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Sales Forecasting and Fraud Detection

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Organizers



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Sales Forecasting and Fraud Detection

- Sales forecasting
 - Cast as regression
 - Time based validation
 - Recency and seasonality bias
 - Sequence to sequence
 - More data
- Recommender systems
- Fraud Detection
 - Common traps



About me



CPMP

RAPIDS and deep learning at NVIDIA

France

Joined 10 years ago · last seen in the past day

[GitHub](#) [Twitter](#) [LinkedIn](#) <https://rapids.ai/>



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Grandmaster

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10		6		607		94		164		12		4		1	
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Organizers

LOGIC

kaggle

LVMH



Sales forecasting

- Predict sales in the future
- From Historical data
 - Several (many) time series, per product, region, and aggregated
- Mind the gap!
 - There is a delay between when training data is collected and prepared and when the model can be put in production





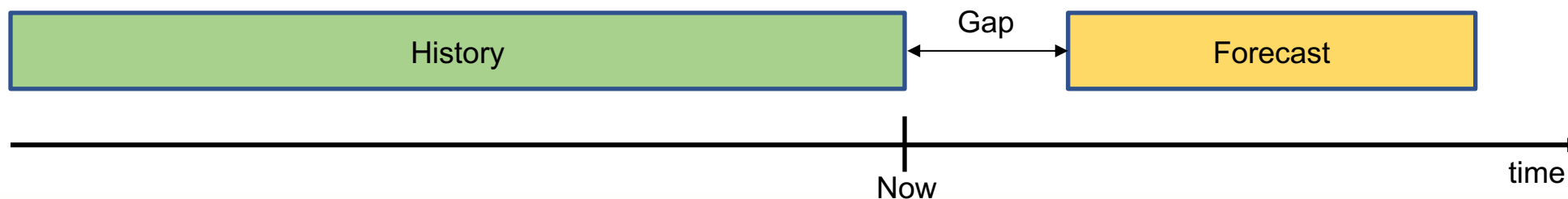
Many models

- Facebook Prophet
- VAR
- ARIMA
- TFT (best deep learning model?)
- ...

Auto regressive models and sequence to sequence models, usually for single series

There is another way!

