Neural Prophet

Extendable and Scalable Forecasting

Oskar Triebe, Stanford University
Facebook Forecasting Summit, October 5th 2020

Oskar Triebe

Raised in Switzerland

BS, ETH Zurich
MS, PhD, Stanford

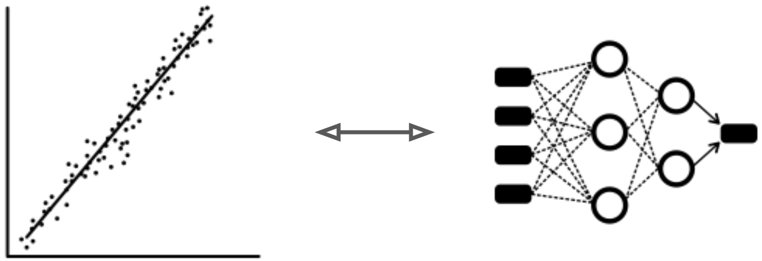
Vectra AI
Merantix
Luminovo

The outdoors
DIY power electronics
Digital human rights

- Motivation
- What is (Neural)Prophet?
- Ar-Net Module
- Development Story
- Hands-On: NeuralProphet
- Outlook

Forecasting Landscape

Chasm



Bridge

- Beginner-friendly
- Interpretable
- Scalable
- Customizable Model
- Extendable Code
- Workflow Integration

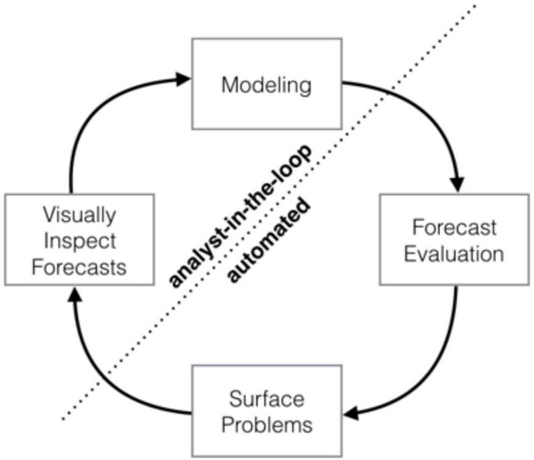
Primer on Facebook Prophet

Forecasting at Scale

Sean J. Taylor*†
Facebook, Menlo Park, California, United States
sjt@fb.com

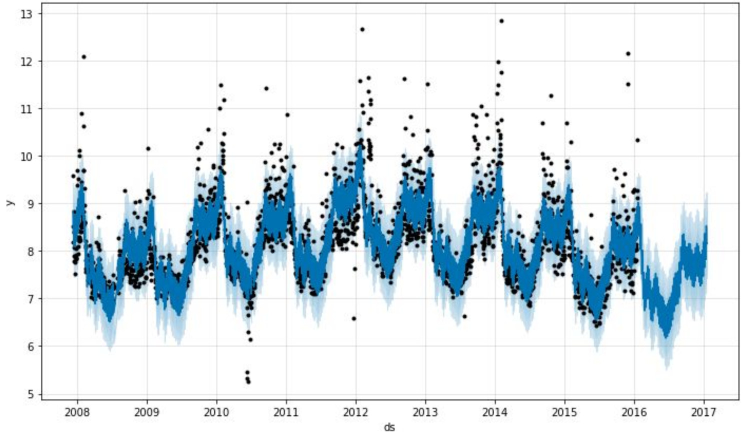
and

Benjamin Letham†
Facebook, Menlo Park, California, United States
bletham@fb.com



https://peerj.com/preprints/3190/

Prophet models interpretable time series components.



$$y(t) = g(t) + s(t) + h(t) + \epsilon_t.$$

$g(t)$ Trend

$h(t)$ Events

$s(t)$ Seasonality

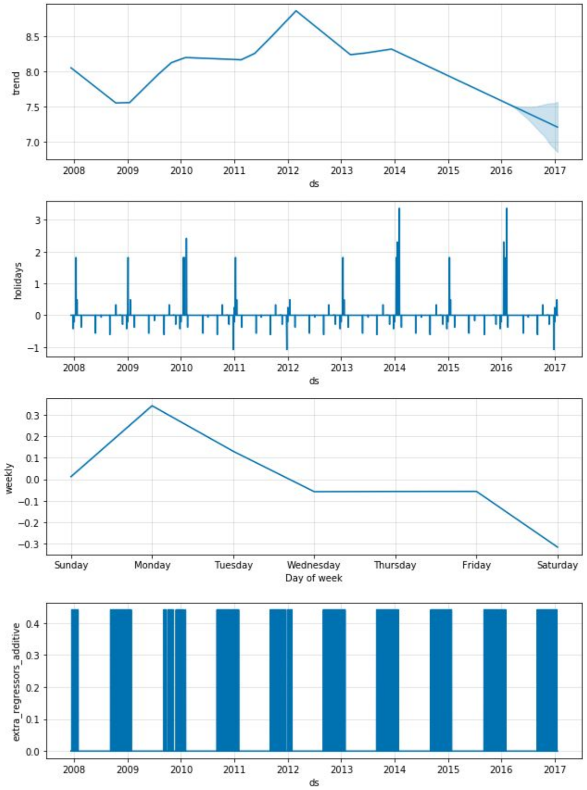
$X(t)$ Regressors

$g(t)$

$h(t)$

$s(t)$

$X(t)$



Why we need NeuralProphet.

Stan

PyTorch

Extensible code.

Models suited for larger datasets.

Lagged input variables.

Tl;dr - NeuralProphet models what Prophet does, …

… and adds:

- Auto-Regression
- Covariates (lagged regressors)
- Configurable nonlinear deep layers
- Tuneable to specific forecast horizons
- Custom metrics and losses
- Workflow tools

AR-Net module

ditto, with same target

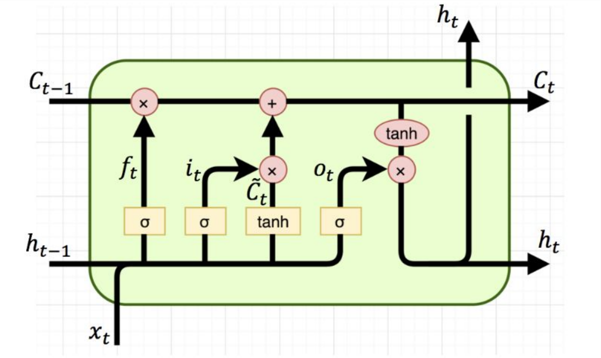
Extensibility:

- Anything trainable by gradient descent can be added as module

How did we get here?

Let's start at the beginning...

TS-Cell



LSTM cell, for illustration

simple
interpretable
performant

Vision at outset:
Build an easy to use general time-series cell.

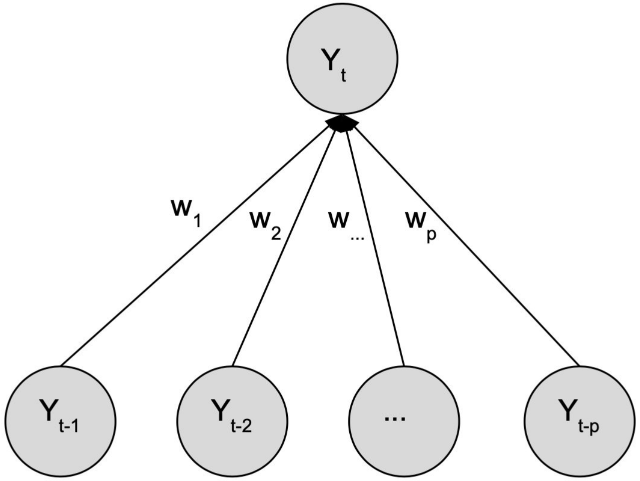
Focusing on Auto-Regression

$$y_t = c + \sum_{i=1}^{i=p} w_i * y_{t-i} + e_t \longrightarrow min_\theta \quad L(y, \hat{y}, \theta)$$

AR-Net is just a simple NN with some tweaks.

