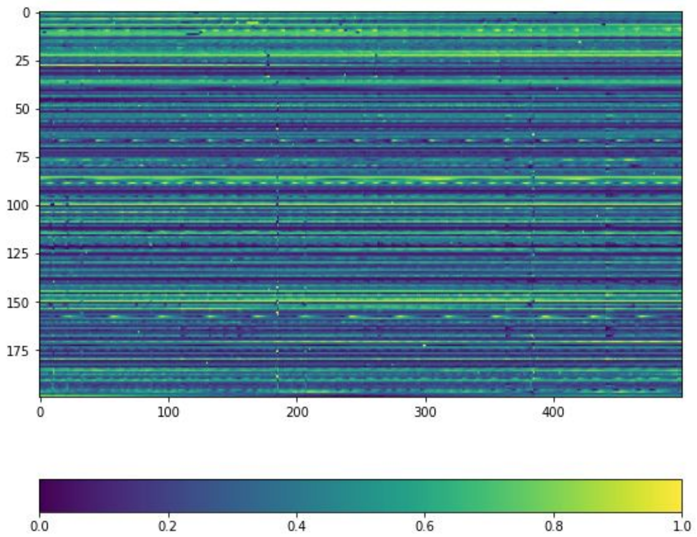
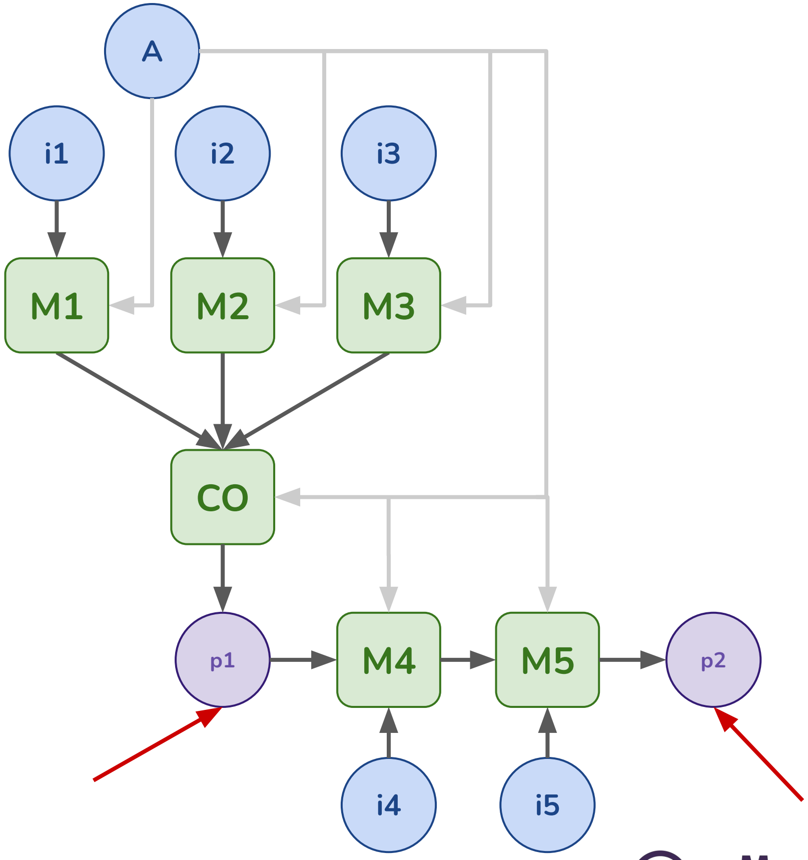
Exoplanets hunting example

- Data preparation
  - Dataset normalization
  - Highly **imbalanced dataset**
- Binary classification/detection task
  - Detect starts with planets
- Model architecture
  - Dense, LSTM, Bidir. LSTM, CNN
- Training & evaluation
  - Use right evaluation metrics for imbalanced datasets



Factory process example

- Data preparation
  - Dealing with **missing values**
  - Dataset normalization
  - Slicing long sequences
- Regression task
  - Predict target variables in future
- Model architecture
  - **Model architecture mimics the process**
- Training & evaluation
  - Masking out missing labels with **custom loss function**



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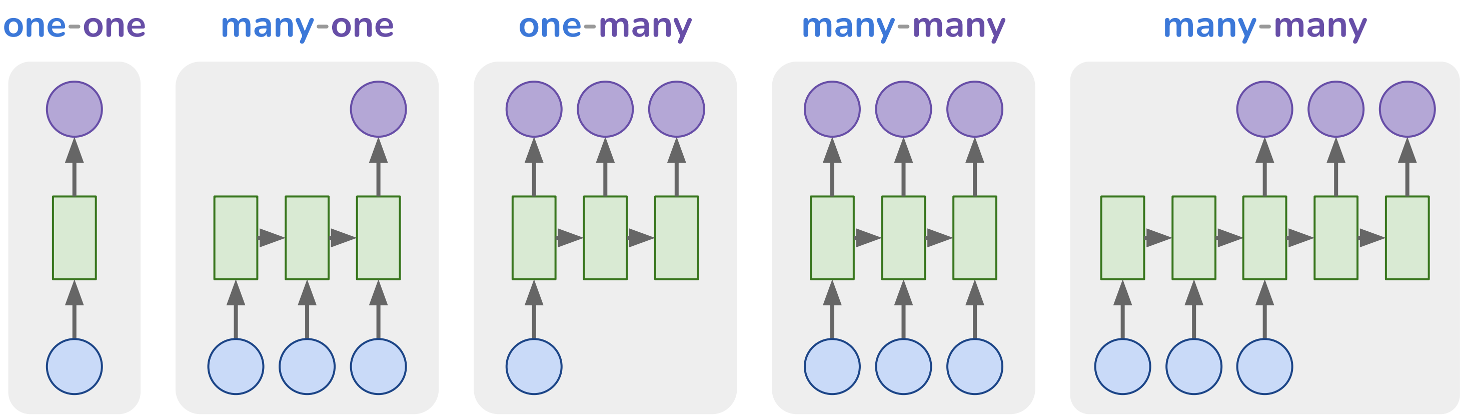
RNN and sequence data



sequence classification

image captioning

time series prediction

machine translation

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*http://karpathy.github.io/2015/05/21/rnn-effectiveness/

RNN for time series prediction

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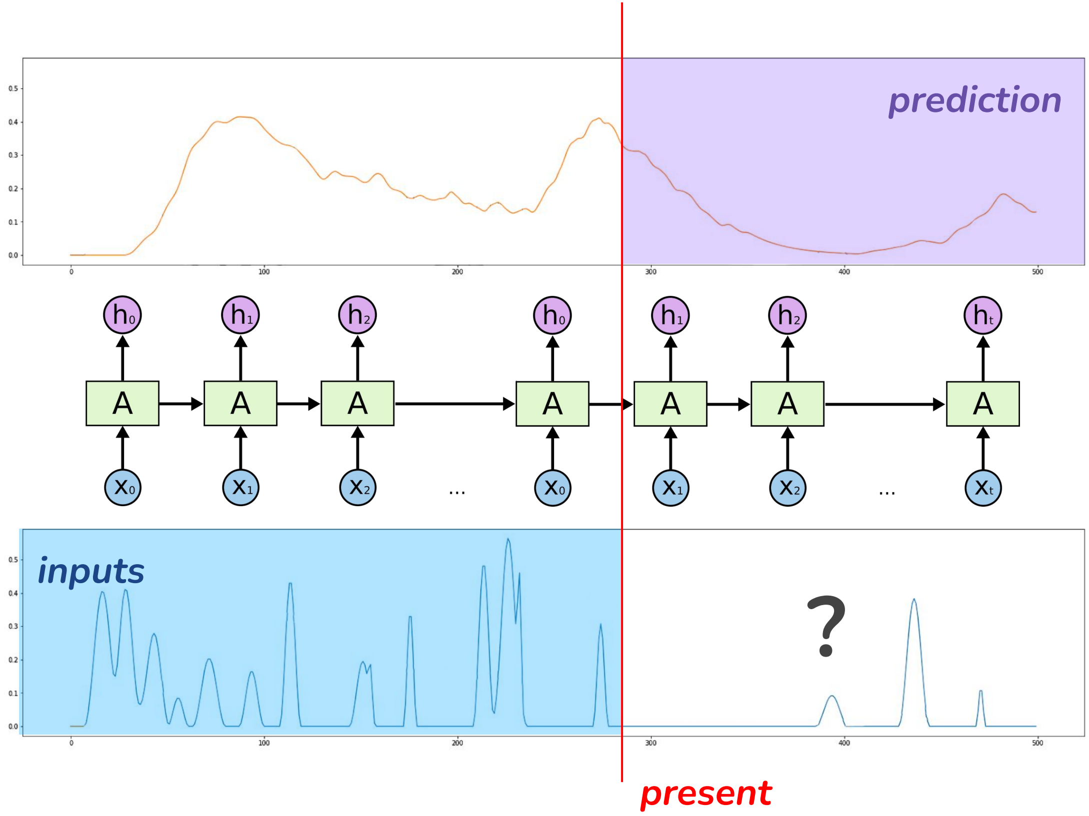
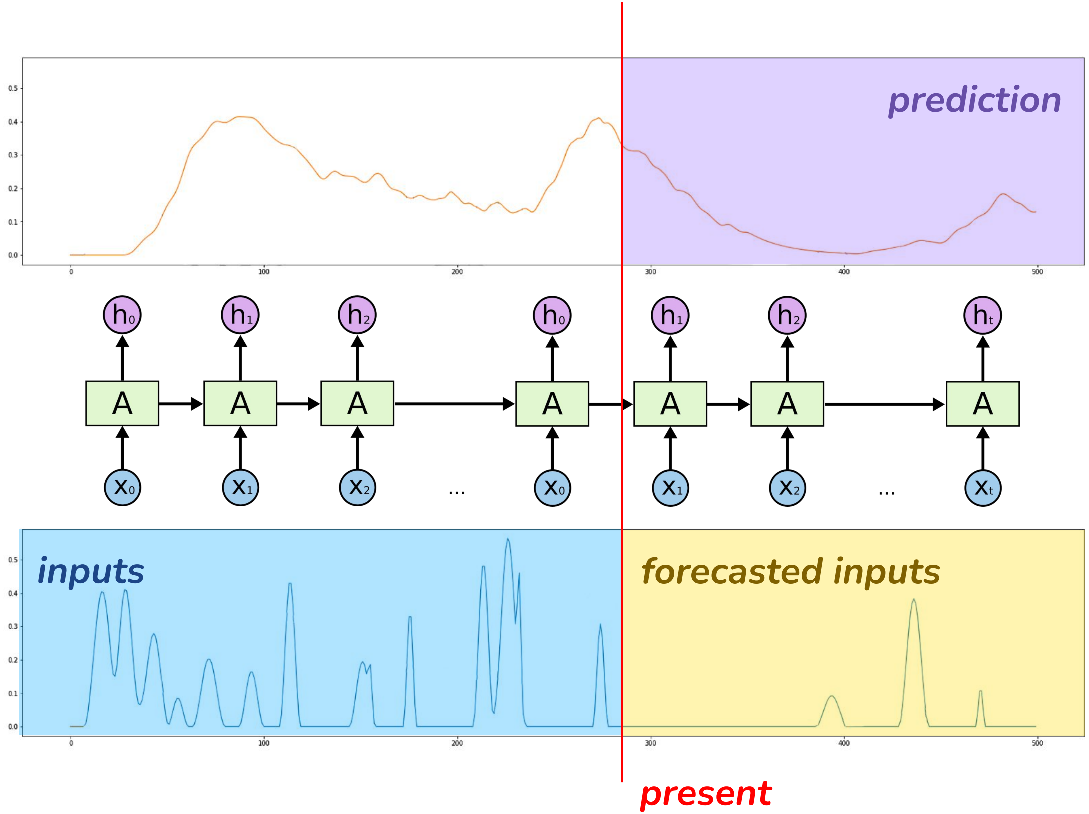
Forecasting from input variables