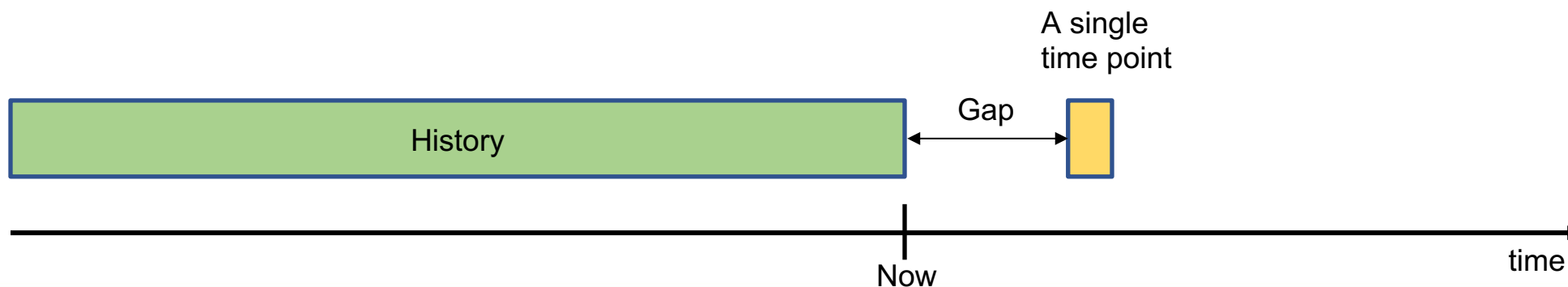
- Cast as regression





Forecasting as Regression

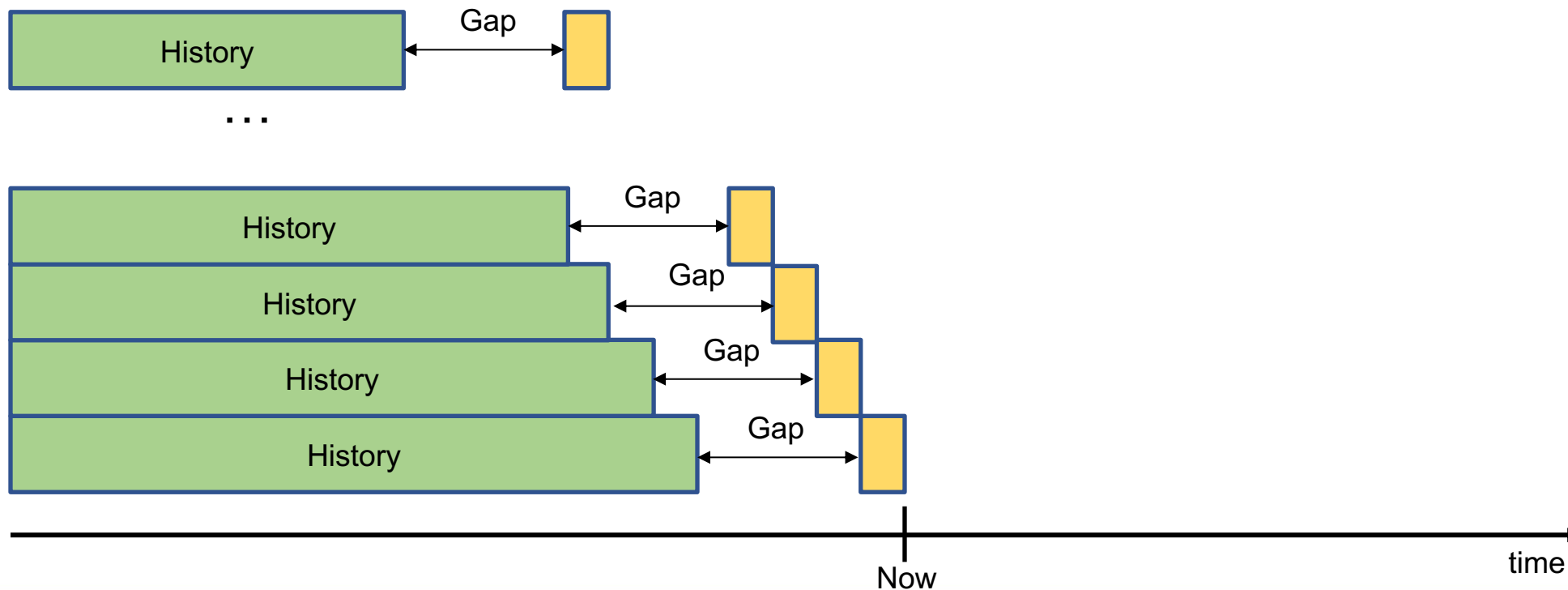
- Sequence to value: single prediction
 - We need to forecast one value
- Generalize to Sequence prediction
 - Iterate single prediction
 - Train several models
 - Train one model





Single regression

- Create training instances by shifting train end date and target date: keep the gap constant!
- Features are aggregates of the history data

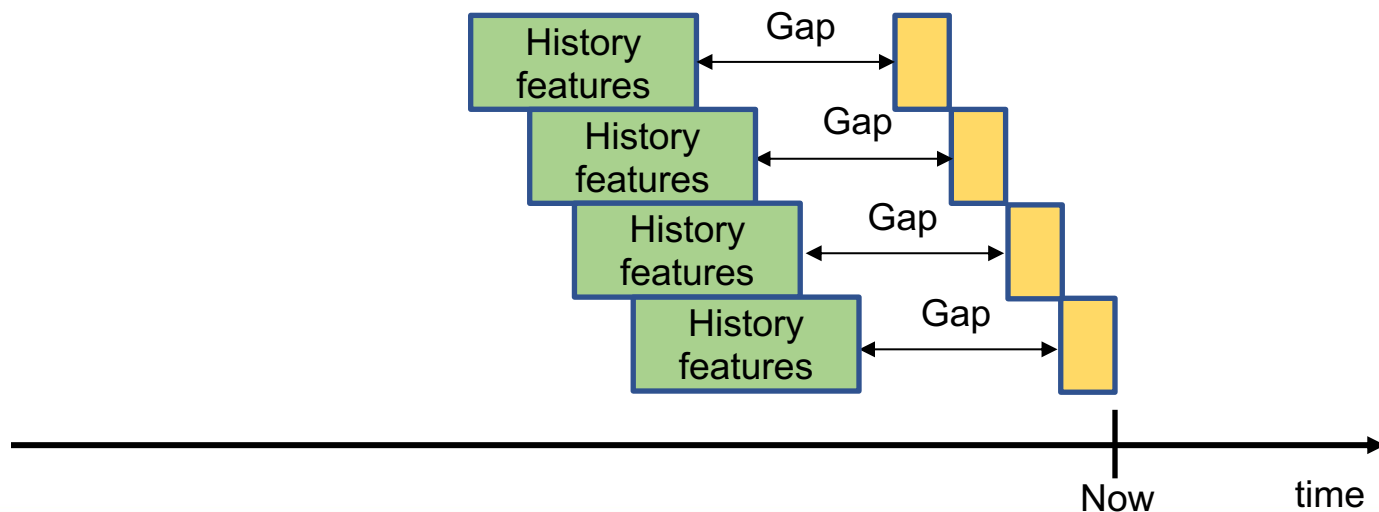




Single regression

- Create training instances by shifting train end date and target date: keep the gap constant!
- Features are aggregates of the history data
 - Last value
 - Min, Max, Median, Mean, Std of last week
 - Min, Max, Median, Mean, Std of last month
 - ...