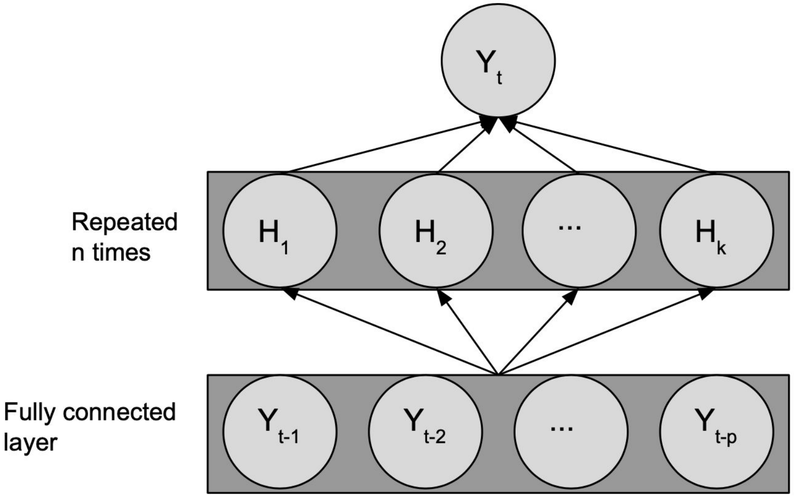
Simplest form: AR-Net(0)

Interpretable

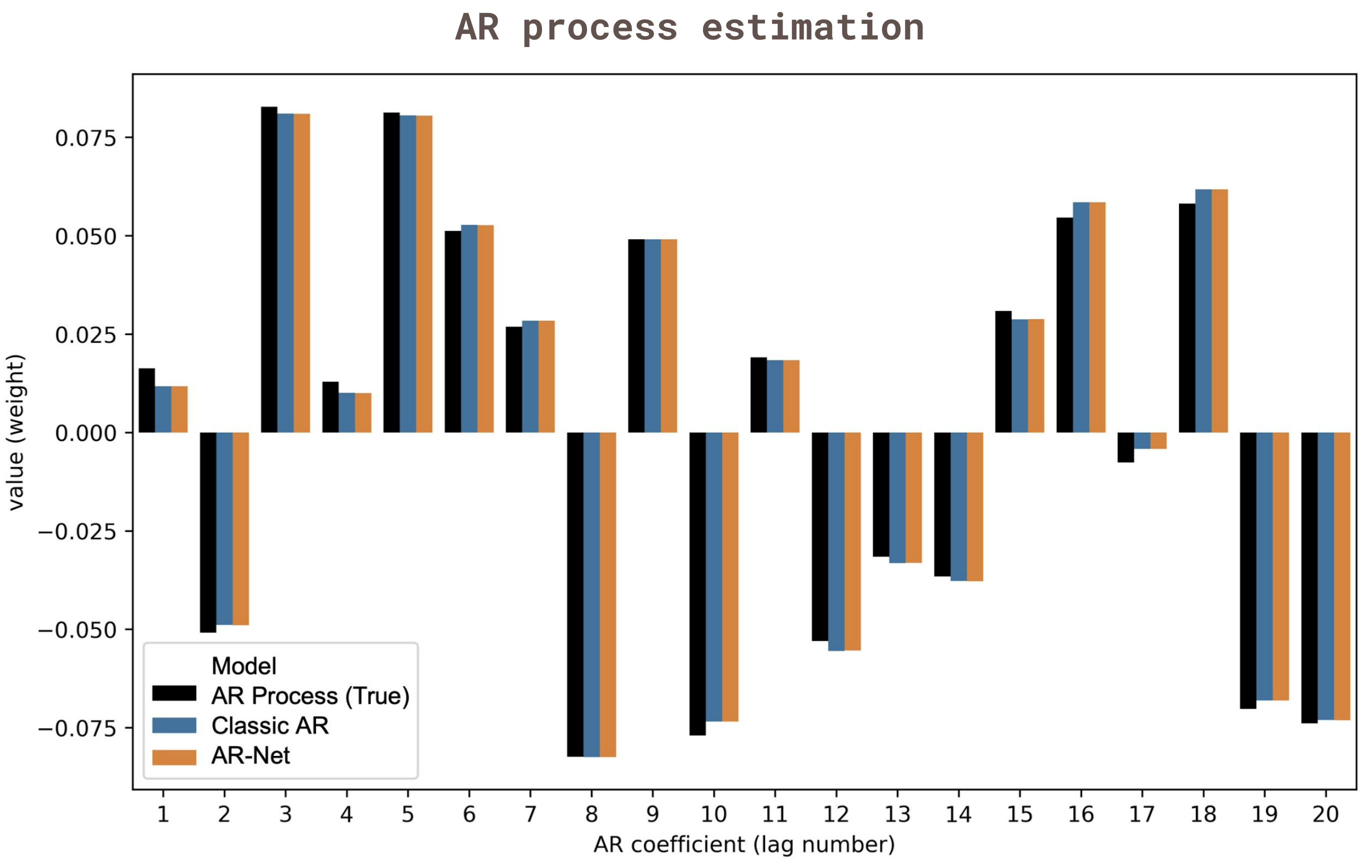


General purpose forecaster: AR-Net(n)

Stronger modeling ability

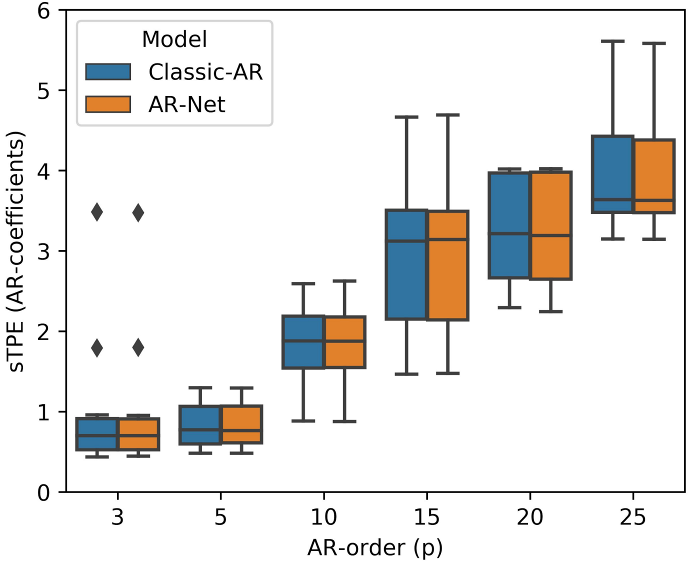


AR-Net finds near identical coefficients.



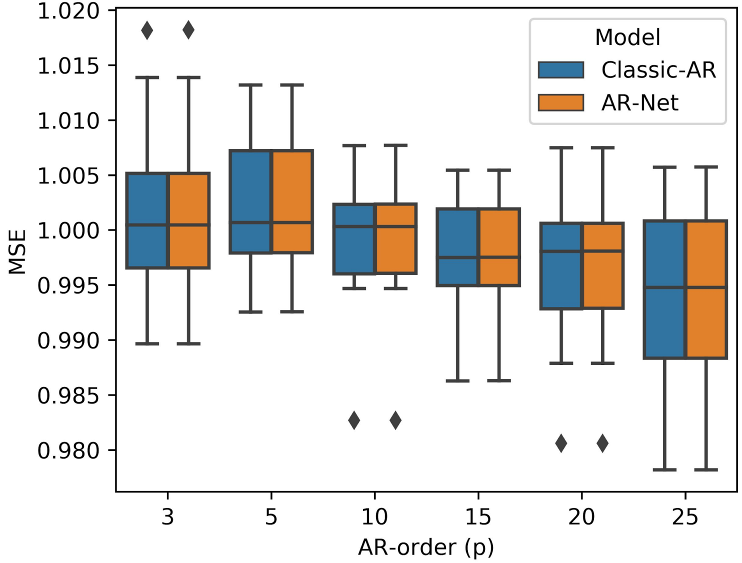
AR-Net is on par with Classic AR.

