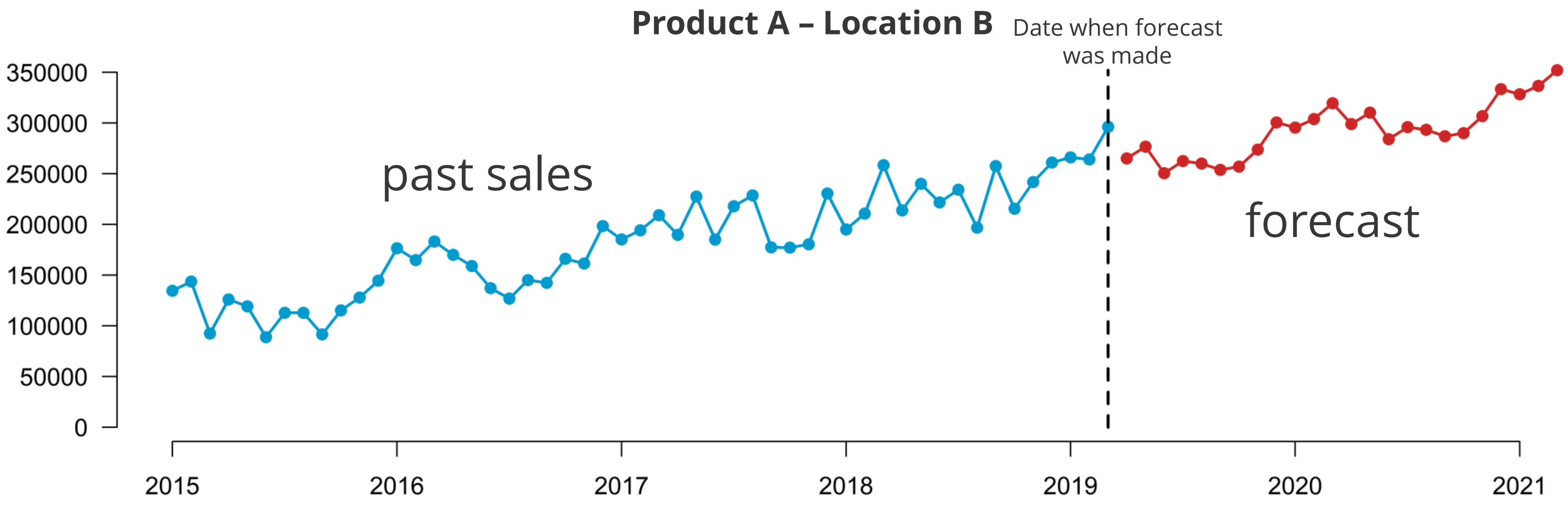
Making your day

Reducing Forecast Instability with Deep Learning

Van Belle, J., Crevits, R., and Verbeke, W. (2022). Improving forecast stability using deep learning. *International Journal of Forecasting.*

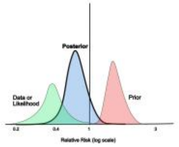
We advise customers on how to make better demand forecasts



What is a good forecast?

Excellent **forecast accuracy** for every product 

Besides that, we need:

- Accuracy on aggregations like Country, Brand, … 
- Probabilistic forecasts 

- Stable forecasts 
- Explainable forecasts 


Supply
Manufacturing
Distribution
Demand

OMP

Paper & Plastics

- DS Smith
- storaenso
- Klabin
- Jindal Films
- Avery Dennison

Consumer Goods

- P&G
- Nestlé
- KraftHeinz
- General Mills
- Tyson

Life sciences

- Johnson & Johnson
- Roche
- novo nordisk
- Bayer
- AstraZeneca

Metals

- ArcelorMittal
- aperam
- Tenaris
- voestalpine ONE STEP AHEAD.
- BEKAERT better together

Packaging

- Smurfit Kappa
- mondi
- Palm
- SAICA
- vpk packaging group

Chemicals

- BASF The Chemical Company
- Dow
- Shell
- DuPont
- EASTMAN

Tires

- Bridgestone
- Michelin
- Goodyear

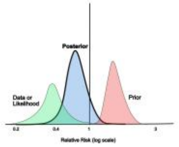
Building products

- UNILIN
- Tarkett
- Shaw FLOORS
- Beaulieu International Group

What is a good forecast?