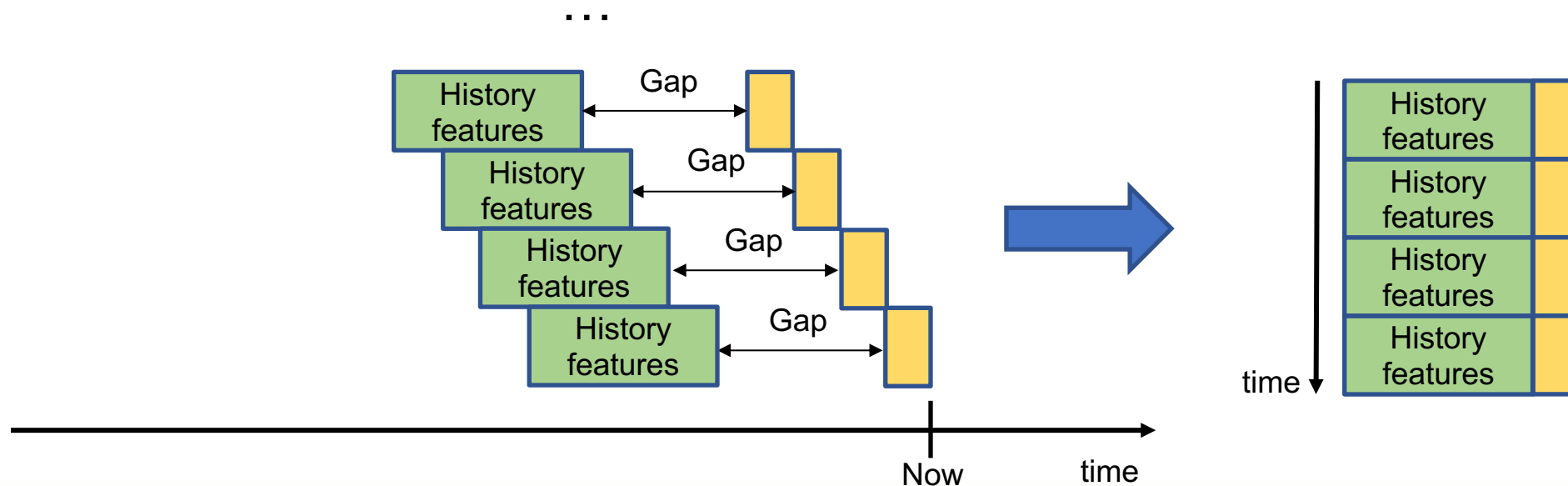
...





Single regression

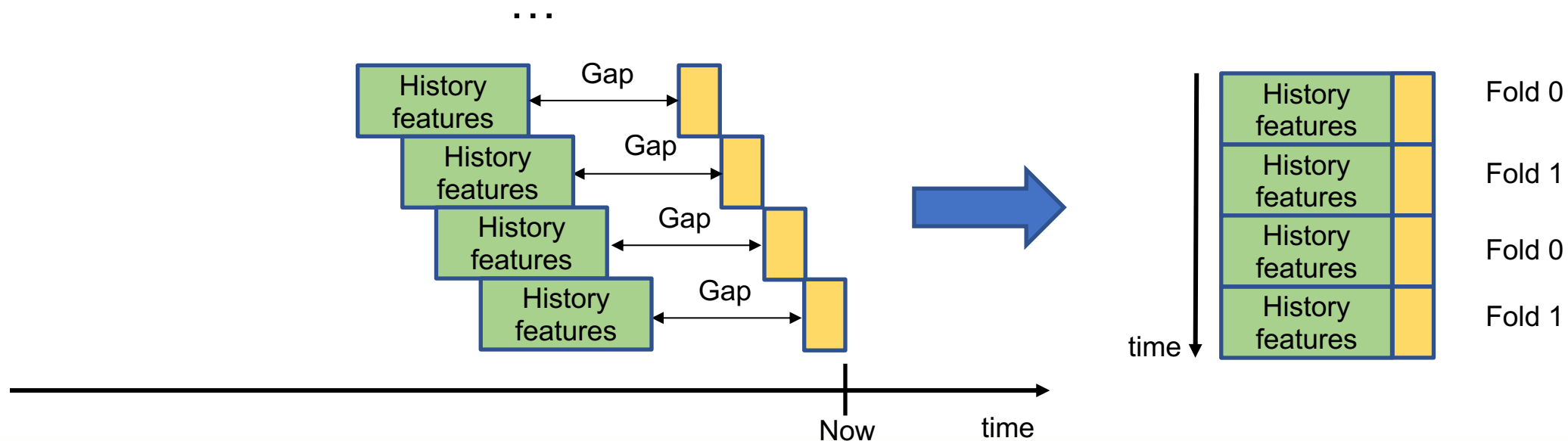
- We then get a regression problem
- Features can come from more than one time series -> multivariate time series