Closeness to true coefficients



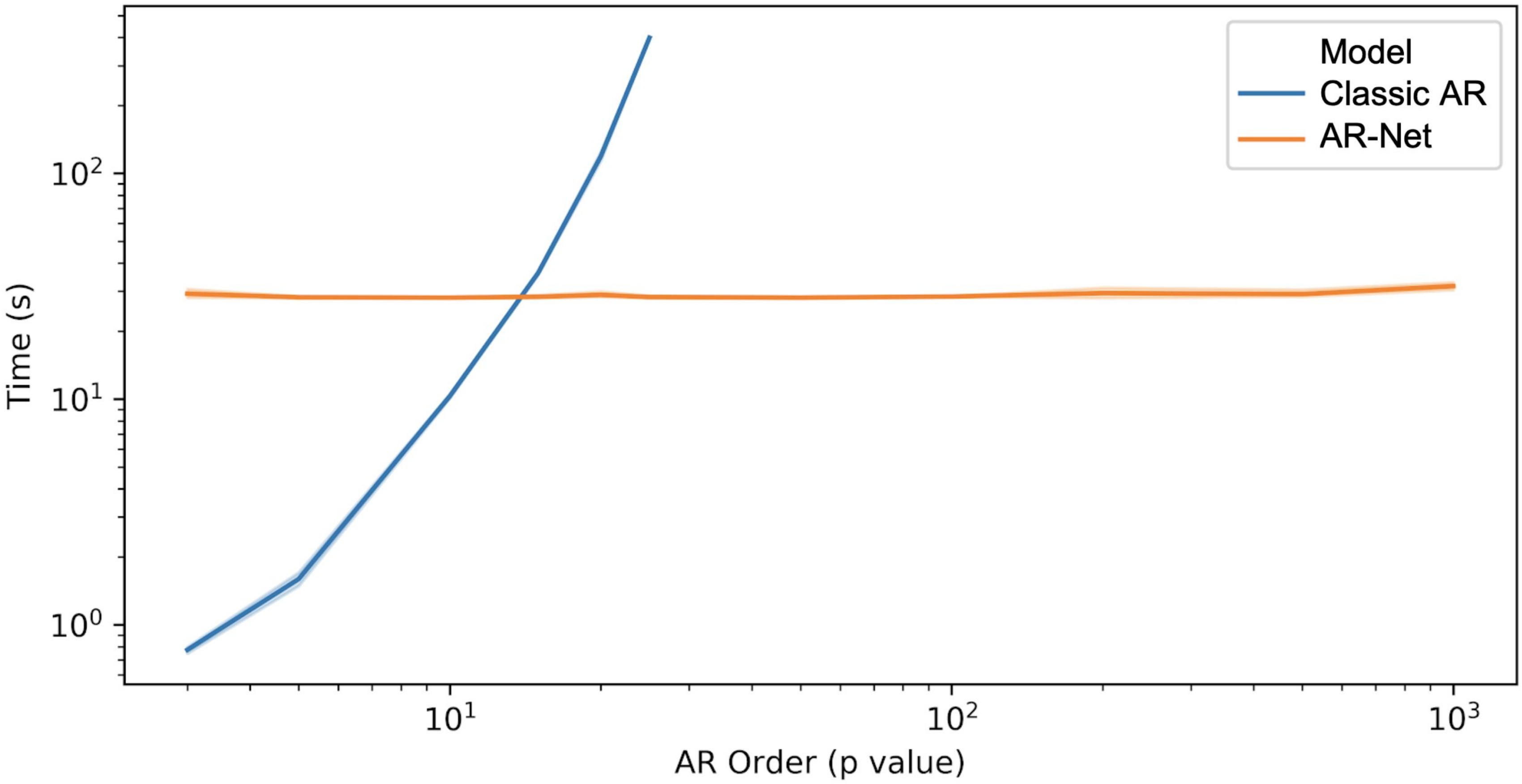
$$sTPE = 100 \cdot \frac{\sum_{i=1}^{i=p} |\hat{w}_i - w_i|}{\sum_{i=1}^{i=p} |\hat{w}_i| + |w_i|}$$

Forecast accuracy

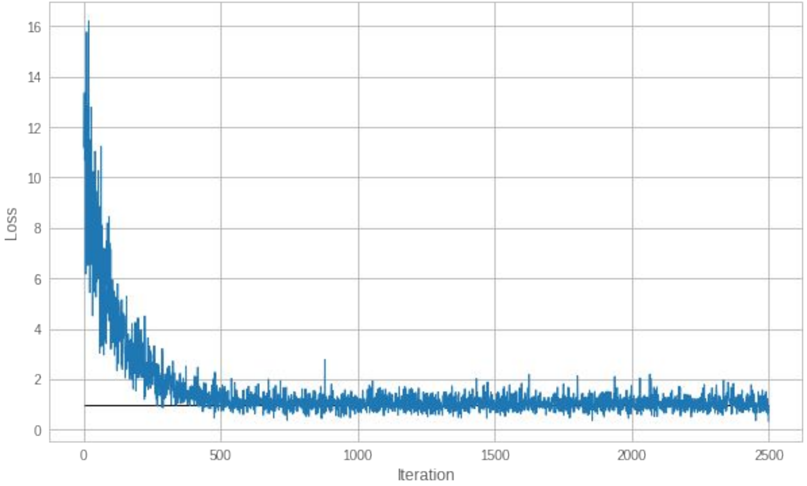


$$MSE = \frac{1}{n} \sum_{1}^{n} (y_t - \hat{y}_t)^2$$

AR-Net is quadratically faster for large p values.



Sparse AR process



Trained with SGD (Adam)

$$min_\theta \quad L(y, \hat{y}, \theta) + \lambda(s) \cdot R(\theta)$$

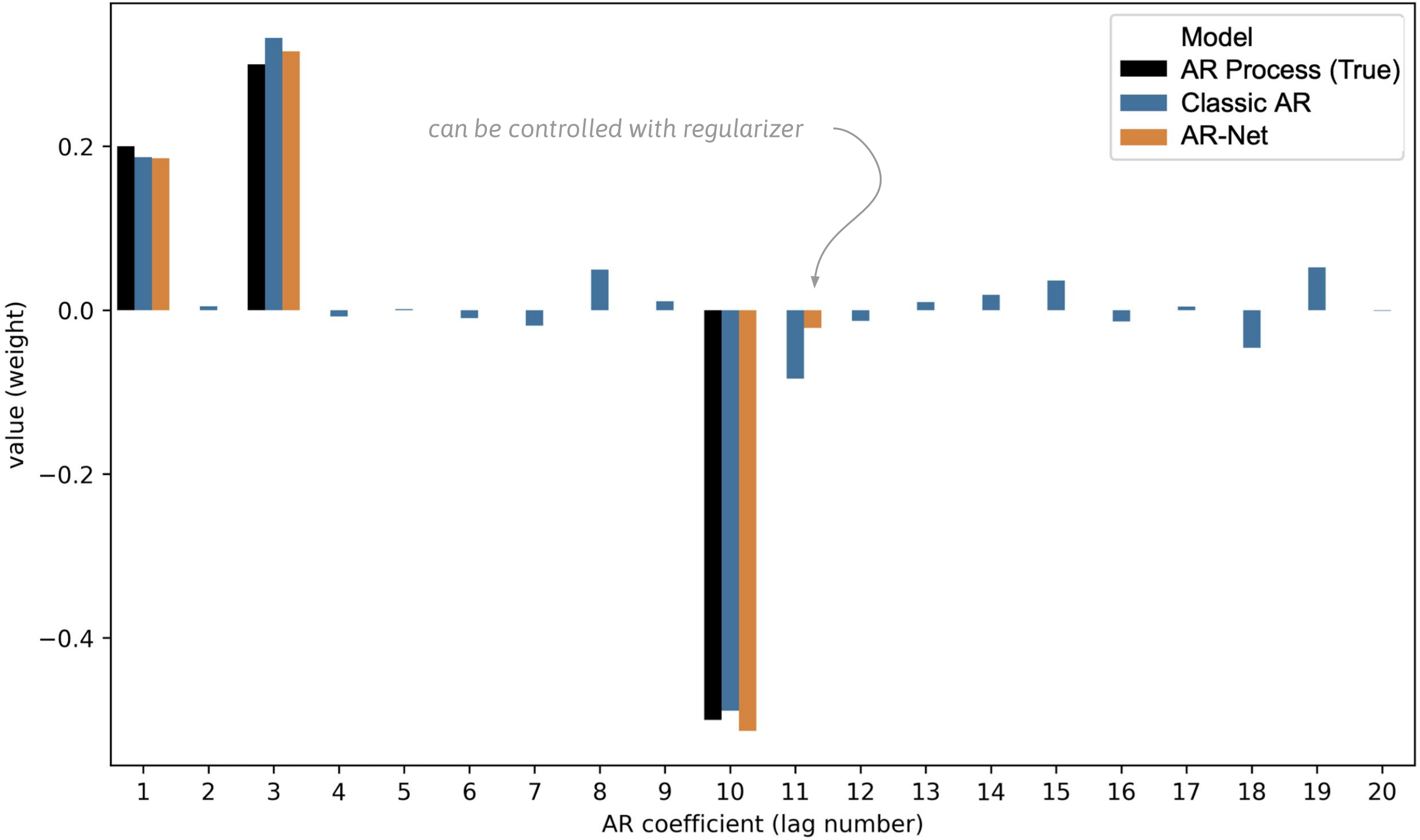
$$\lambda(s) = c_\lambda \cdot (s^{-1} - 1)$$