Excellent **forecast accuracy** for every product

Besides that, we need:

- Accuracy on aggregations like Country, Brand, … 
- Probabilistic forecasts 

- **Stable forecasts**
- Explainable forecasts

What is forecast stability? Example

- **Example: a pharmaceutical company forecasts two times:**
  - 6 months ahead: to forecast the amount of bulk product needed
  - 3 months ahead: to forecast how much is needed of each SKU

What is forecast stability?
Example

- **Example: a pharmaceutical company forecasts two times:**
  - 6 months ahead: to forecast the amount of bulk product needed
  - 3 months ahead: to forecast how much is needed of each SKU

Date when forecast was made		Period to be forecasted
May 2023		November 2023
	6 months ahead forecast →	100

What is forecast stability? Example

- **Example: a pharmaceutical company forecasts two times:**
  - 6 months ahead: to forecast the amount of bulk product needed
  - 3 months ahead: to forecast how much is needed of each SKU

Date when forecast was made | **Period to be forecasted**

May 2023 | November 2023

6 months ahead forecast → 100

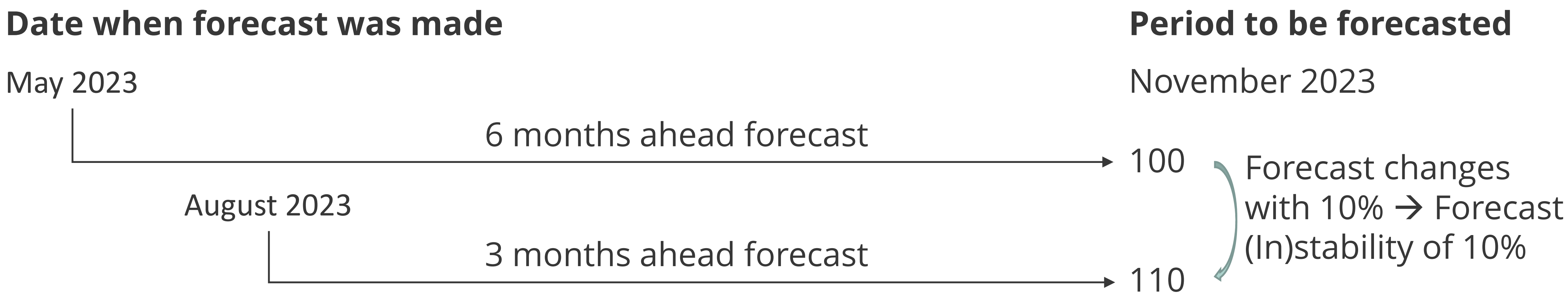
August 2023

3 months ahead forecast → 110

Forecast changes with 10% → Forecast (In)stability of 10%

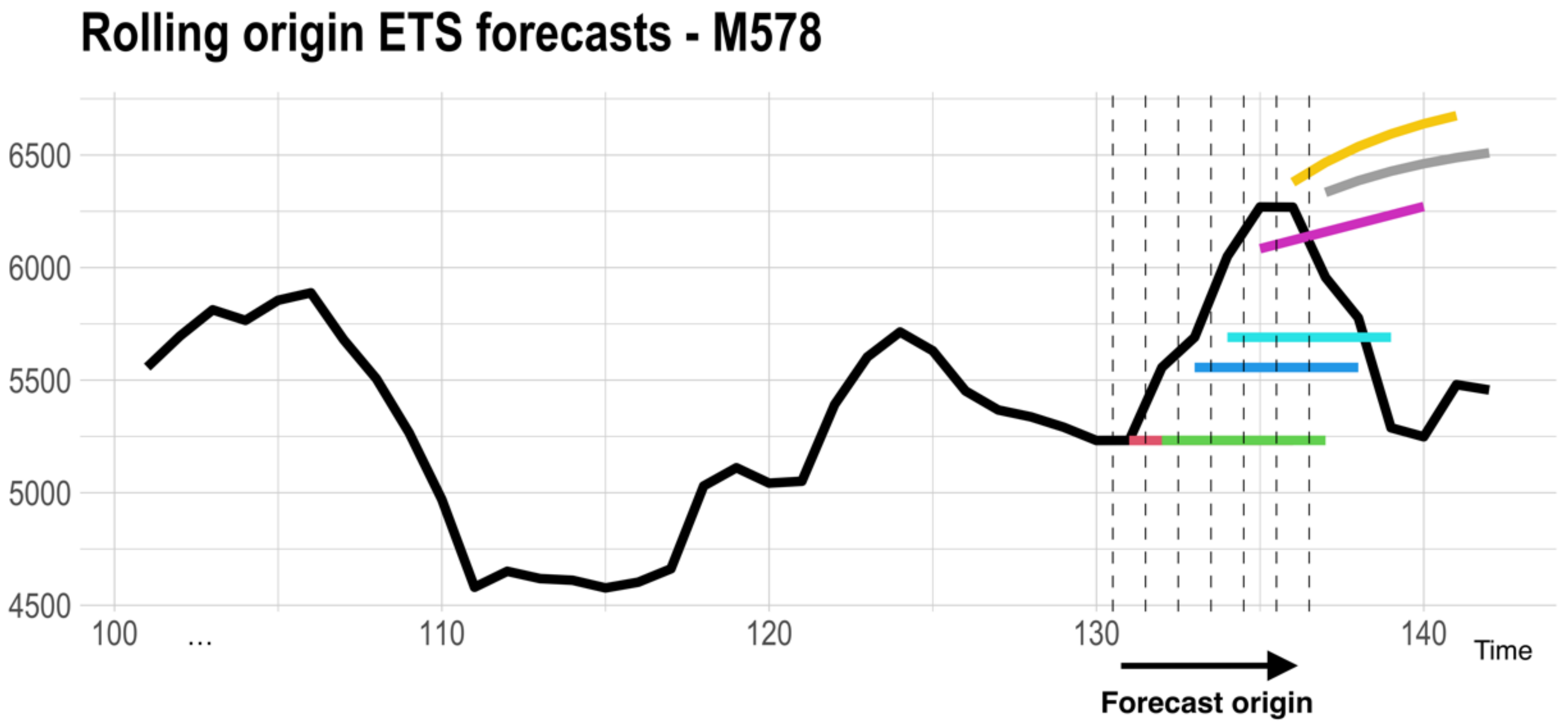
What is forecast stability? Example

- **Example: a pharmaceutical company forecasts two times:**
  - 6 months ahead: to forecast the amount of bulk product needed
  - 3 months ahead: to forecast how much is needed of each SKU



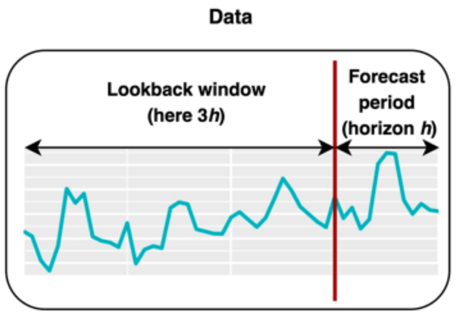
→A change of 10% is good if it effectively brings the forecast closer to the actual.
→The change of 10% causes a change in the supply planning based on the forecast.
→Changing the plan has a cost (Li and Disney, 2017)

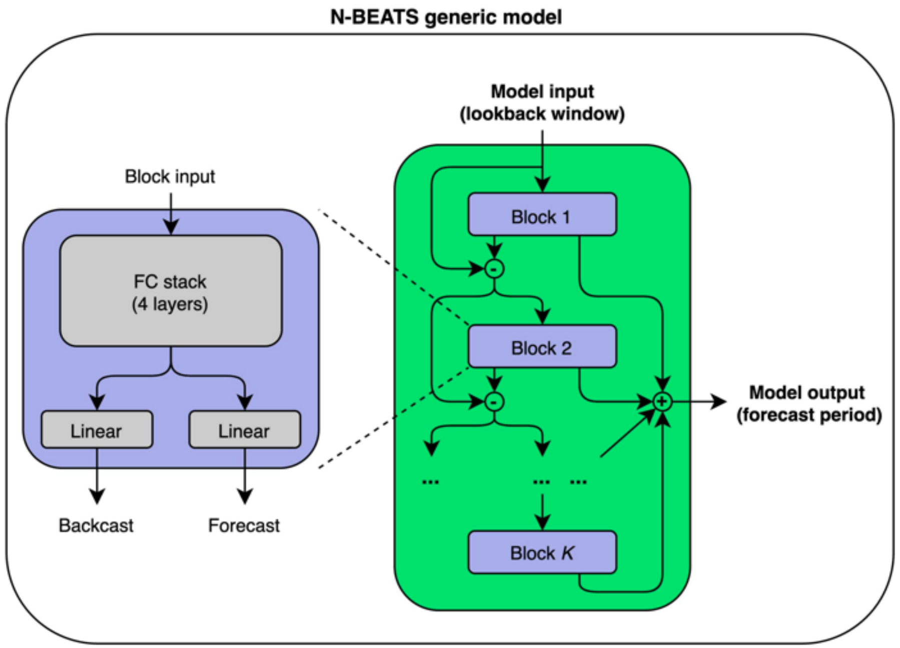
Goal: reduce rolling origin forecast instability without a loss in accuracy



N-BEATS (Oreshkin et al., 2020)

- Univariate time series point forecasting
- Global: train one model with a set of global model parameters that are estimated jointly across time series
- N-BEATS: global deep learning model for univariate time series point forecasting
  - State-of-the-art performance on M3 and M4 competition data sets