Single regression

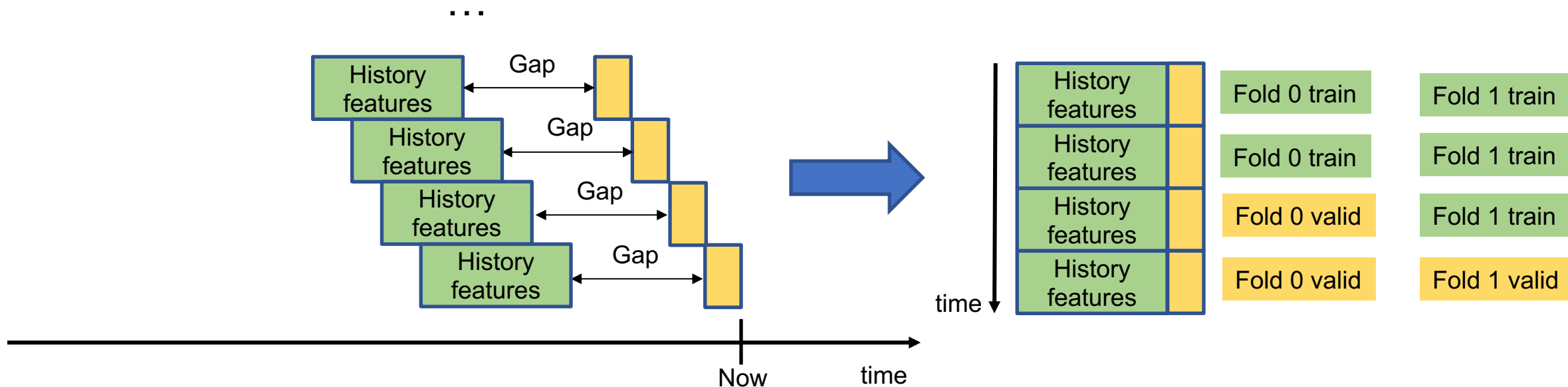
- Cross validation
- Never ever use for training data which is in the future of validation
- Example with 2 folds





Single regression

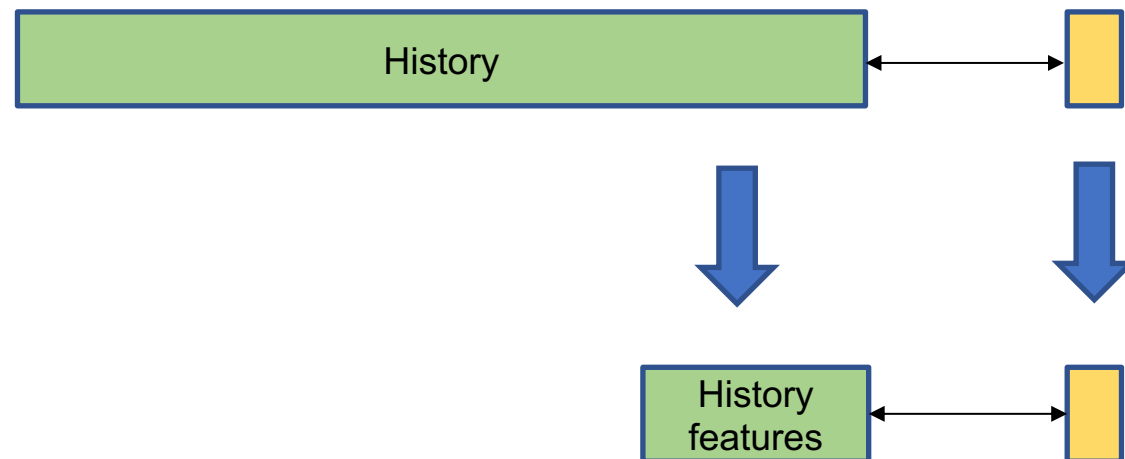
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De-trending