$$s = \frac{\hat{p}_{data}}{p_{model}}$$

$$c_\lambda \approx \frac{\sqrt{\hat{L}}}{100}$$

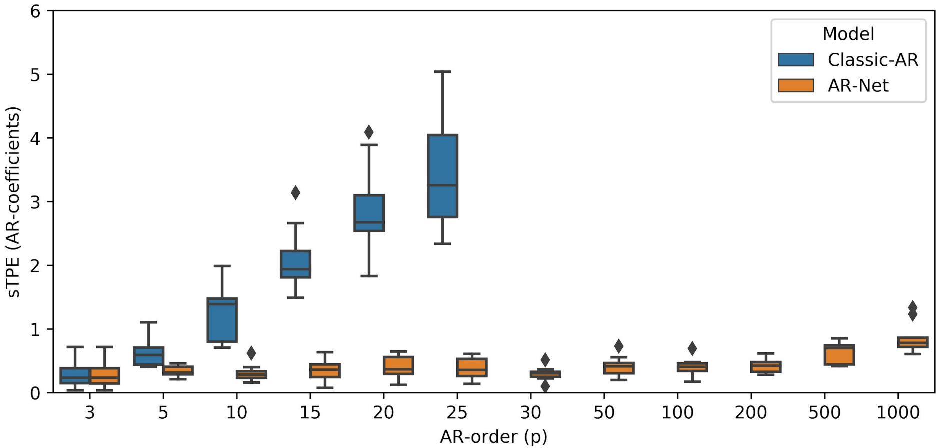
$$R(\theta) = \frac{1}{p} \sum_{i=1}^{p} \frac{2}{1 + \exp(-c_1 \cdot |\theta_i|^{\frac{1}{c_2}})} - 1$$

Yes, we can automatically learn sparse AR-Coefficients.

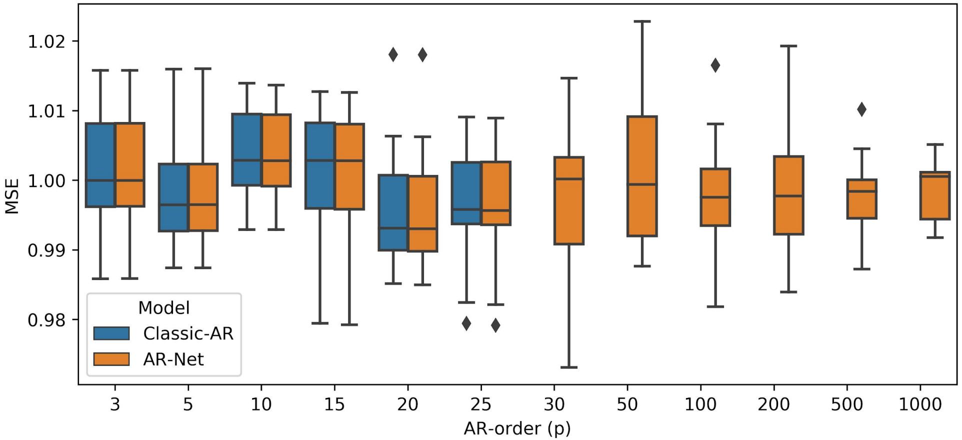


Sparse AR-Net surpasses Classic AR and scales to large orders.

Closeness to true coefficients



MSE loss on forecast target

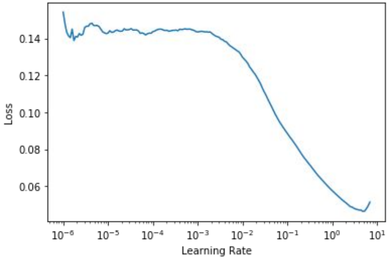


AR-Net v 1.0 builds on Fastai2 on PyTorch.

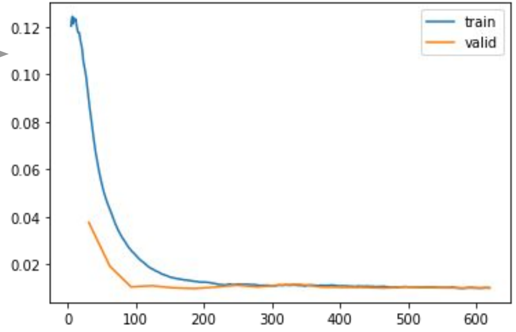
any time series

```
learn = init_ar_learner(
          series=df,
          ar_order=3,
          n_forecasts=1,
          valid_p=0.25,
          sparsity=1.0/2.0,
)

lr = learn.lr_find()[0]
learn.fit_one_cycle(n_epoch=10, lr)
print(coeff_from_model(learn.model))
```



epoch	train_loss	valid_loss	mae	time
0	0.091714	0.037677	0.165344	00:00
1	0.043905	0.019270	0.112051	00:00
2	0.026220	0.010630	0.083301	00:00
3	0.018274	0.011065	0.084113	00:00
4	0.014546	0.010218	0.081142	00:01
5	0.013065	0.009898	0.080138	00:00
6	0.012065	0.010537	0.083343	00:01
7	0.011674	0.011297	0.085578	00:00
8	0.011395	0.010602	0.082547	00:00
9	0.011284	0.011390	0.085972	00:00
10	0.011243	0.011658	0.086935	00:00




```
ar coeff [[0.19132832, 0.3154733, -0.5822663, -0.049190696, 0.0042145597, 0.0015144324]]
```

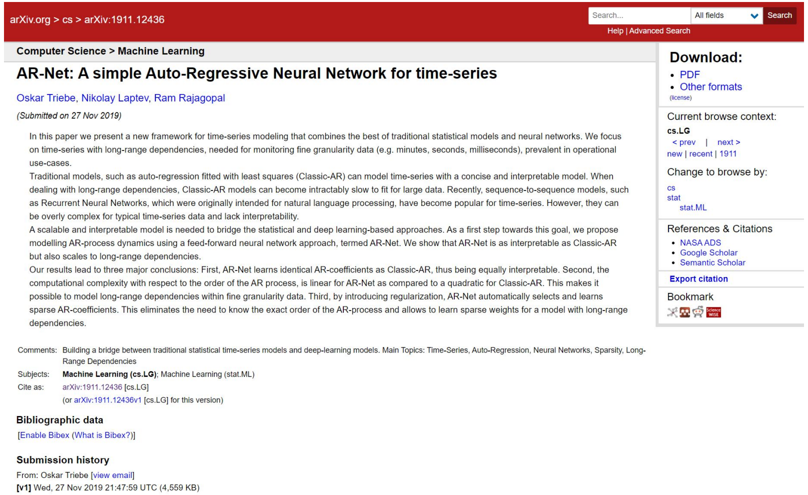
building on open-source Fastai2, PyTorch, Python

Available on Arxiv and Github.