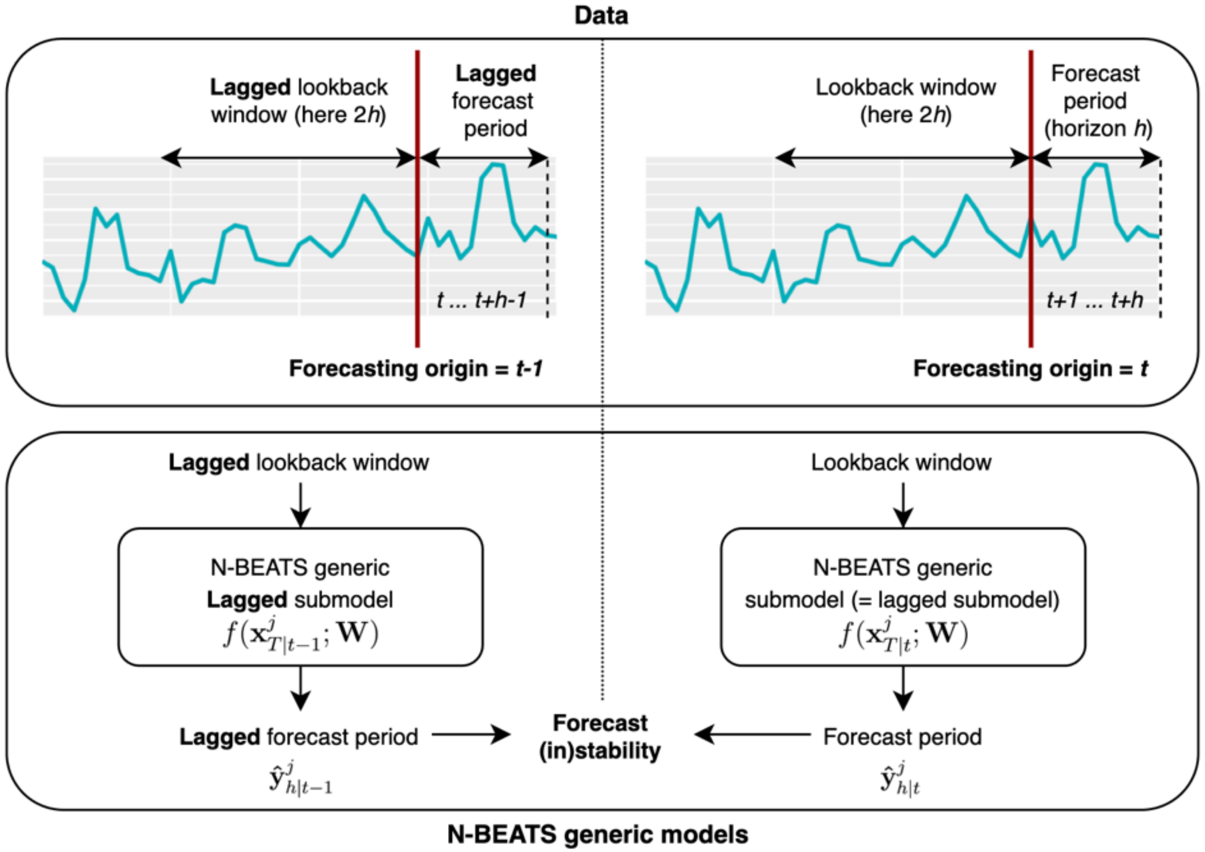




$$\mathbf{W}^* = \arg\min_{\mathbf{W}} \sum_j L(\mathbf{y}^j_{h|t}, \hat{\mathbf{y}}^j_{h|t})$$

$$\hat{\mathbf{y}}^j_{h|t} = f(\mathbf{x}^j_{T|t}; \mathbf{W})$$

N-BEATS-S: reduce forecast instability for deep learning models



N-BEATS-S

=

N-BEATS

+

adding forecast (in)stability component to loss function to optimize forecasts from both

(1) traditional forecast accuracy and
(2) forecast stability perspective

Experiment: sMAPE per horizon on M4 data

Forecast accuracy

$$\mathrm{sMAPE} = \frac{200}{h}\sum_{i=1}^{h}\frac{|y_{t+i} - \hat{y}_{t+i|t}|}{|y_{t+i}| + |\hat{y}_{t+i|t}|}$$

Time	131	132	133	134	135	136	137	138	139	140	141	142
Actuals	5232	5556	5690	6050	6270	6268	5956	5777	5288	5248	5480	5456
MNN	5232	5232	5232	5232	5232	5232						
MNN		5232	5232	5232	5232	5232	5232					
MNN			5556	5556	5556	5556	5556	5556				
MNN				5690	5690	5690	5690	5690	5690			
MAN			...		6084	6121	6159	6196	6234	6271		
MAdN						6379	6467	6538	6594	6639	6675	
MAdN							6334	6386	6428	6462	6488	6510

Forecast updating generally gives rise to more accurate period-specific forecasts