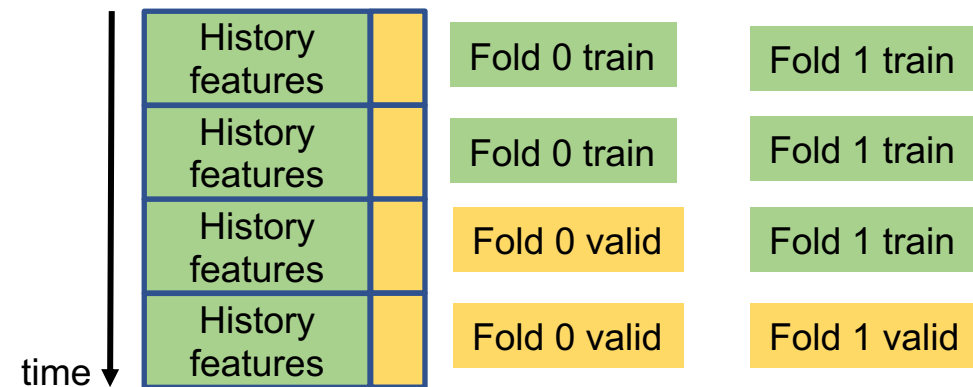
- Gradient boosting (e.g. XGBoost) cannot extrapolate!
 - Often heard to dismiss it for forecasting
- Predict the residual of the trend
 - Modify the target!
- New target is original target minus
 - Mean value over last month
 - Same value a year ago (yearly seasonality)
 - Same value last week (weekly seasonality)
 - A linear baseline that combines the above
- Baseline can be even more complex!
 - I won a 2nd prize using a sequence to sequence NN model as baseline
 - XGBoost to predict the residuals





Recency bias

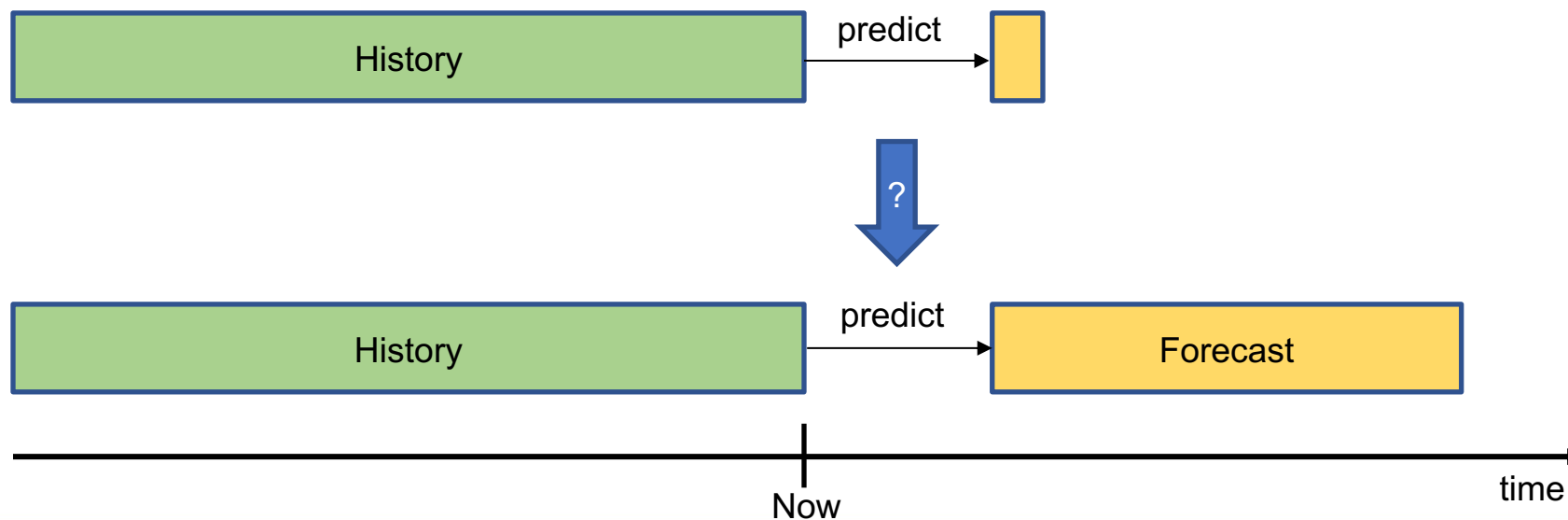
- Last known value is a great predictor
- More recent samples are more important
- Weight samples by recency when training
- Weight last year same period more if there is a yearly seasonality





Sequence to sequence

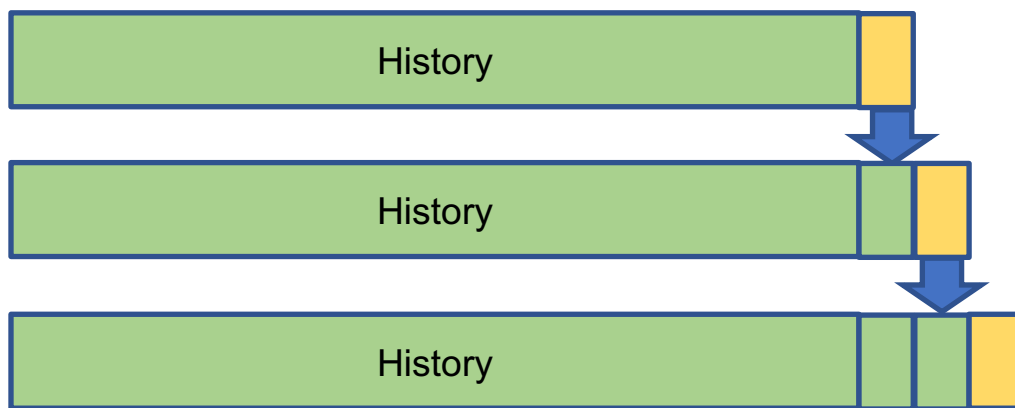
- We have shown how to train a model to predict one time period in the future
- How do we predict a sequence in the future with it?
- XGBoost cannot predict sequences!