AR-Net

Paper on Arxiv

https://arxiv.org/abs/1911.12436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Computer Science > Machine Learning

AR-Net: A simple Auto-Regressive Neural Network for time-series

Oskar Triebe, Nikolay Laptev, Ram Rajagopal

(Submitted on 27 Nov 2019)

In this paper we present a new framework for time-series modeling that combines the best of traditional statistical models and neural networks. We focus on time-series with long-range dependencies, needed for monitoring fine granularity data (e.g. minutes, seconds, milliseconds), prevalent in operational use-cases.
Traditional models, such as auto-regression fitted with least squares (Classic-AR) can model time-series with a concise and interpretable model. When dealing with long-range dependencies, Classic-AR models can become intractably slow to fit for large data. Recently, sequence-to-sequence models, such as Recurrent Neural Networks, which were originally intended for natural language processing, have become popular for time-series. However, they can be overly complex for typical time-series data and lack interpretability.
A scalable and interpretable model is needed to bridge the statistical and deep learning-based approaches. As a first step towards this goal, we propose modelling AR-process dynamics using a feed-forward neural network approach, termed AR-Net. We show that AR-Net is as interpretable as Classic-AR but also scales to long-range dependencies.
Our results lead to three major conclusions: First, AR-Net learns identical AR-coefficients as Classic-AR, thus being equally interpretable. Second, the computational complexity with respect to the order of the AR process, is linear for AR-Net as compared to a quadratic for Classic-AR. This makes it possible to model long-range dependencies within fine granularity data. Third, by introducing regularization, AR-Net automatically selects and learns sparse AR-coefficients. This eliminates the need to know the exact order of the AR-process and allows to learn sparse weights for a model with long-range dependencies.

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Comments: Building a bridge between traditional statistical time-series models and deep-learning models. Main Topics: Time-Series, Auto-Regression, Neural Networks, Sparsity, Long-Range Dependencies

Subjects: **Machine Learning (cs.LG)**; Machine Learning (stat.ML)

Cite as: arXiv:1911.12436 [cs.LG]

(or arXiv:1911.12436v1 [cs.LG] for this version)

Bibliographic data

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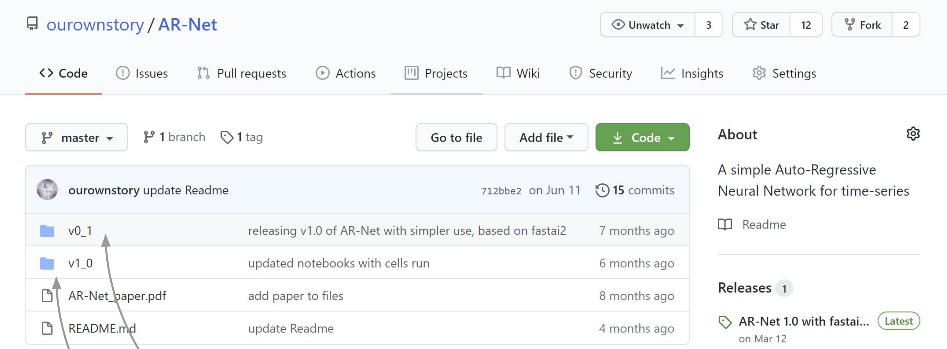
Submission history

From: Oskar Triebe [view email]

[v1] Wed, 27 Nov 2019 21:47:59 UTC (4,559 KB)

Code on Github

https://github.com/ourownstory/AR-Net



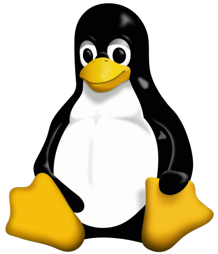
v 0.1: plain PyTorch

v 1.0 built on Fastai2

Developing an open-source package

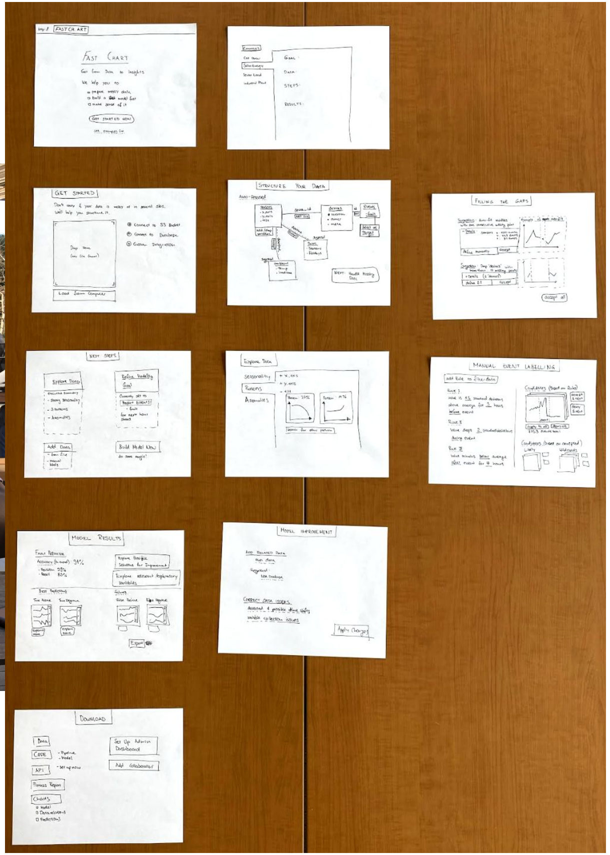
For the first time.

Thank you to all open-source contributors, you have left us a huge legacy!



Interview lots of people. Prototype. Iterate.

Dev Story



Welcome to fastai v2

> *NB: This is still in early development. Use v1 unless you want to contribute to the next version of fastai*

CI passing | pypi version v0.0.30 | conda version v0.0.30 | Build fastai2 images passing

That's actually what I ended up doing …

… and back to plain PyTorch

Design challenges.

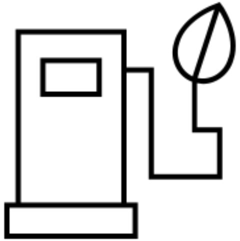
Pun intended.

User ⟷ Coder

Explicit ⟷ Implicit

bug ¯\(°_o)/¯

A car is more than an engine.



Preprocessing

Diagnostics

Deployment

That’s why we will include helpful tools to streamline your workflow.

Beta NeuralProphet

Model components

Code snippets & plots

S	*Seasonality*	
T	*Trend*	
E/H	*Events / Holidays*	
?	*Uncertainty*	
_	*Sparsity / Regularization*	Priors → Regularization
AR	*Autoregression*	AR-Net
X	*Covariates / Regressors*	Lagged and future-known
NN	*Nonlinear (deep) layers*	

Piecewise linear trend

- N changepoints
- Segmentwise independent
- Automatic changepoint detection
- Optional logistic growth

$$g(t) = (k + \mathbf{a}(t)^\intercal \boldsymbol{\delta})t + (m + \mathbf{a}(t)^\intercal \underbrace{\boldsymbol{\gamma}}_{-s_j\delta_j}),$$

Seasonality

- N Fourier terms
- Automatic yearly, weekly, daily

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi n t}{P}\right) + b_n \sin\left(\frac{2\pi n t}{P}\right)\right)$$

$$s(t) = X(t)\boldsymbol{\beta}.$$

$$X(t) = \left[\cos\left(\frac{2\pi(1)t}{365.25}\right), \ldots, \sin\left(\frac{2\pi(10)t}{365.25}\right)\right]$$

We added Covariates and Auto-Regression as AR-Net.