Forecasting from input variables



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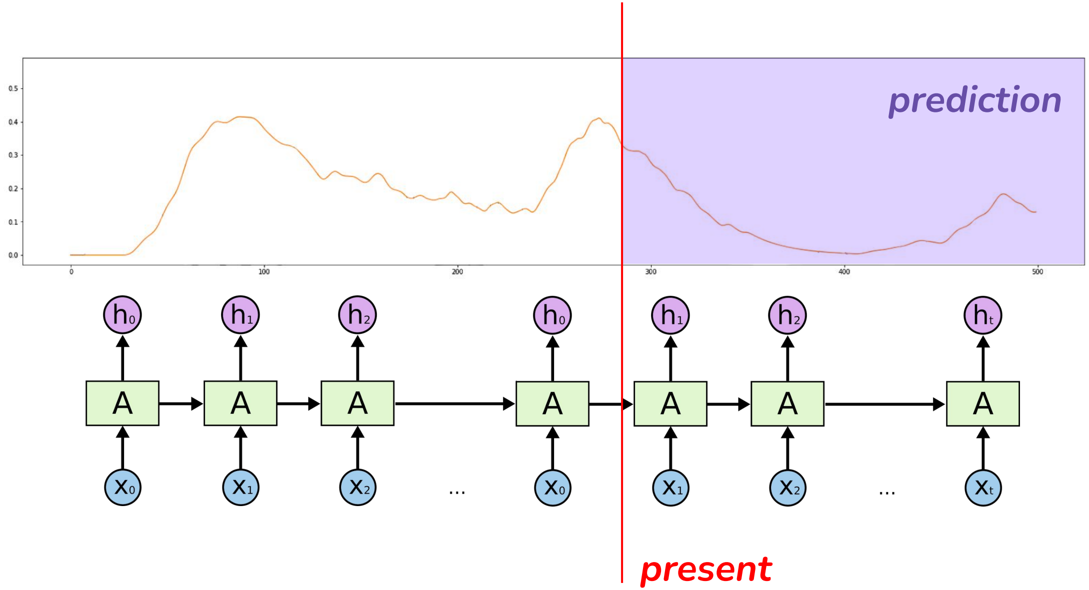
Forecasting from historical values



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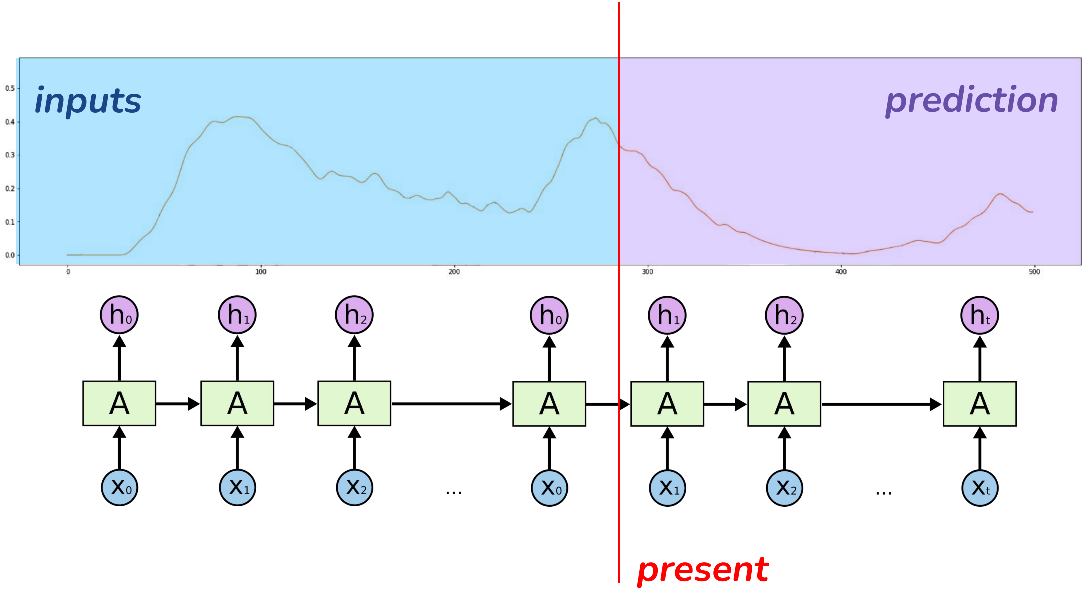
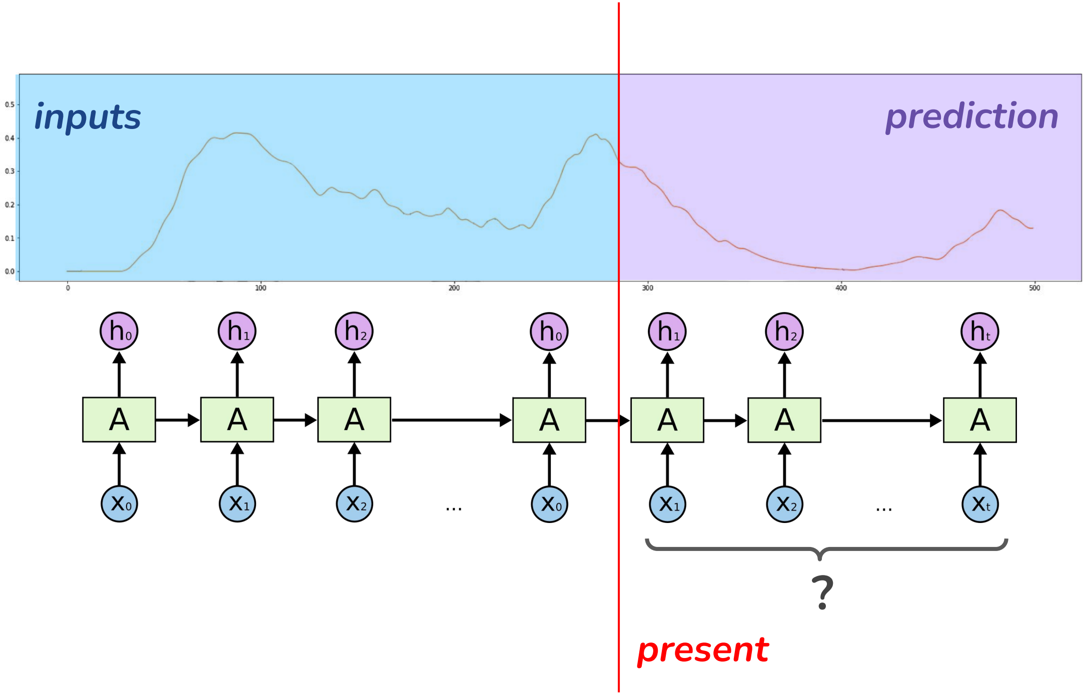
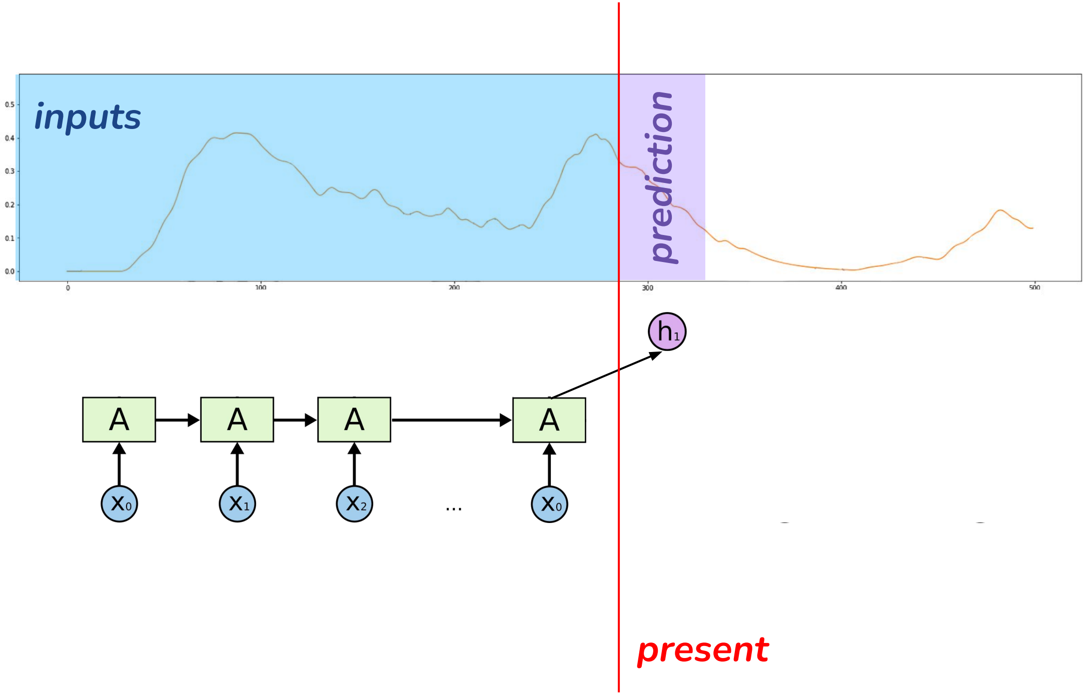
Forecasting from historical values