Sequence to sequence

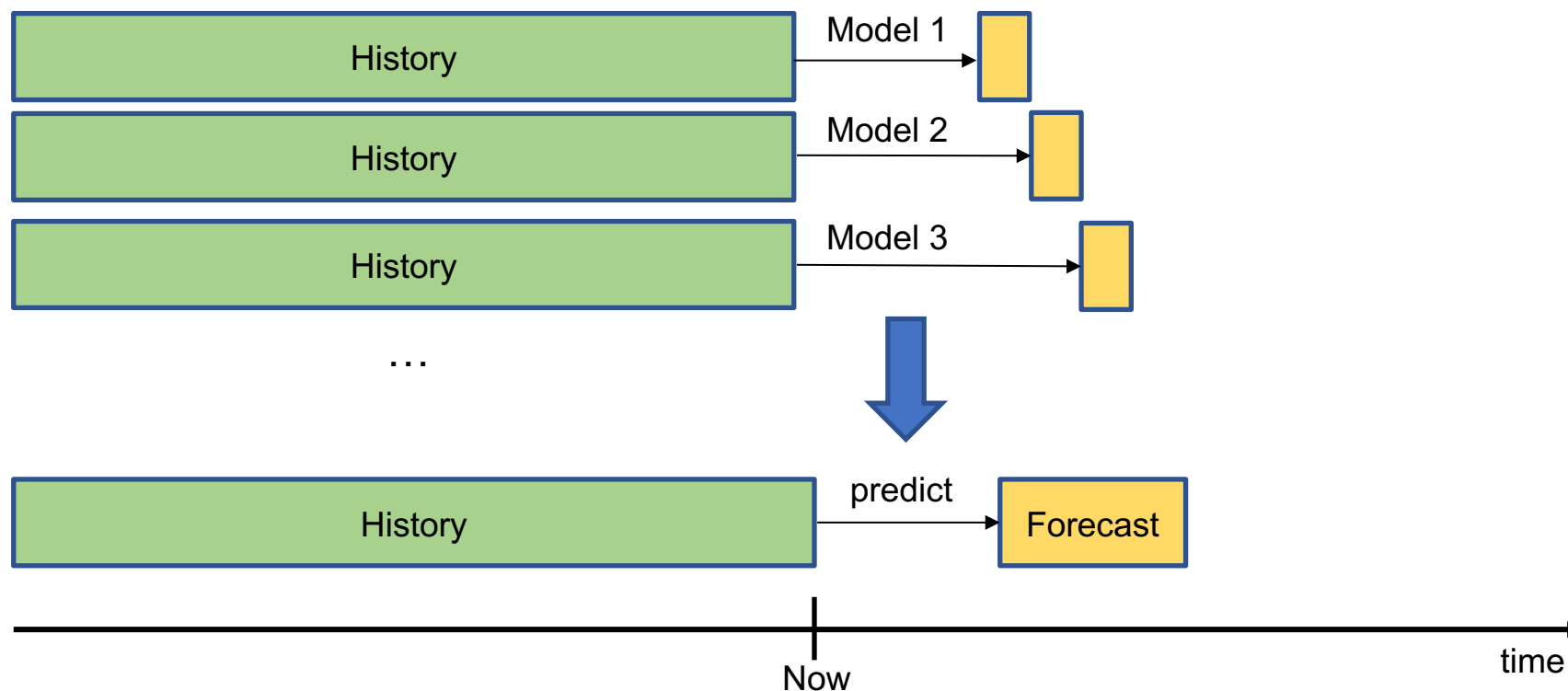
- If gap is negligible, predict next period, then use the prediction as additional history to predict one period more, etc



- Main disadvantage: prediction errors accumulate, and compound effect can be really bad