→ benefits

Horizon h	1	2	3	4	5	6	Overall
sMAPE	3.63	7.6	11.39	14.12	14.45	13.89	10.85

Experiment:
sMAPE per horizon on M4 data

Forecast stability

$$\text{sMAPC} = \frac{200}{h-1}\sum_{i=1}^{h-1}\frac{|\hat{y}_{t+i|t} - \hat{y}_{t+i|t-1}|}{|\hat{y}_{t+i|t}| + |\hat{y}_{t+i|t-1}|}$$

Time	131	132	133	134	135	136	137	138	139	140	141	142
Actuals	5232	5556	5690	6050	6270	6268	5956	5777	5288	5248	5480	5456
MNN	5232	5232	5232	5232	5232	5232						
MNN		5232	5232	5232	5232	5232	5232					
MNN			5556	5556	5556	5556	5556	5556				
MNN				5690	5690	5690	5690	5690	5690			
MAN			...		6084	6121	6159	6196	6234	6271		
MAdN						6379	6467	6538	6594	6639	6675	
MAdN							6334	6386	6428	6462	6488	6510

Forecast updating induces instability which leads to revisions to supply plans
→ costs

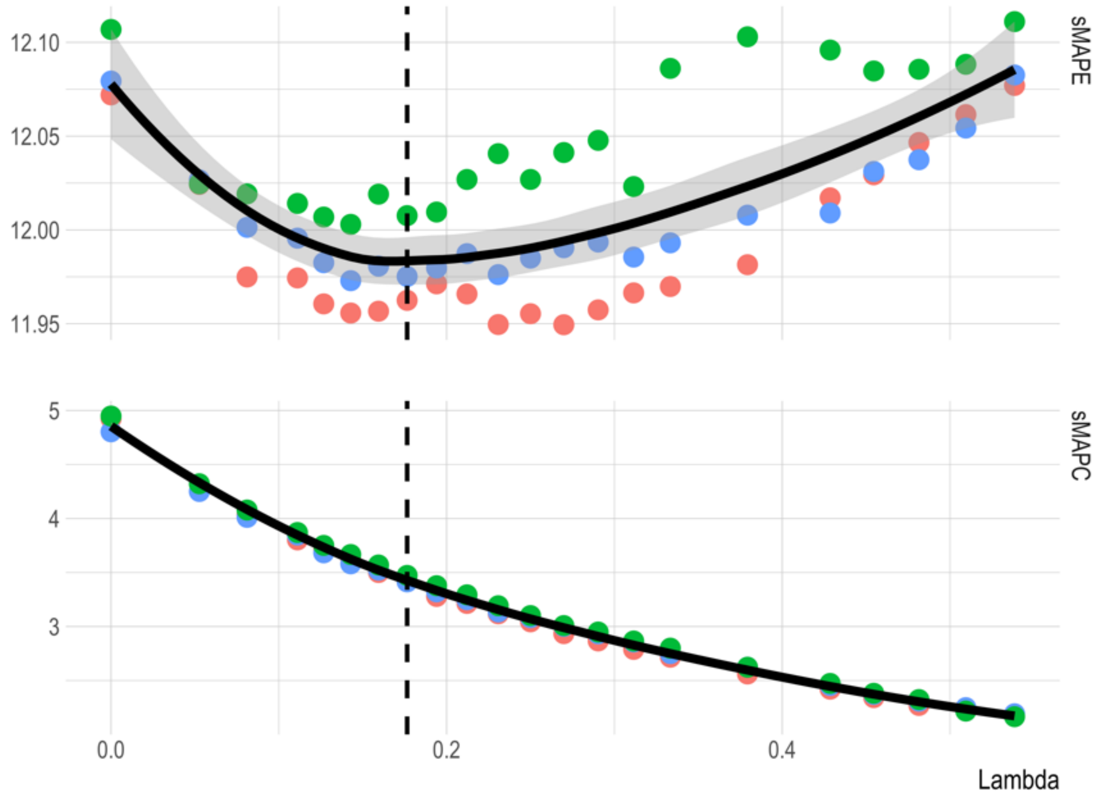
Empirical evaluation

- **Rolling forecasting origin evaluation on M3 (1,428) and M4 (48k) monthly data sets: 13 series of 1- to 6-month ahead forecasts**
- **N-BEATS-S (vs. N-BEATS)**
  - More stable forecasts without causing a loss in forecast accuracy
  - Even improvements in forecast accuracy