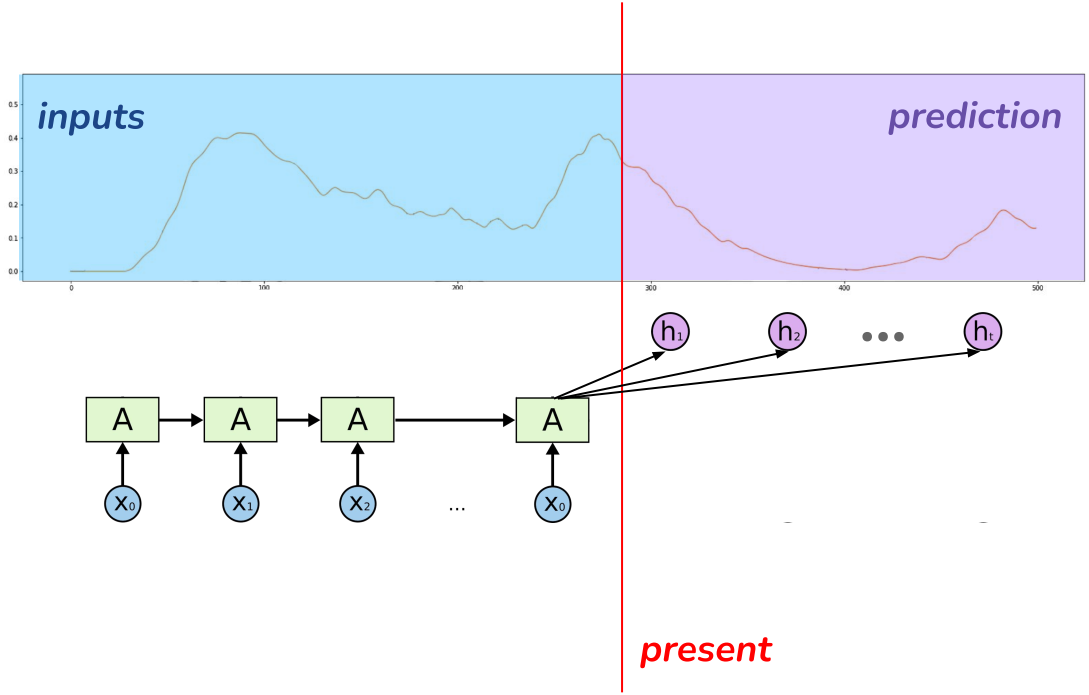
Forecasting from historical values



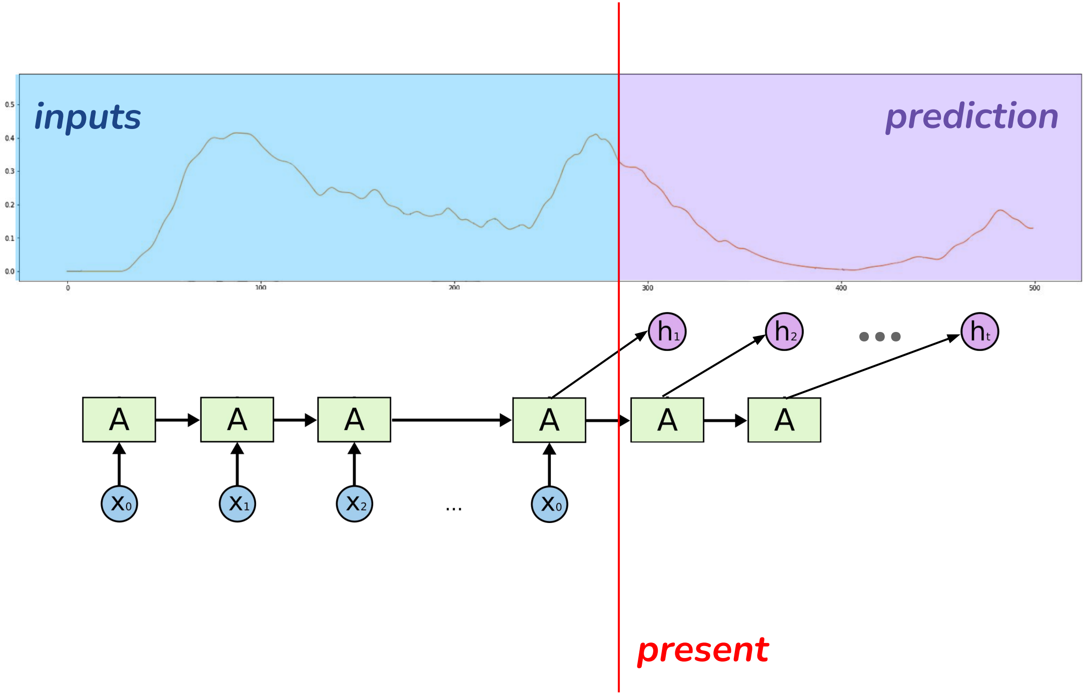
Forecasting – one step ahead



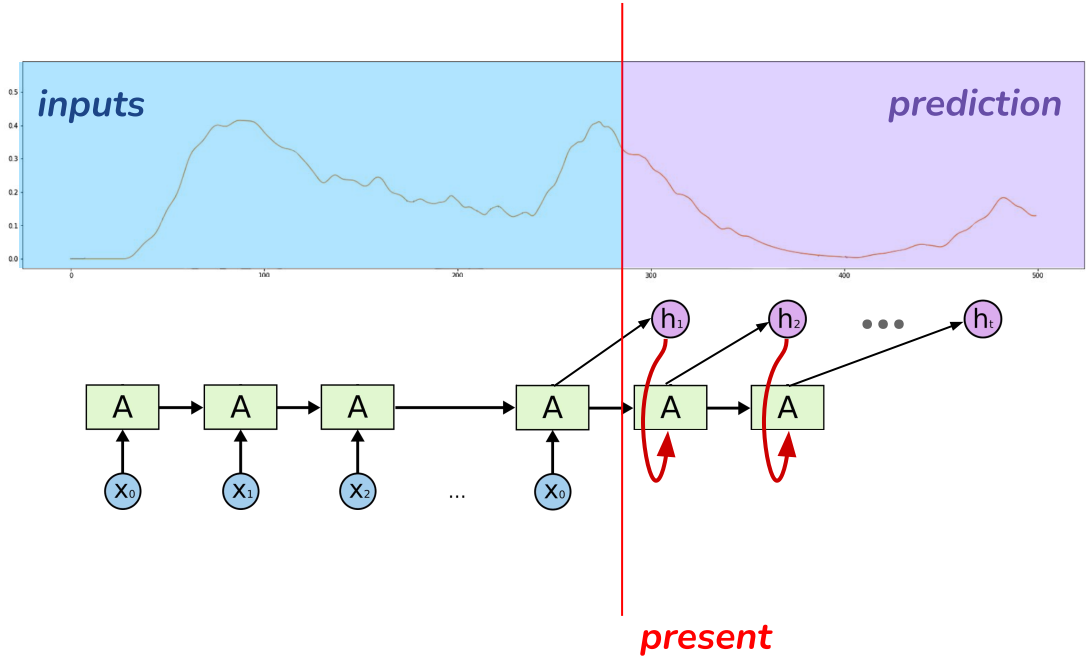
Forecasting – flat multi-step prediction



Forecasting – developed multi-step predition



Forecasting – developed multi-step predition



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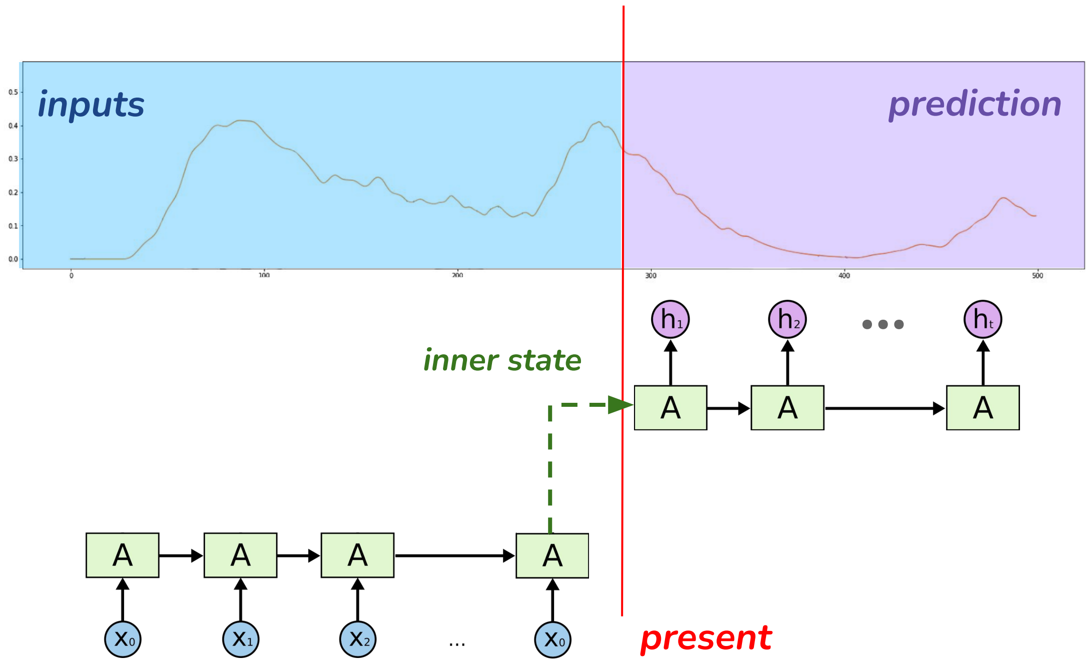
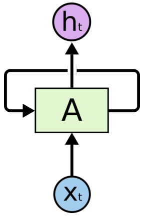
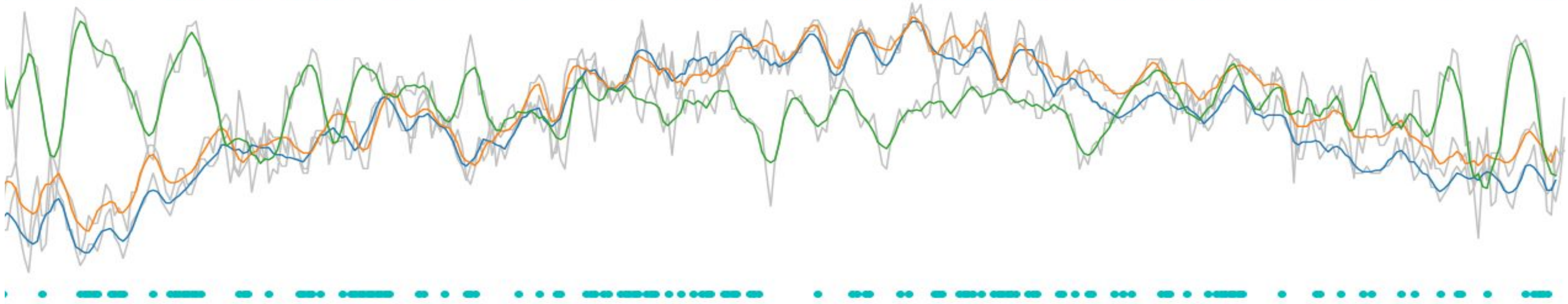
Forecasting – encoder & decoder