Sequence to sequence

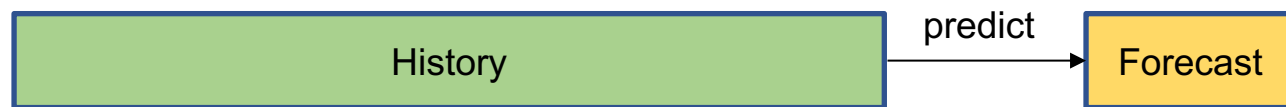
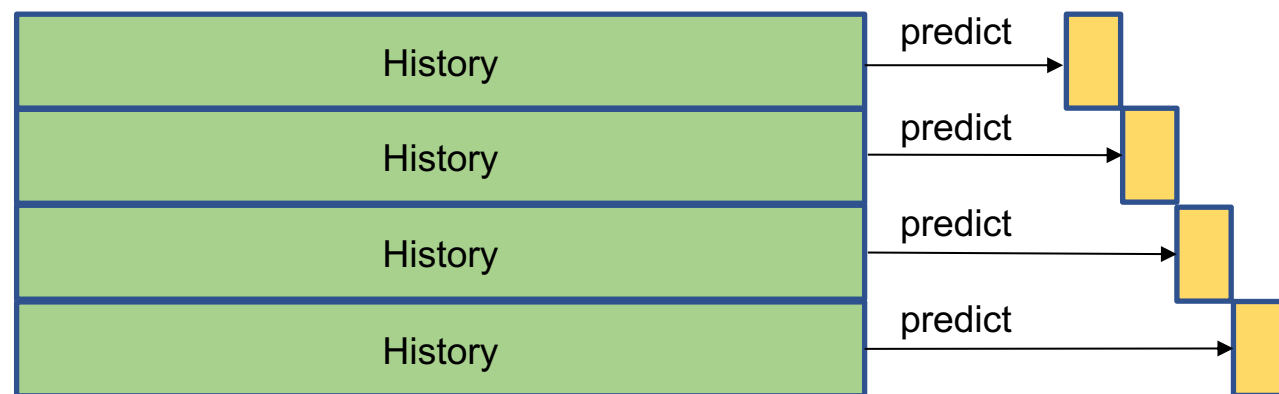
- Train N models where N is the length of the sequence to predict, with increasing gaps





Sequence to sequence

- Train one model
- Each sample becomes N samples, with increasing gap values



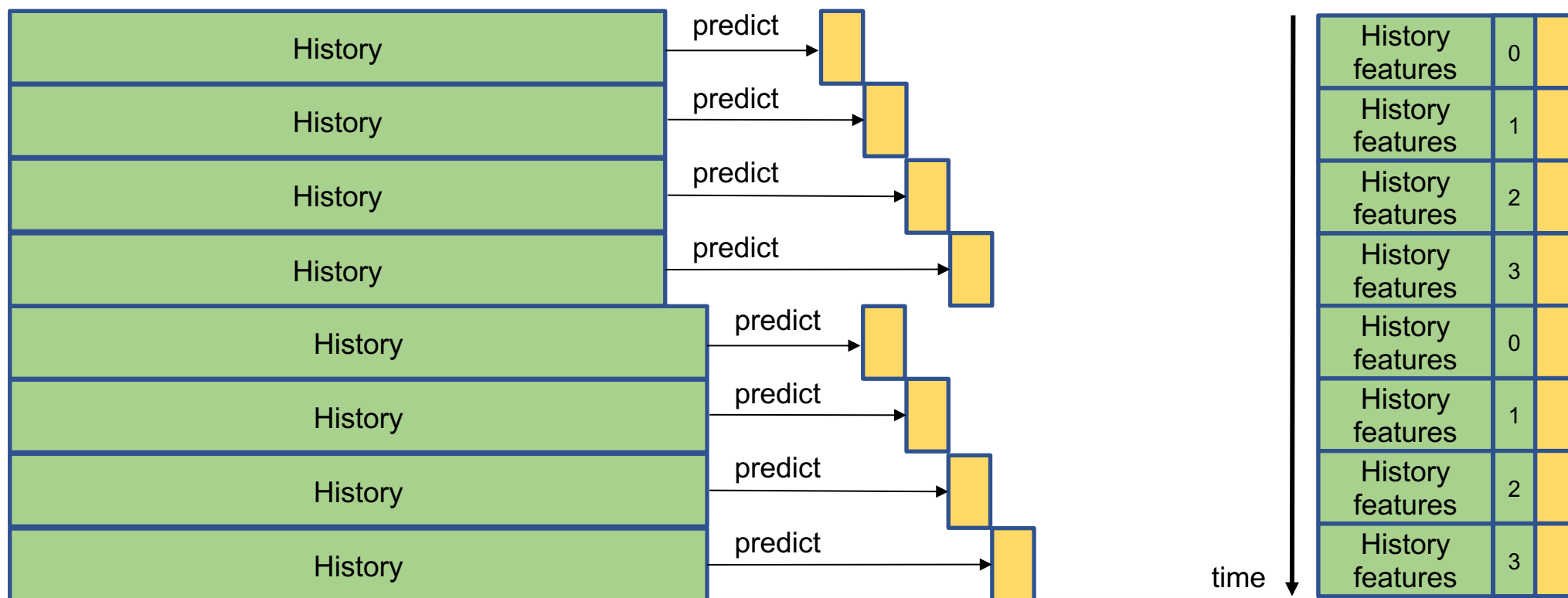
Gap		
History features	0	
History features	1	
History features	2	
History features	3	