Events / Holidays

- Automatic for given country
- Various user-defined formats

$$h(t) = Z(t)\boldsymbol{\kappa}.$$

$$Z(t) = [\mathbf{1}(t \in D_1), \ldots, \mathbf{1}(t \in D_L)]$$

Future-Known Regressors

- Single weight

Lagged Covariates

- AR-Net (y as target)

Auto-Regression

- AR-Net

Beta NeuralProphet

Model components

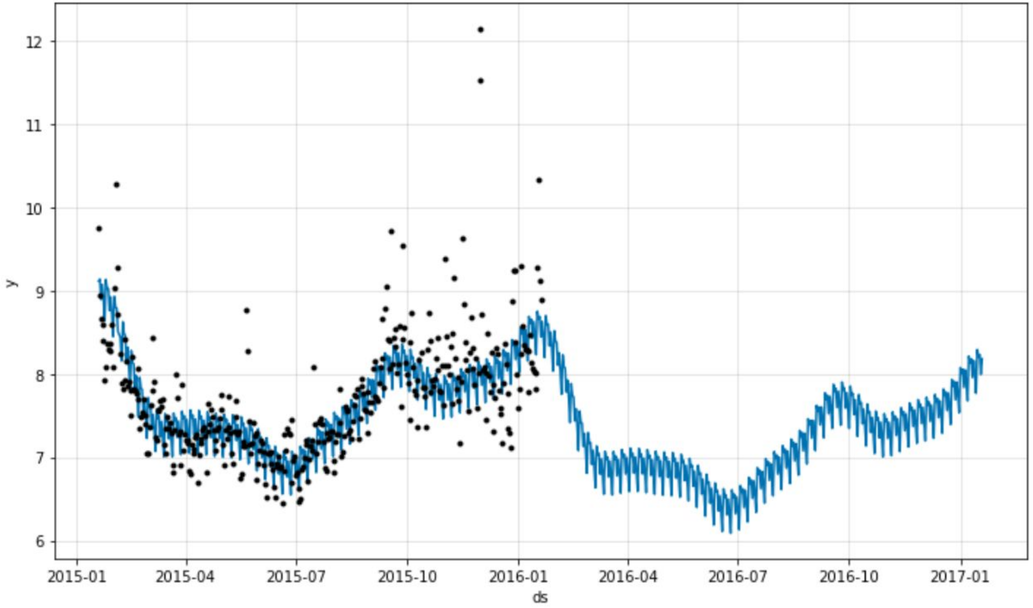
Code snippets & plots

Few lines from data to forecast.

NeuralProphet

```
# linear time-dependent model
m = NeuralProphet()
metrics = m.fit(df)
future = m.make_future_dataframe(df, future_periods=365)
forecast = m.predict(future)
fig_fcst = m.plot(forecast[-730:])
```

```
Disabling daily seasonality. Run NeuralProphet with daily_seasonality=True to override this.
```




```
import pandas as pd
from neuralprophet.neural_prophet import NeuralProphet
```

```
df = pd.read_csv('../data/example_wp_log_peyton_manning.csv')
```

```
n_forecasts=1,
n_lags=0,
n_changepoints=5,
learning_rate=1.0,
loss_func='Huber',
normalize_y=True,
num_hidden_layers=0,
d_hidden=None,
ar_sparsity=None,
trend_smoothness=0,
trend_threshold=False,
yearly_seasonality='auto',
weekly_seasonality='auto',
daily_seasonality='auto',
seasonality_mode='additive',
seasonality_reg=None,
data_freq='D',
impute_missing=True,
verbose=False,
```

Validate model performance without extra lines.

NeuralProphet

```
# or evaluate while training
m = NeuralProphet()
metrics = m.fit(df, validate_each_epoch=True, valid_p=0.2)
metrics.tail()
```

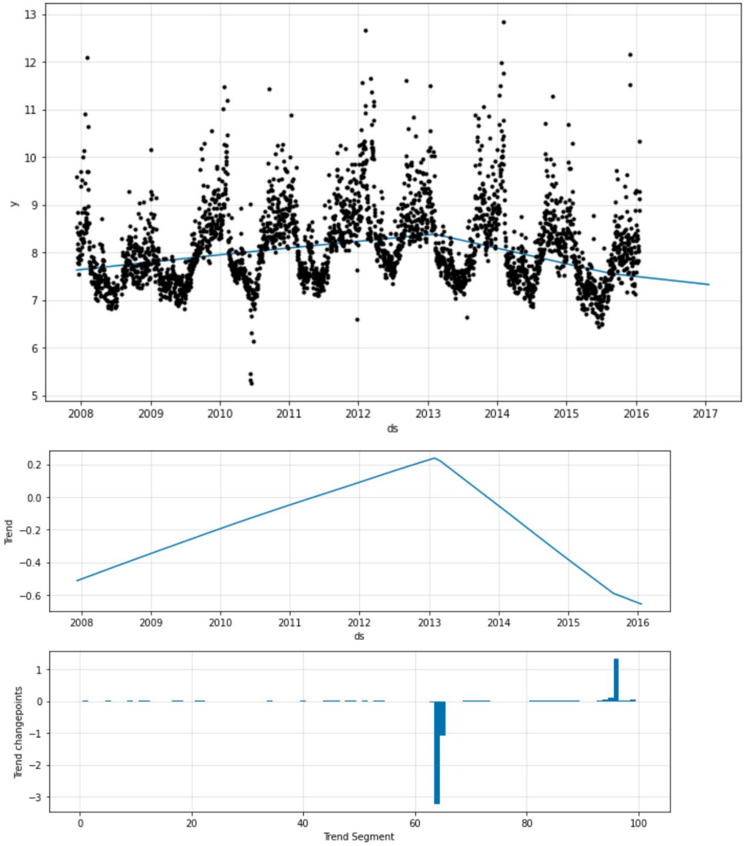
```
Disabling daily seasonality. Run NeuralProphet with daily_seasonality=True to override this.
```

	SmoothL1Loss	MAE	RegLoss	SmoothL1Loss_val	MAE_val
35	0.163102	0.371323	0.0	0.485371	0.779465
36	0.161851	0.369609	0.0	0.368921	0.648736
37	0.161122	0.369219	0.0	0.366328	0.648230
38	0.168598	0.376638	0.0	0.348269	0.627886
39	0.167961	0.375777	0.0	0.362161	0.642699

```
# split manually
m = NeuralProphet()
df_train, df_val = m.split_df(df, valid_p=0.2)
train_metrics = m.fit(df_train)
val_metrics = m.test(df_val)
```