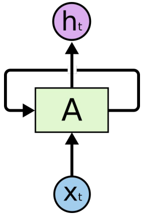


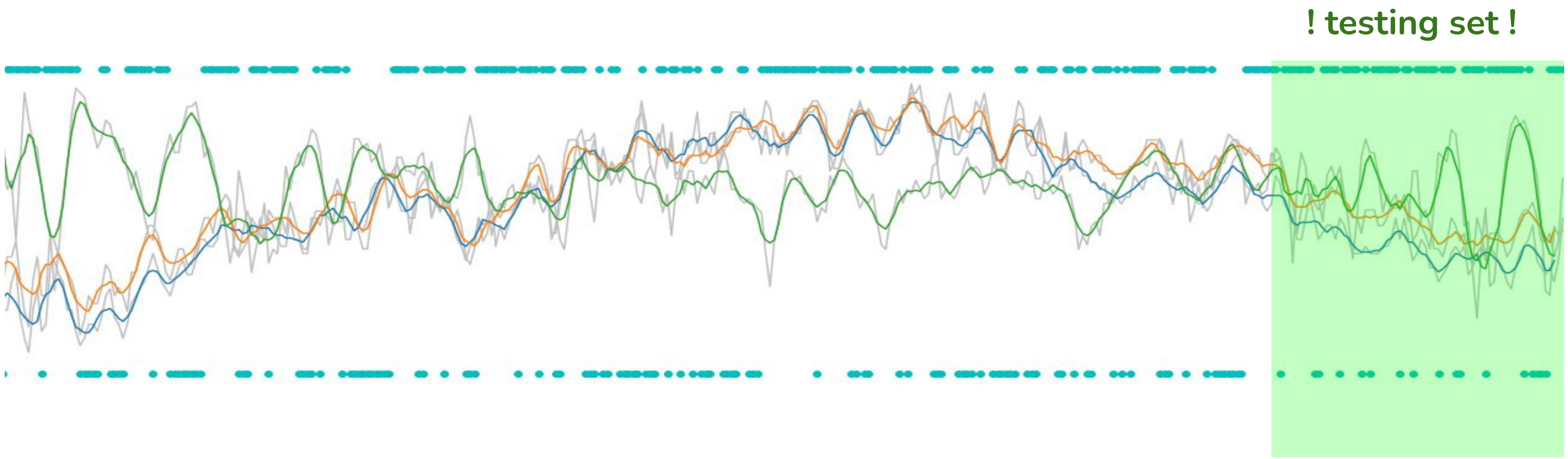
Training set construction



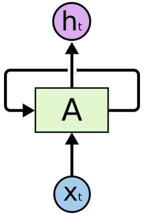


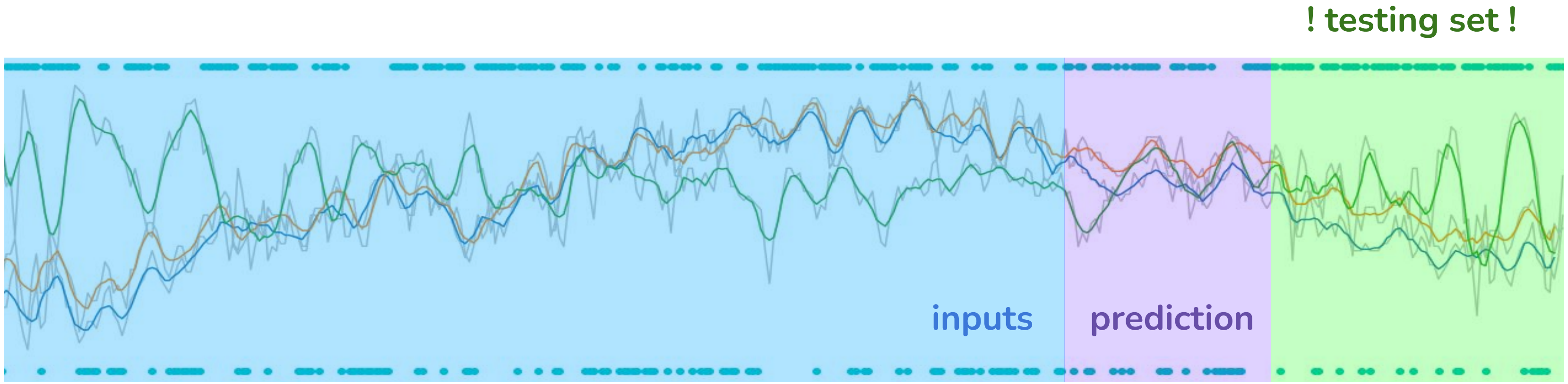
Training set construction



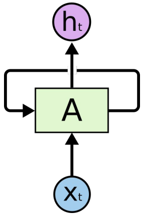


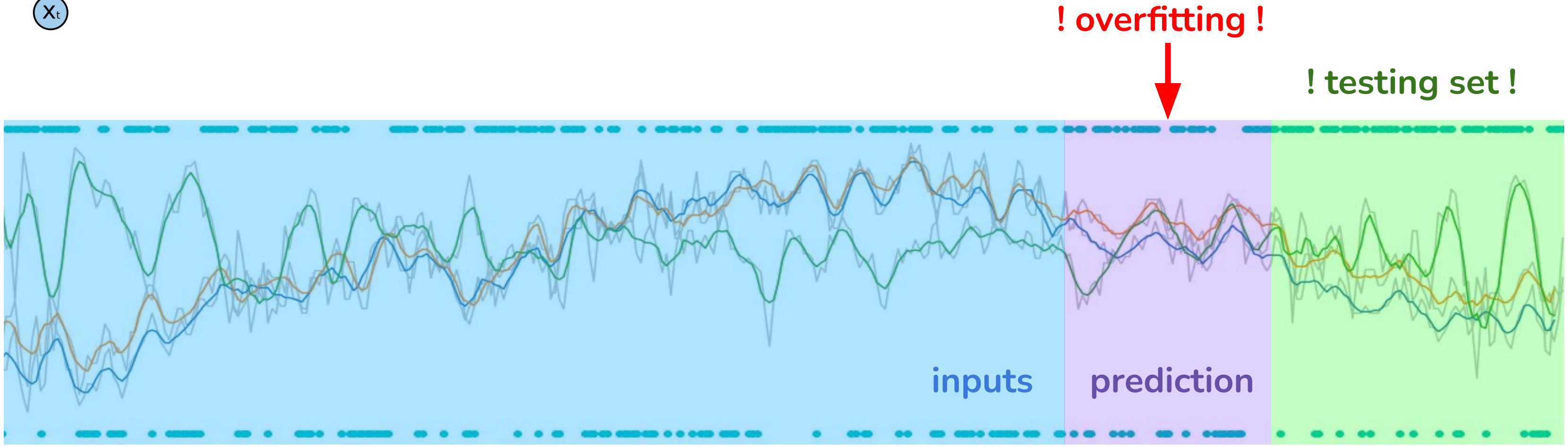
Training set construction



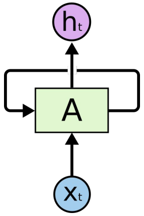


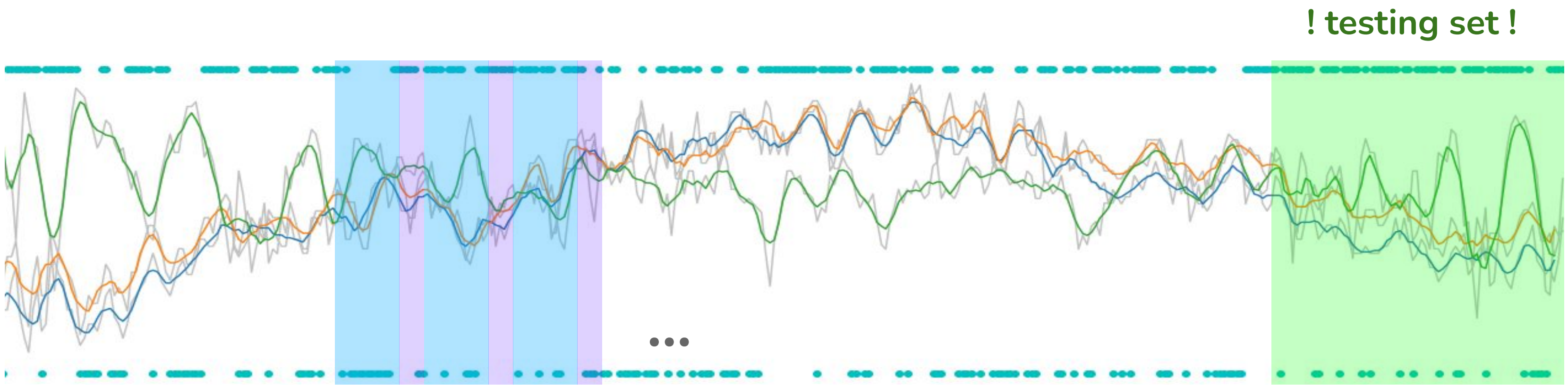
Training set construction





Training set construction





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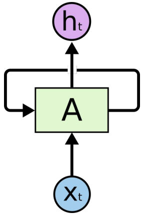
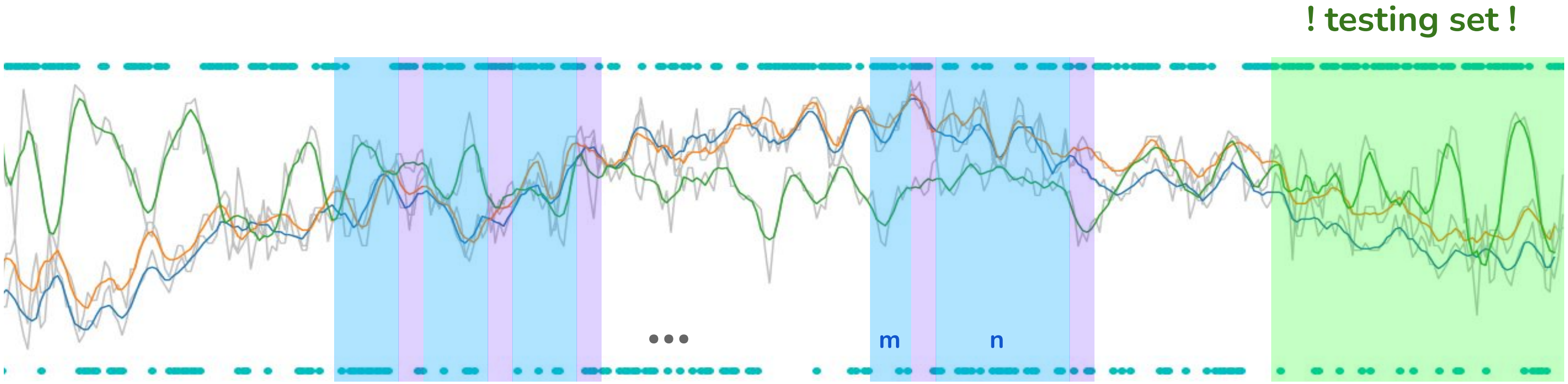
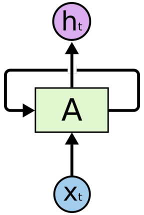
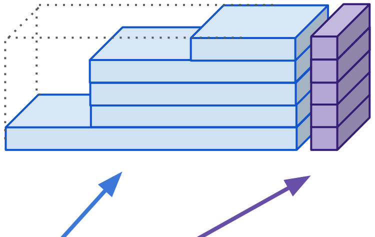
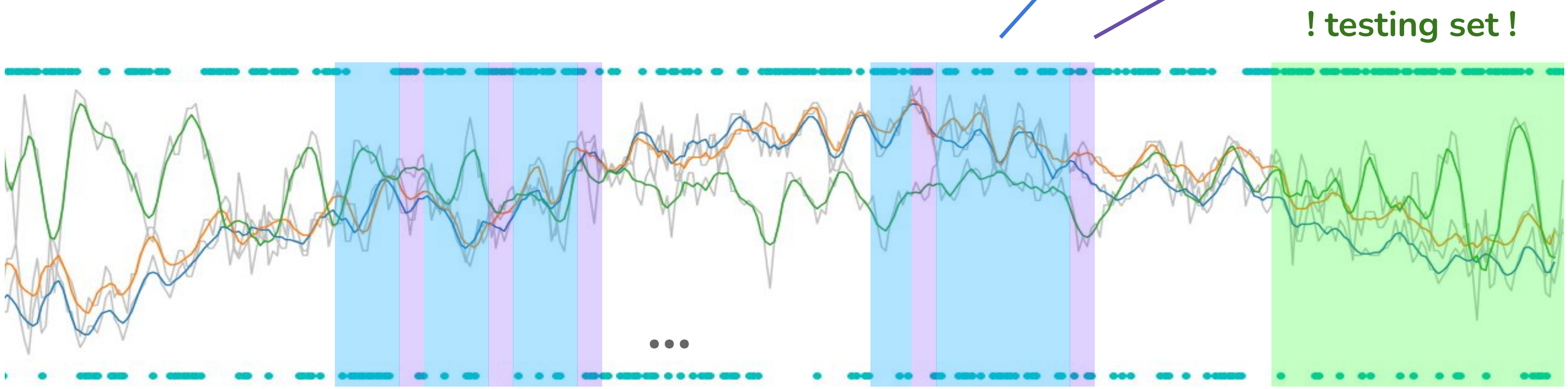