time ↓



Sequence to sequence

- Combine with time-based split





Sales forecasting

- Target is not symmetric, over predicting maybe fine
 - Unsold products can be sold later
 - Missing products cannot be sold
- Not true for some products
 - Limited shelf life, e.g. dairy
 - Deadline, e.g. Christmas tree
- Quantile regression
 - Weight over prediction error differently than under prediction error



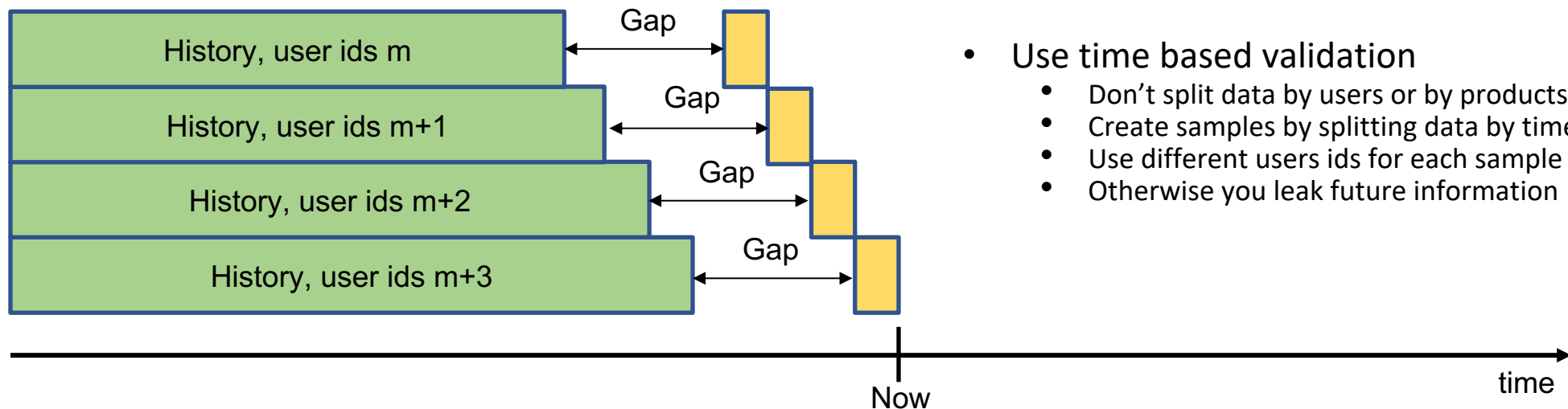
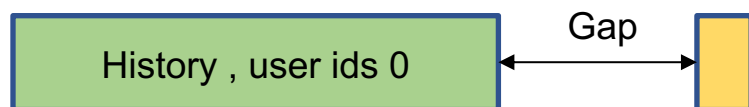
More Data Than Past Sales

- History data
 - Actual sales, not demand
 - Sales may have been limited by inventory
 - Sales maybe impacted by pricing, marketing campaigns, holidays, events
- Include inventory information in model input
 - Estimate unmet demand in the past
 - Product cannibalization
- Include pricing, campaigns, holidays, events
 - Multivariate time series



Recommender Systems

Most of what precedes applies to recsys!



- Mind the gap
- Recency bias
 - Recent trends may dominate
- Use time based validation
 - Don't split data by users or by products
 - Create samples by splitting data by time
 - Use different users ids for each sample
 - Otherwise you leak future information



Fraud detection

- Can be cast as a binary forecasting
- Given some history, is the current tentative payment a fraud?

Many issues

- Very imbalanced (fortunately)
- Ground truth is known with some delay
 - Large gap
- Little relevant history (when a fraud pattern is detected then fraudsters adapt)

Maybe better to see it as anomaly detection

- Model usual behavior (amounts, frequency, locations, etc)
- Flag large deviations



Fraud detection Ground Truth

- Hard to get
- In one case I was asked to build a credit card fraud detection
- I got access to a 300M credit card transactions
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- Great data
- All labelled as fraud/non fraud!



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- Once I delivered a model I learned that the GT was in fact the output of a legacy pipeline the customer wanted to replace...



Online Commerce Topics

- Decompose the problem into a regression
- Proper sampling for training
- Avoid future leaking into training
- Sales forecasting is more than univariate time series forecasting
- Lessons relevant to recys
- Fraud detection deserves a full presentation

 **kaggle**TM
days