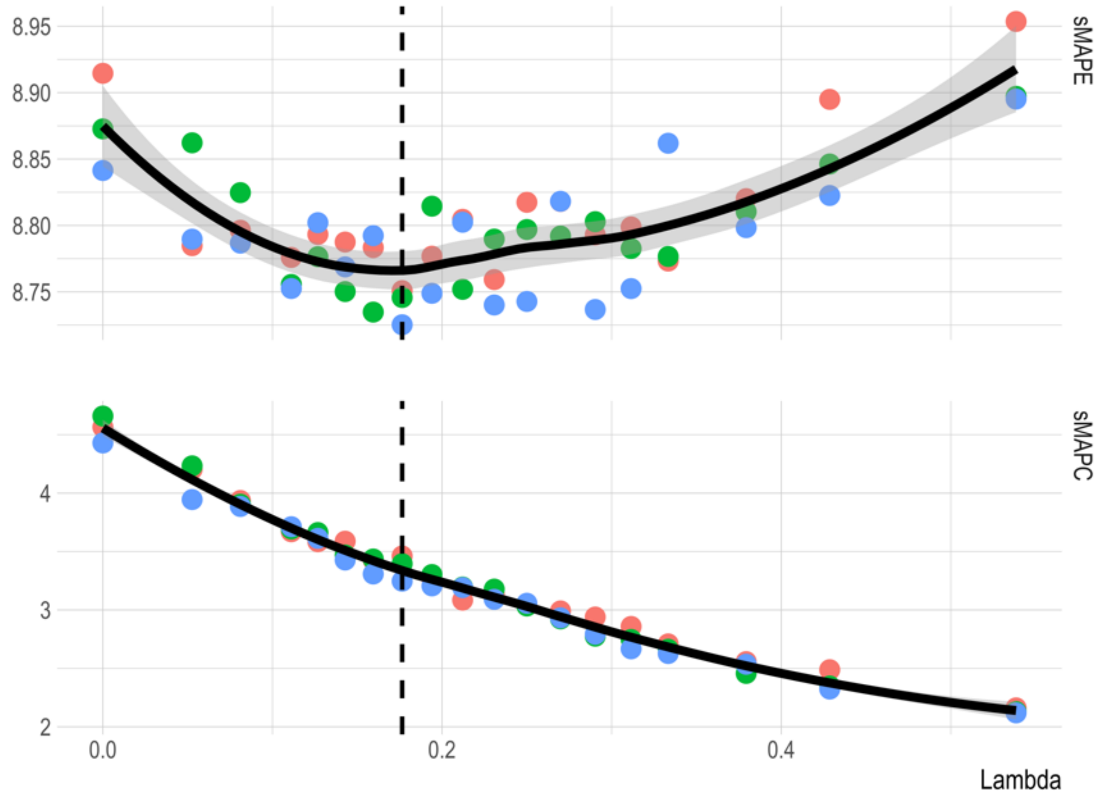
	M3 monthly		M4 monthly	
	sMAPE	sMAPC	sMAPE	sMAPC
N-BEATS	11.47	3.90	9.29	4.56
N-BEATS weight decay	11.50	3.75	9.28	4.26
N-BEATS dropout	-	-	9.37	4.59
N-BEATS *T* ensemble	11.42	3.87	9.06	4.08
N-BEATS origin ensemble	11.60	1.35	9.72	1.54
N-BEATS-S	11.40	2.85	9.23	3.22
N-BEATS-S weight decay	11.41	2.74	9.24	3.05
N-BEATS-S *T* ensemble	11.37	2.32	9.06	2.74
N-BEATS-S origin ensemble	11.59	1.07	9.77	1.17
ETS	11.34	3.21	9.98	4.37

	M3 monthly		M4 monthly	
	RMSSE	RMSSC	RMSSE	RMSSC
N-BEATS	1.110	0.397	1.275	0.622
N-BEATS weight decay	1.093	0.396	1.302	0.613
N-BEATS dropout	-	-	1.307	0.640
N-BEATS *T* ensemble	1.086	0.381	1.234	0.551
N-BEATS origin ensemble	1.183	0.160	1.360	0.233
N-BEATS-S	1.088	0.317	1.278	0.467
N-BEATS-S weight decay	1.094	0.329	1.306	0.459
N-BEATS-S *T* ensemble	1.102	0.272	1.237	0.399
N-BEATS-S origin ensemble	1.161	0.136	1.377	0.188
ETS	1.048	0.411	1.322	0.595