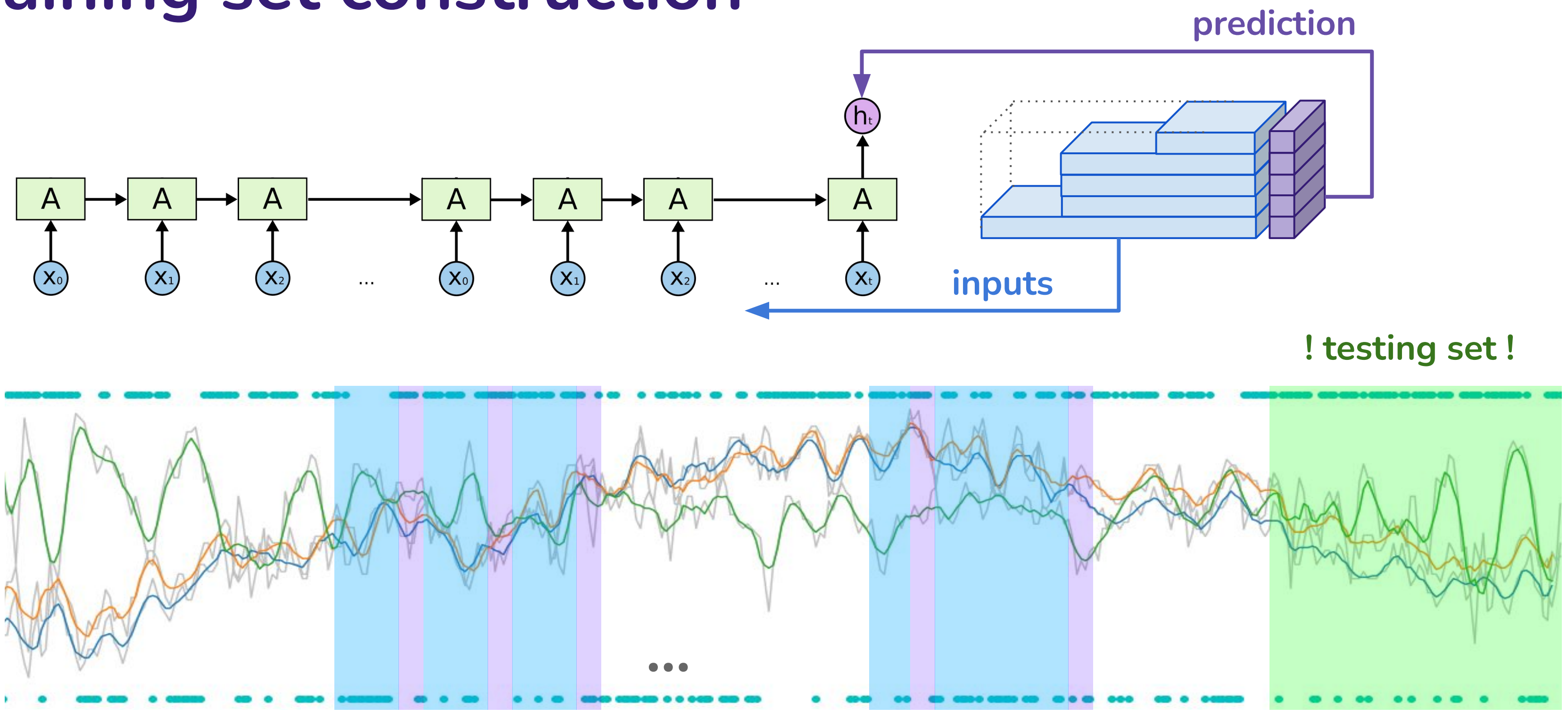
Training set construction







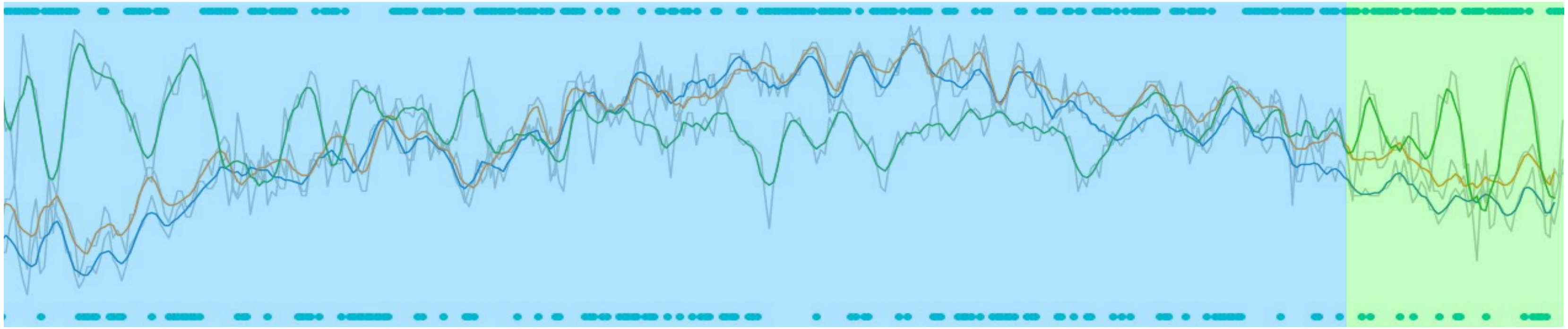
Training set construction



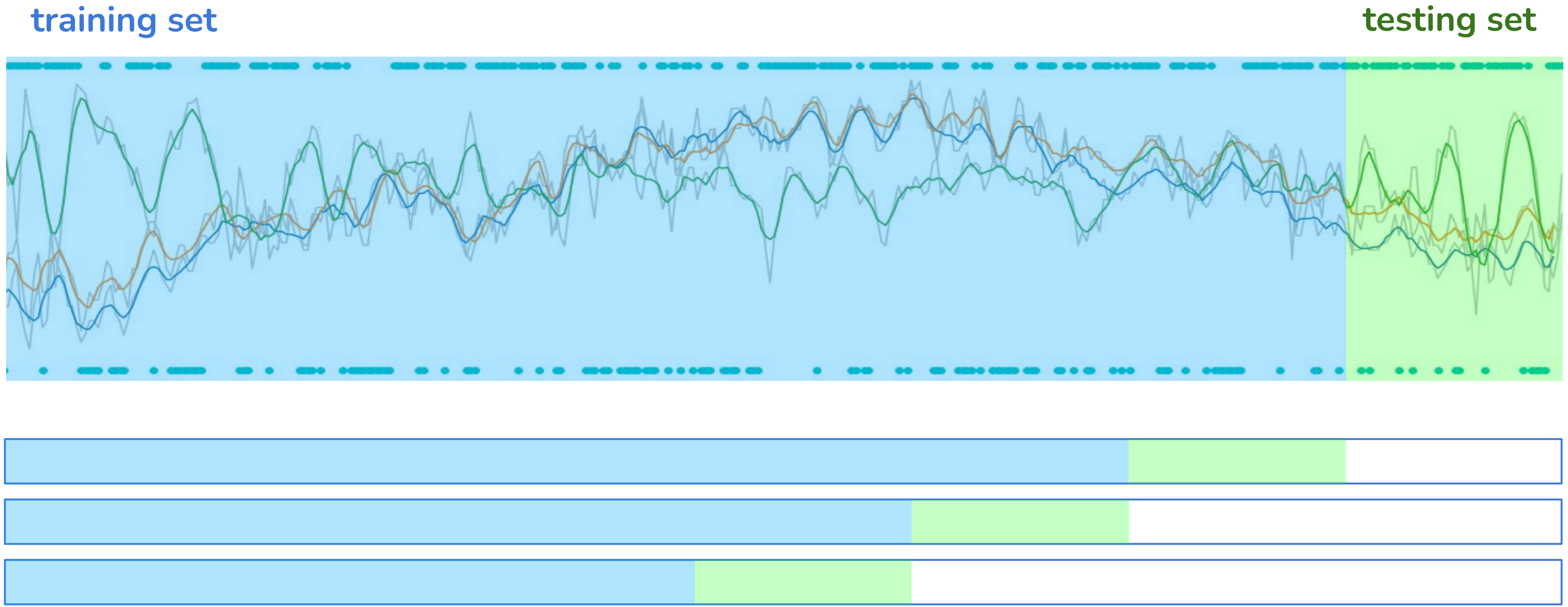
Training set construction

training set

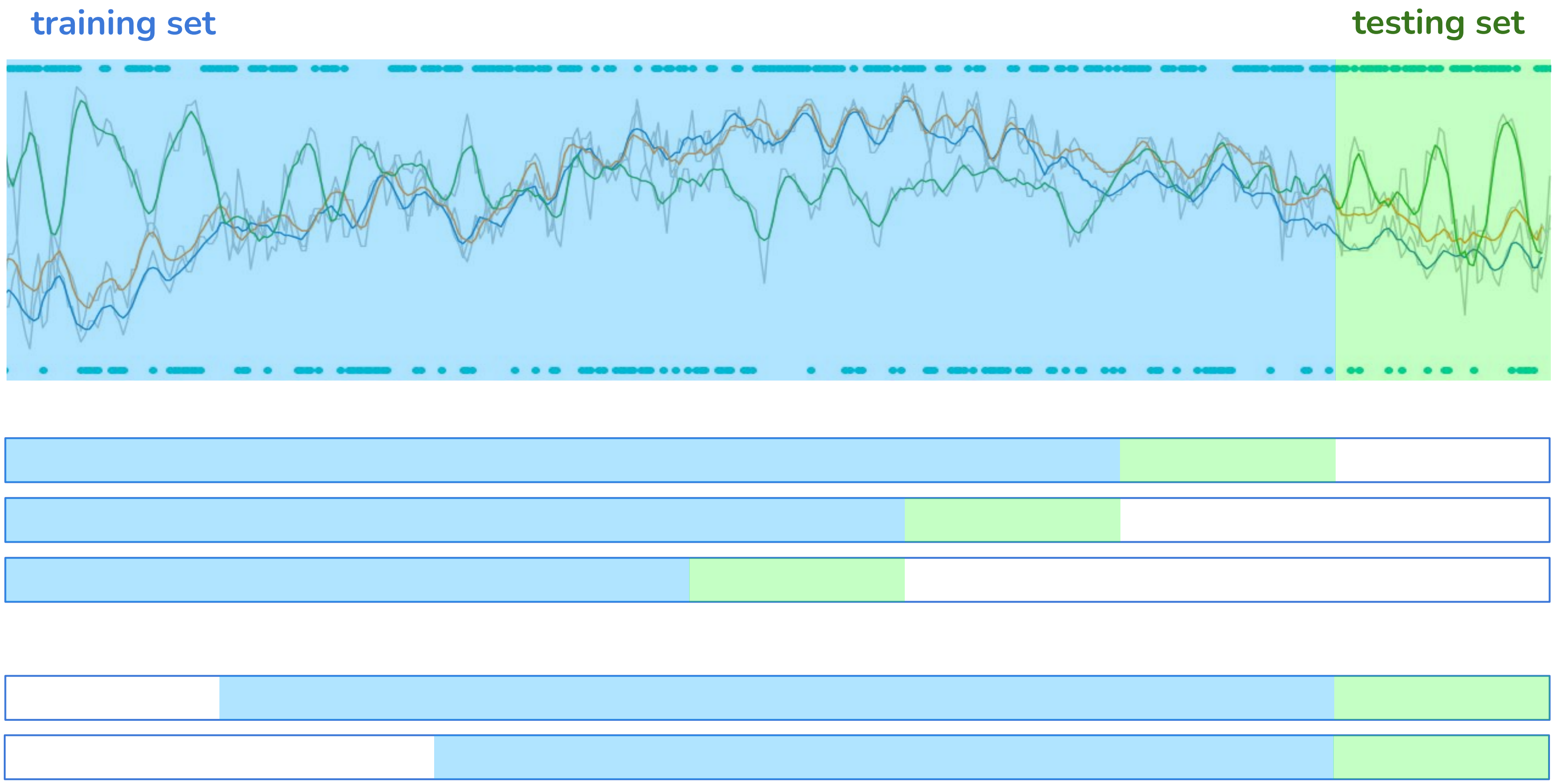
testing set



Training set construction



Training set construction

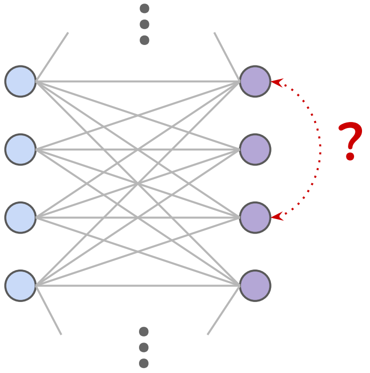


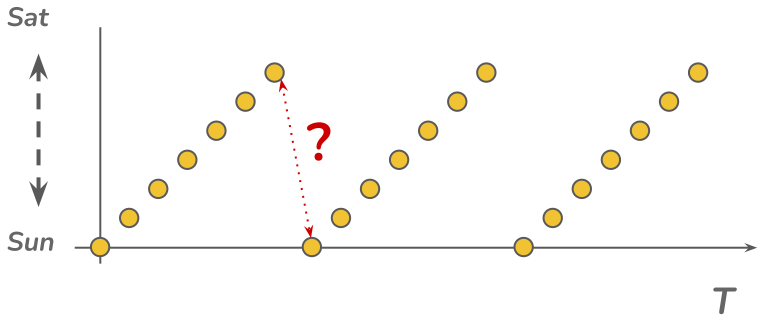
Feature Encoding – Seasonal dummy variables