Trend

NeuralProphet

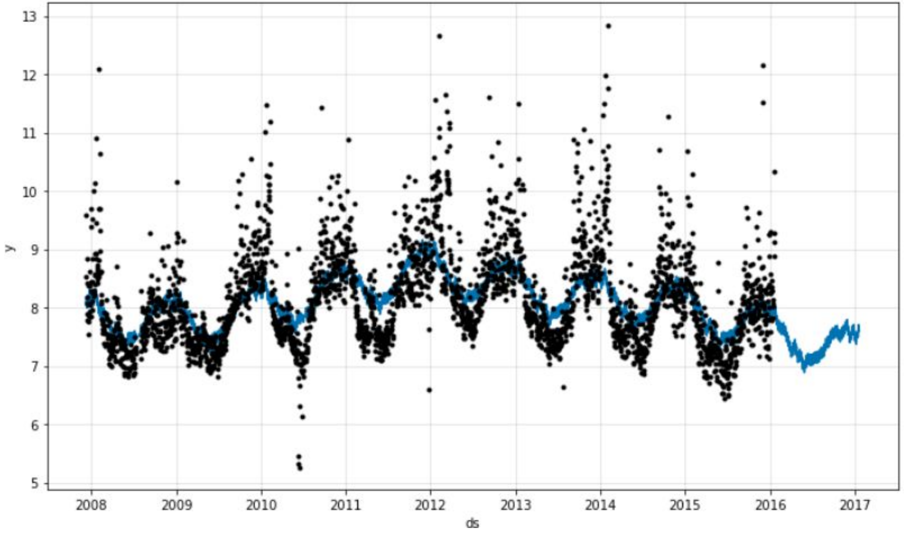


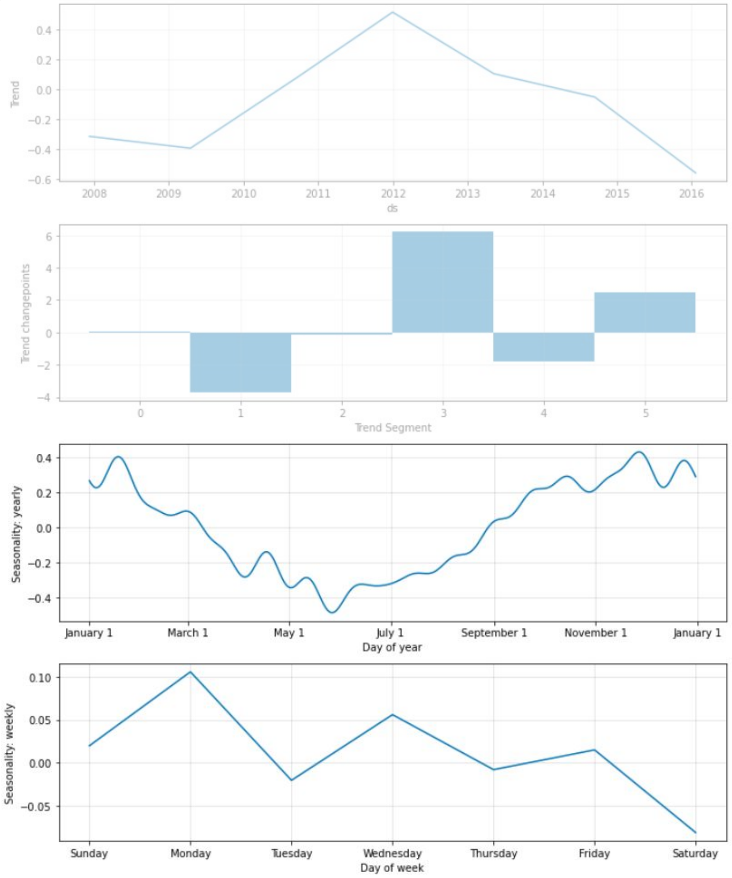

```
m = NeuralProphet(
    n_changepoints=100,
    trend_smoothness=2,
    yearly_seasonality=False,
    weekly_seasonality=False,
    daily_seasonality=False,
)
metrics = m.fit(df)
```

Seasonality


```
m = NeuralProphet(
    yearly_seasonality=16,
    weekly_seasonality=8,
    daily_seasonality=False,
    seasonality_reg=1,
)
metrics = m.fit(df)
```

```
NOTICE: A Regularization strength for the seasonal Fourier Terms
was set.Please note that this feature is experimental.
```





Events can be added in different forms.

NeuralProphet

```
superbowls = pd.DataFrame({'event': 'superbowl',
'ds': pd.to_datetime(['2010-02-07', '2014-02-02', '2016-02-07'])})
```

```
events_df = pd.concat((superbowls, playoffs))
```

```
m = NeuralProphet()
```

```
m = m.add_country_holidays("US")
```

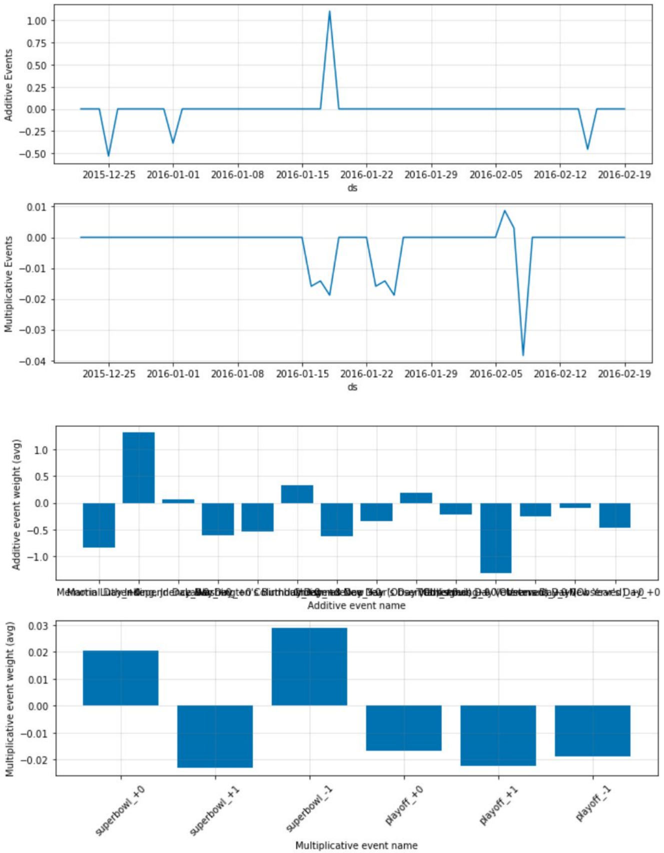
```
m = m.add_events(
    ["superbowl", "playoff"],
    lower_window=-1,
    upper_window=1,
    mode="multiplicative",
    regularization=0.5
)
```

```
history_df = m.create_df_with_events(df, events_df)
metrics = m.fit(history_df)
```

```
Disabling daily seasonality. Run NeuralProphet with daily_seasonality=
True to override this.
```

```
future = m.make_future_dataframe(
    history_df,
    events_df,
    future_periods=30,
    n_historic_predictions=30
)
```

```
forecast = m.predict(future)
```



Lagged Covariates / Auto-Regression

```
m = NeuralProphet(
    n_forecasts=30,
    n_lags=60,
    ar_sparsity=0.1,
    yearly_seasonality=False,
    weekly_seasonality=False,
    daily_seasonality=False,
)
```

```
df = pd.read_csv('../data/example_wp_log_peyton_manning.csv')
df['A'] = df['y'].rolling(7, min_periods=1).mean()
df['B'] = df['y'].rolling(60, min_periods=1).mean()
m = m.add_covariate(name='A')
m = m.add_regressor(name='B')
```

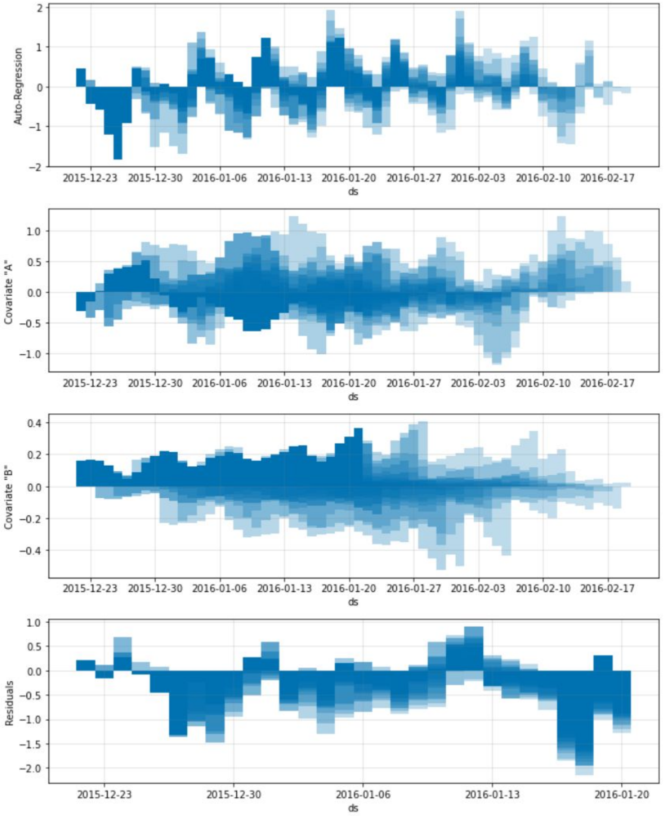
```
metrics = m.fit(df)
future = m.make_future_dataframe(df, n_historic_predictions=30)
forecast = m.predict(future)
```

Future-known regressors are similar

Tune.

```
m = NeuralProphet(
    n_forecasts=30,
    n_lags=60,
    learning_rate=1.0,
    loss_func='Huber',
    normalize_y=True,
    num_hidden_layers=2,
    d_hidden=64,
)
```