Adding stability in the loss has a regularization effect



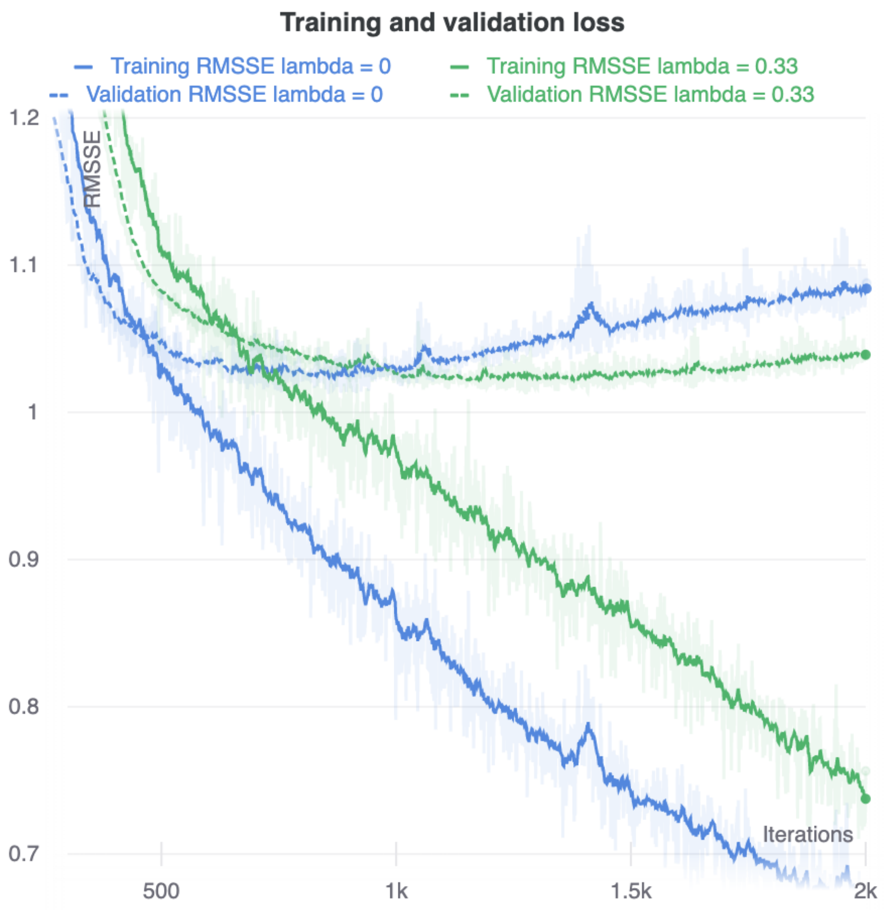
M3 monthly validation data

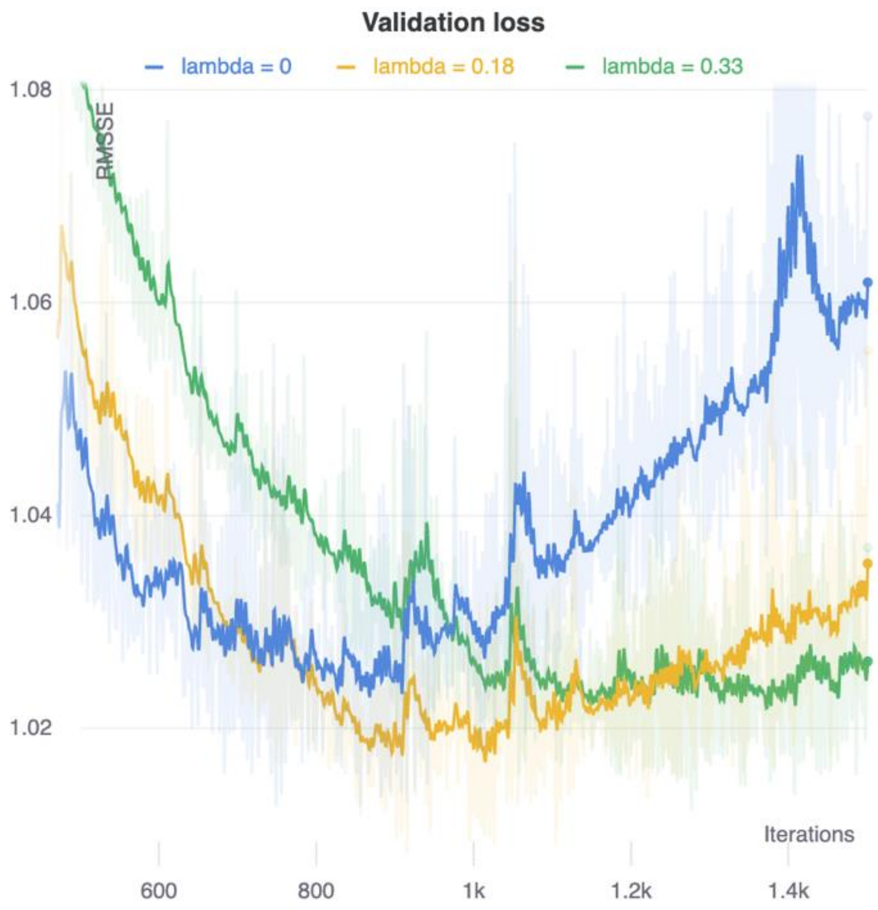


M4 monthly validation data

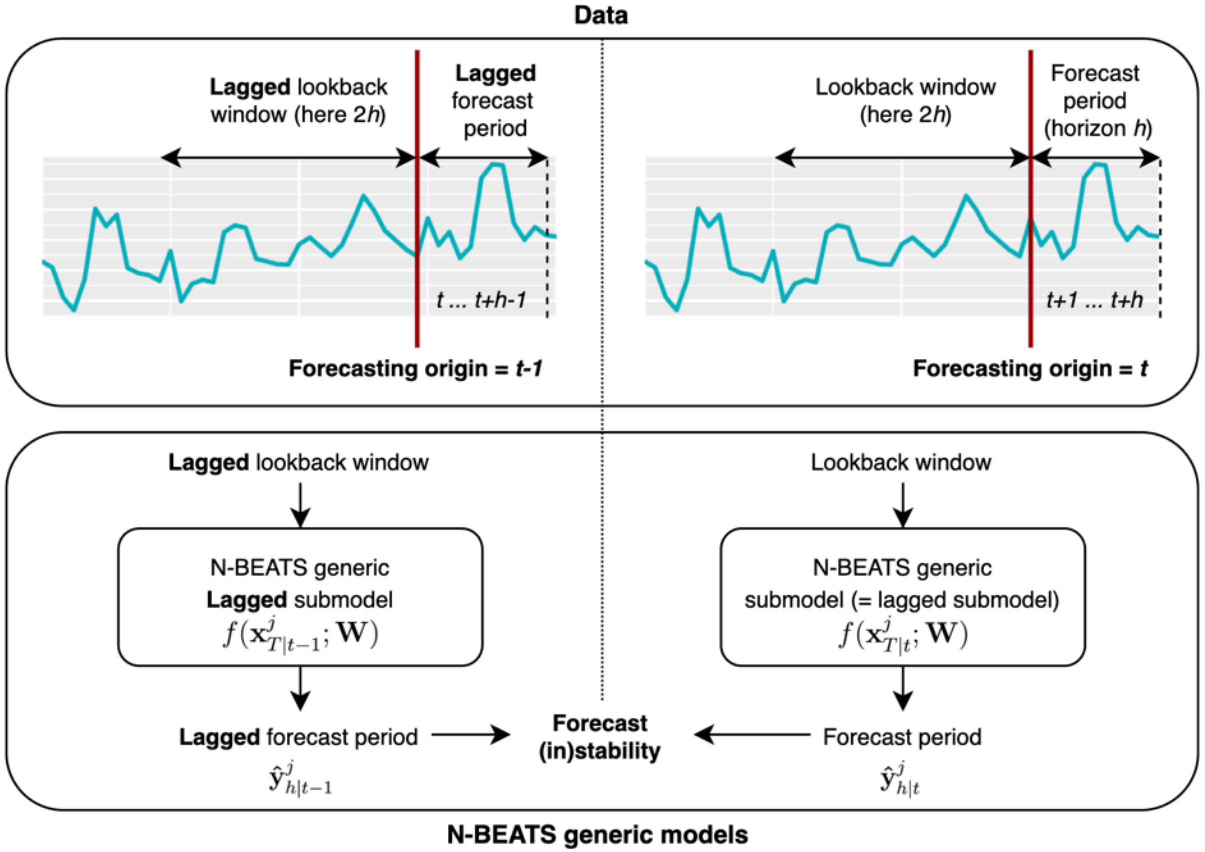
Higher lambda → greater weight for instability component in optimization

Stability in the loss has a regularization effect, preventing overfitting





N-BEATS-S: reduce forecast instability for deep learning models



N-BEATS-S

=

N-BEATS

+

adding forecast (in)stability component to loss function to optimize forecasts from both

(1) traditional forecast accuracy and

(2) forecast stability perspective

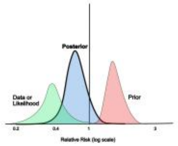
Conclusion

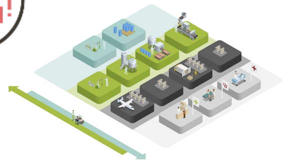
- **N-BEATS-S**
  - Optimize forecasts from both **accuracy** and **stability** perspective by adding forecast instability component to loss function
  - Forecast instability: variability in forecasts for a specific time period due to updating forecasts when new observations become available

- **N-BEATS-S vs. N-BEATS**
  - Experimental results for monthly M3/M4 data
  - More stable forecasts without causing loss in accuracy
  - Even improvements in accuracy → regularization

What is next?

Make one forecast version which is:

- Accurate on ‘all’ levels of detail  
- Stable 
- Probabilistic 

- Explainable and trustworthy 
- Evaluated on supply chain goals 

What is next?

Make one forecast version which is:

- Accurate on ‘all’ levels of detail
- Stable
- Probabilistic
- Explainable and trustworthy
- Evaluated on supply chain goals