- *(hour of day, day of week, ...)*
- *Numerical variables*
- *One-hot encoding*

Sun	0	0	0	0
Mon	**1**	0	0	0
Tue	0	**1**	0	0
Wed	0	0	**1**	0
Thu	0	0	0	**1**
Fri	0	0	0	0
Sat	0	0	0	0

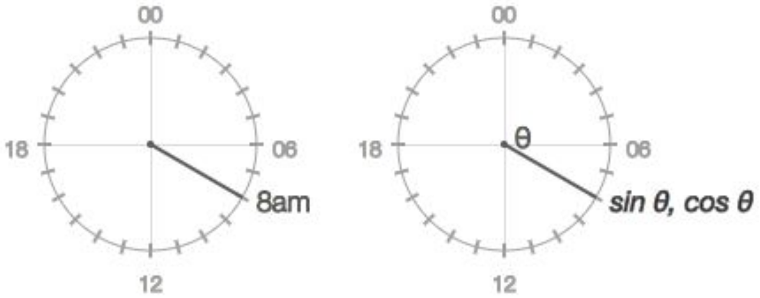
T →

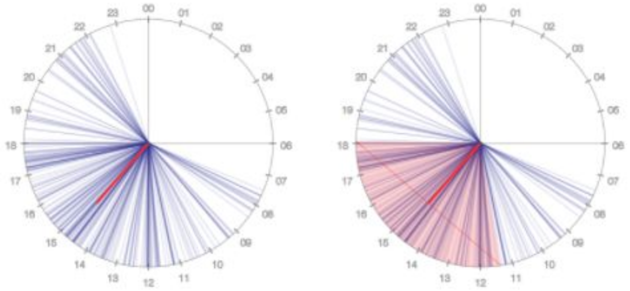




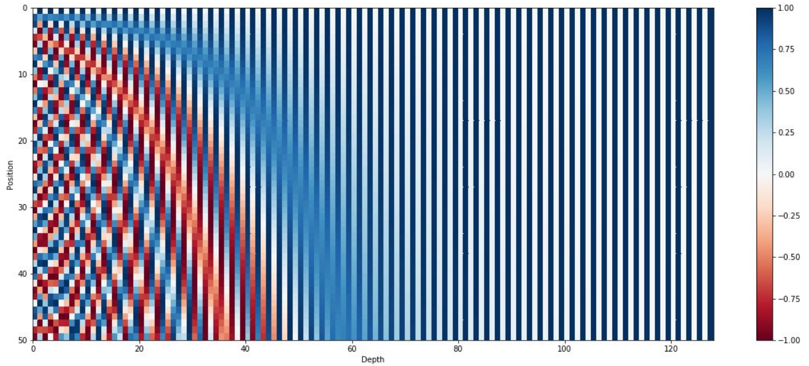
https://medium.com/life-at-hopper/ai-in-travel-part-2-representing-cyclic-and-geographic-features-4ada33dd0b22
https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

Feature Encoding – Seasonal dummy variables





- *Circular encoding*
- *Positional embedding (transformers)*



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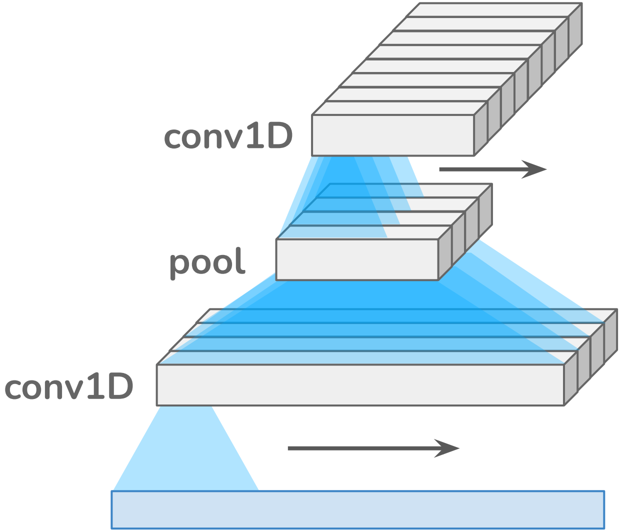
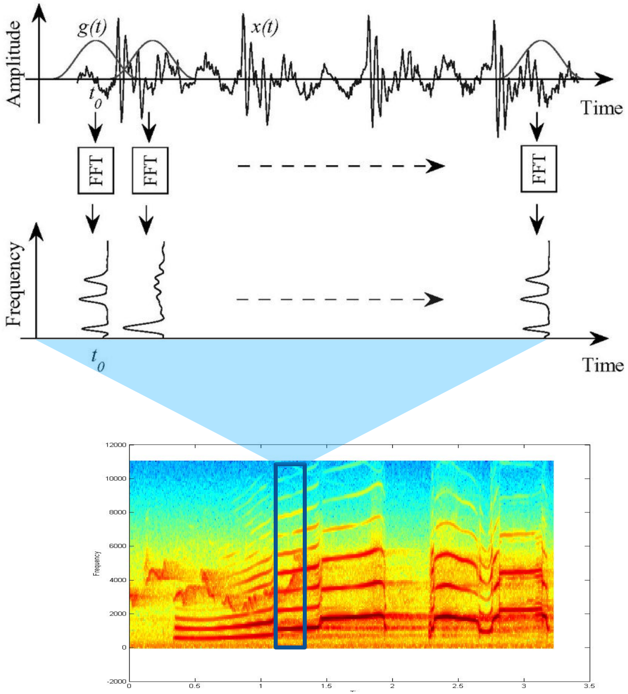
https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

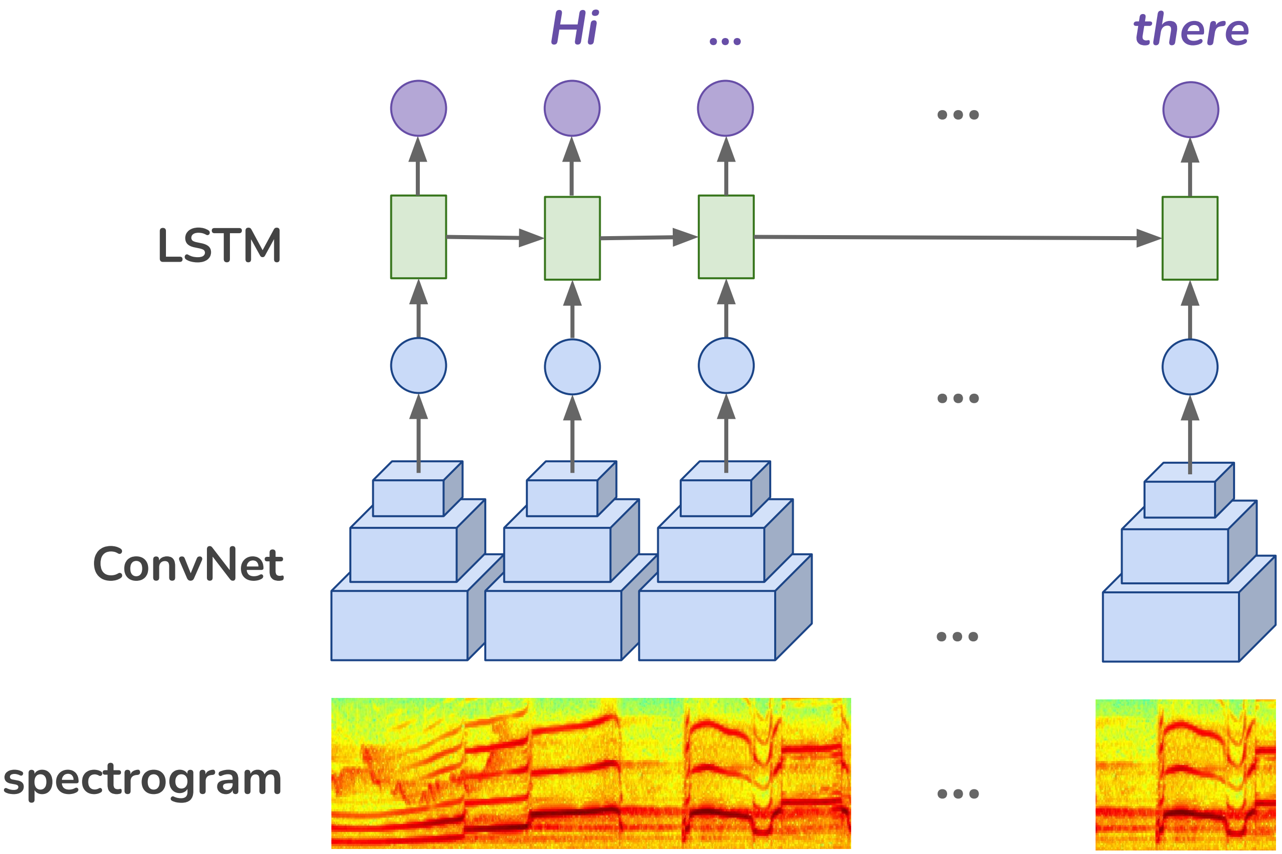
Feature Encoding II

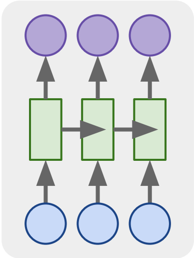
- Exchange for extra dimension
  - 1D Convolution & pooling
  - Short-Time Fourier Transform





Advanced architectures





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Additional learning materials

- Classical time series
  - Time series course – *a book-like explanation of basic principles of time-series and classical analysis*
  - Statistical forecasting – *detailed notes on classical time series analysis and ARIMA models*
- Keras
  - Guides - *code examples for most of the basics in Keras*
  - Examples - *huge selection of code examples from different areas (time series, vision, ...)*
  - Blog – *good selection of advanced application of Keras on practical problems*
- Interesting blogs
  - Adam Geitgey – *Machine learning is fun – great selection of simple examples from various areas*
  - Christopher Olah – *very well-described principles of neural networsk (with a lot of visual insights)*
  - Andrej Karpathy – *some very interesting insights (including the debug recipes for NNs)*
  - Distill – *Chris Olah and Shan Carter collaboration – open problems in deep learning & advanced topics*
- Tech companies blogs
  - DeepMind (Google) – *top research in artificial intelligence – usually acompanied with science papers*
  - OpenAI – *started as non-commercial research group / answer to Deepmind*
  - Facebook – *many interesting projects sometimes with free-to-use pre-learned models*
  - Amazon – *many interesting machine learning articles sometimes with detailed papers*

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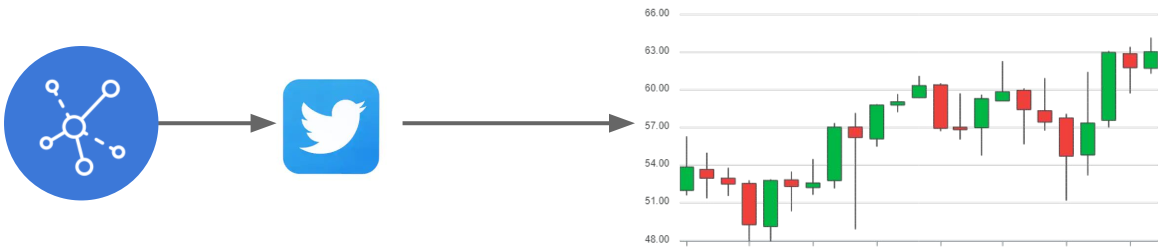
Time series prediction from textual data



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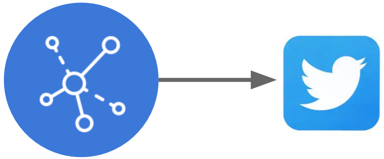
Time series prediction from textual data



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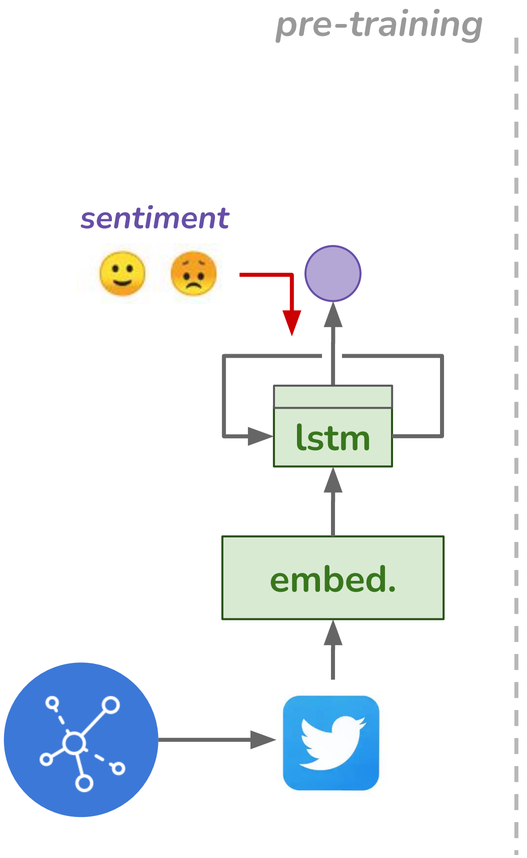
Pre-training with additional data



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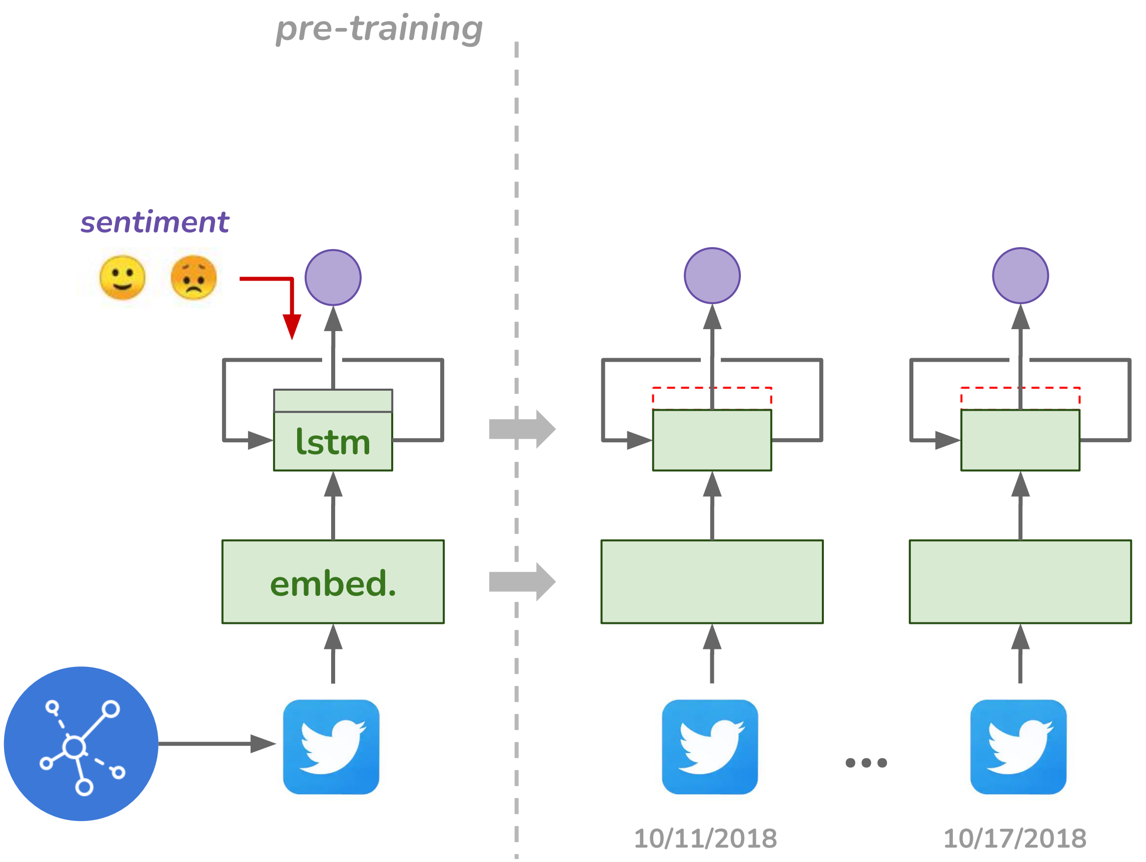
Transfering model & exposing feature layer



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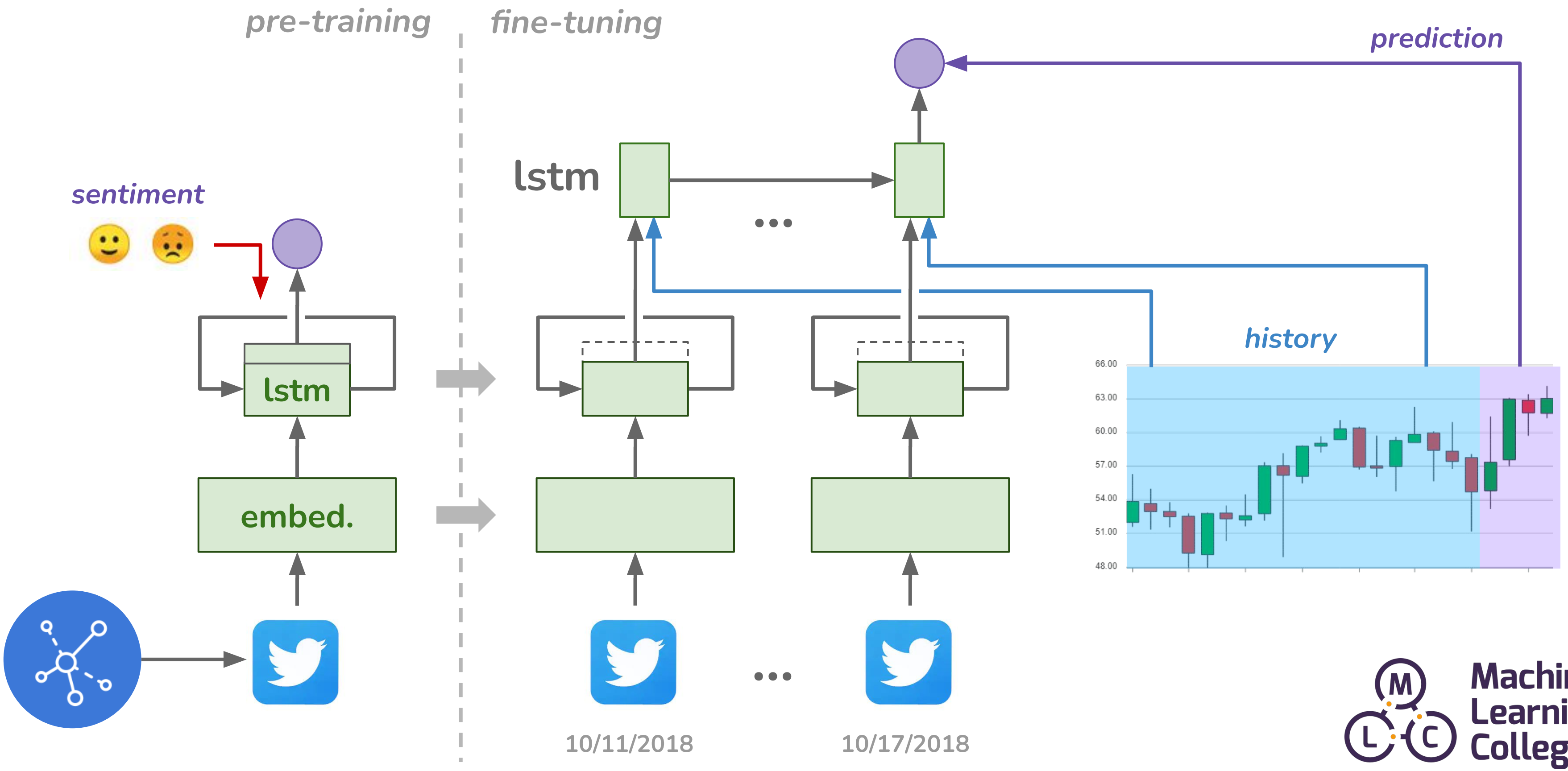
Fine-tuning with time series target data



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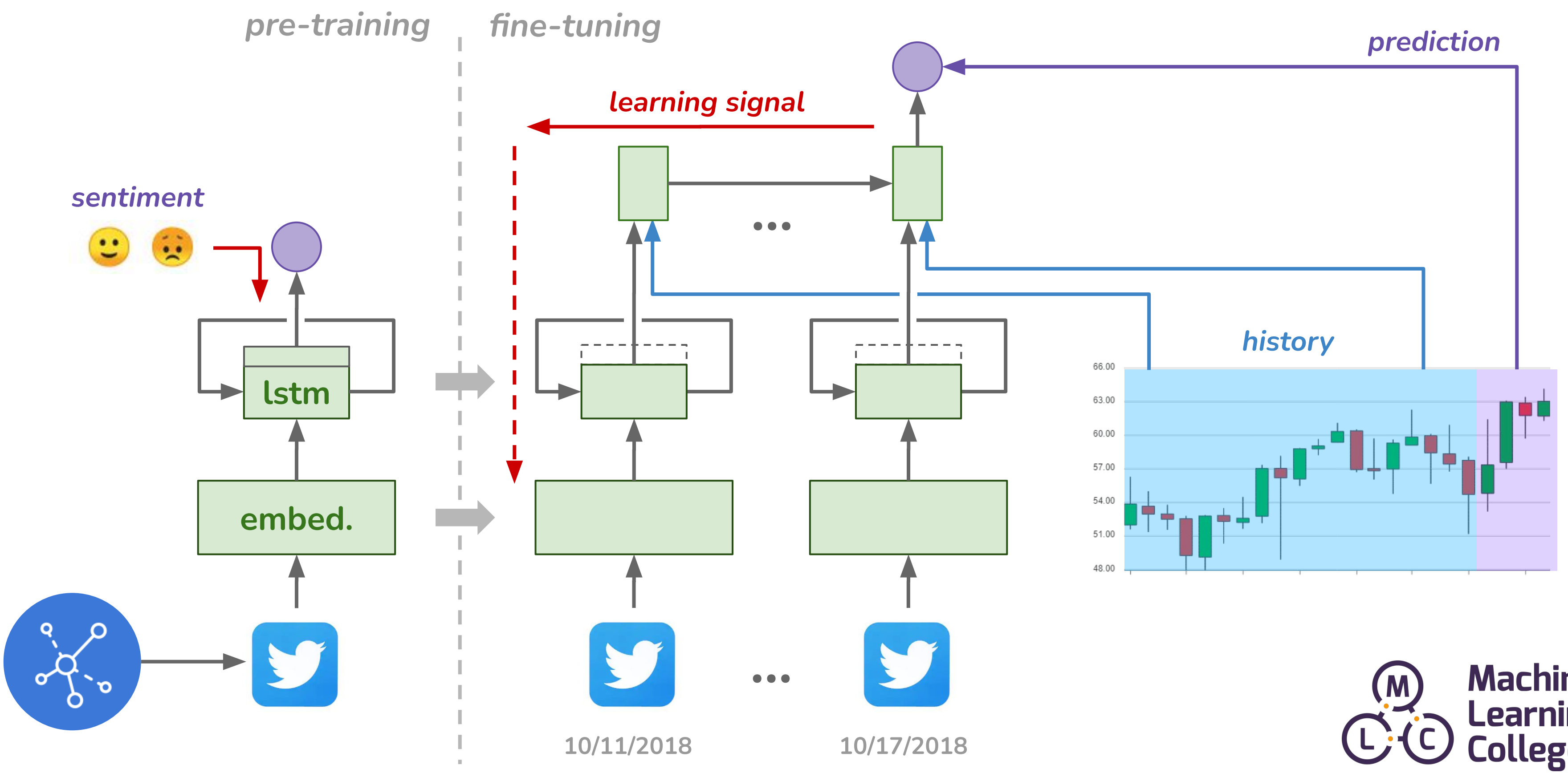
Fine-tuning with time series target data



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