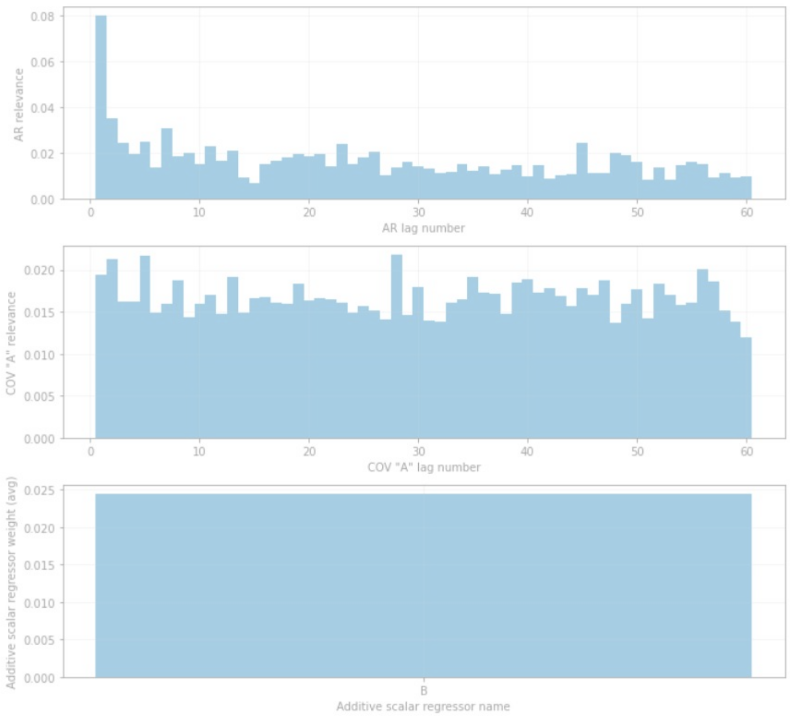
```
fig_comp = m.plot_components(forecast[60:])
```



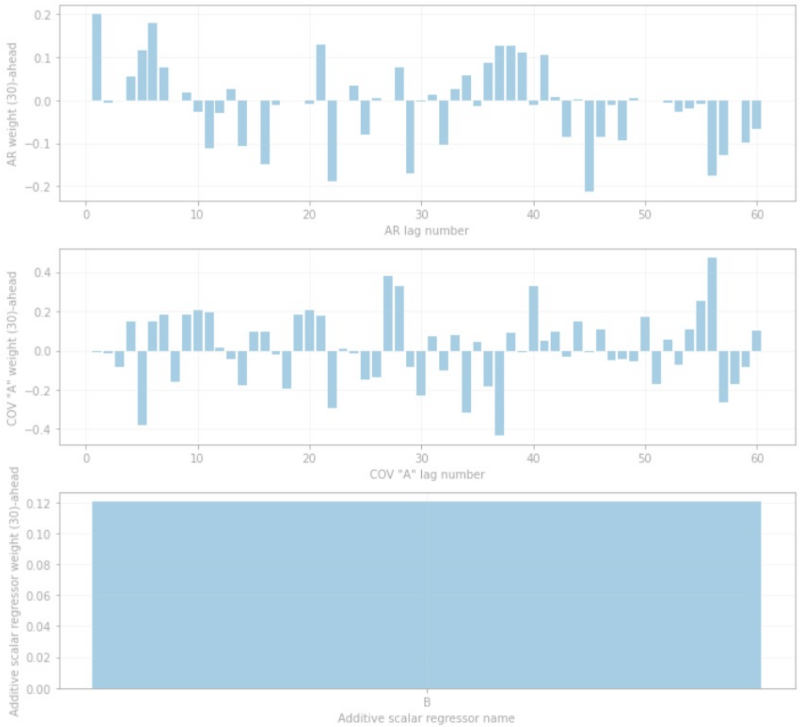
Lagged Covariates / Auto-Regression: Interpret.

NeuralProphet

```
fig_param = m.plot_parameters()
```



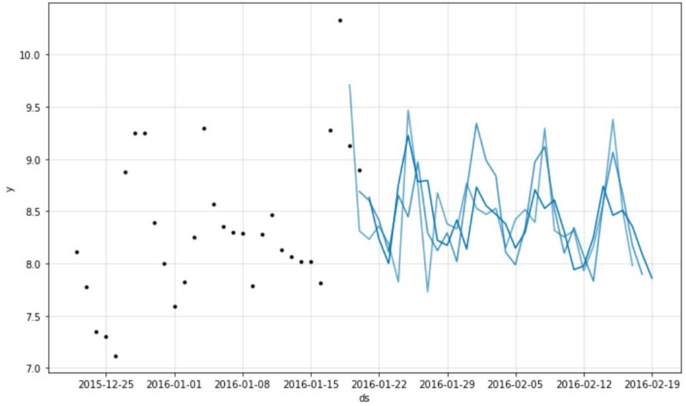

```
fig_param30 = m.highlight_nth_step_ahead_of_each_forecast(30).plot_parameters()
```



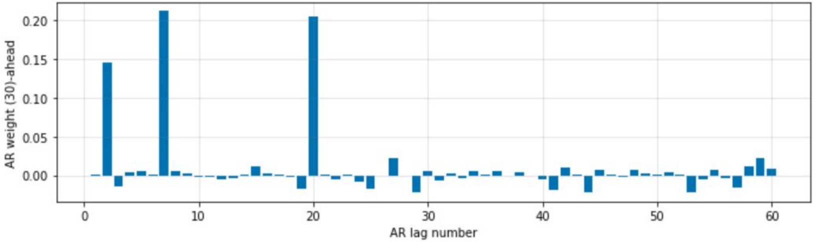
Focus on a specific forecast.

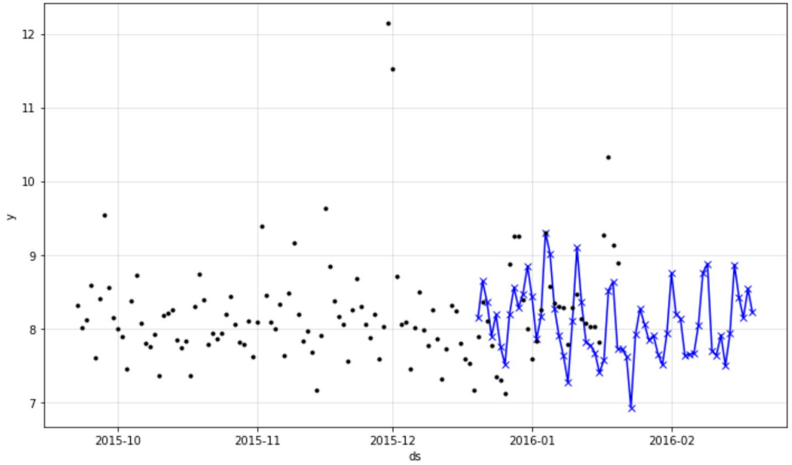
NeuralProphet

```
fig_prediction = m.plot_last_forecast(forecast[60:],
include_previous_forecasts=2)
```

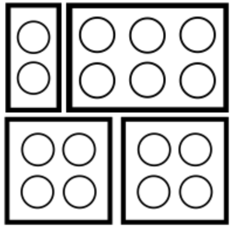



```
fig_param = m.highlight_nth_step_ahead_of_each_forecast(30).
plot_parameters()
```





NeuralProphet in a nutshell.



https://github.com/ourownstory/neural_prophet

Continues the legacy of Prophet in PyTorch.

Extensible to future state-of-the-art in forecasting.

Workflow-aware with tools for diagnostics and more.

Outlook

Next:

Presenting at ISF

Public Beta release (code + journal paper)

Future:

V 1.0 Workflow utilities, robustify training, model extensions

V 2.+ Modularize, integrate other frameworks (data, deployment)

V 3.+ Web GUI, port to other languages

THANK YOU, dear collaborators and advisors!


Nikolay Laptev


Oskar Triebe


Hansika Hewamalage


Italo Lima


Caner Komurlu


Gonzague Henri


Ram Rajagopal


Riley De Haan

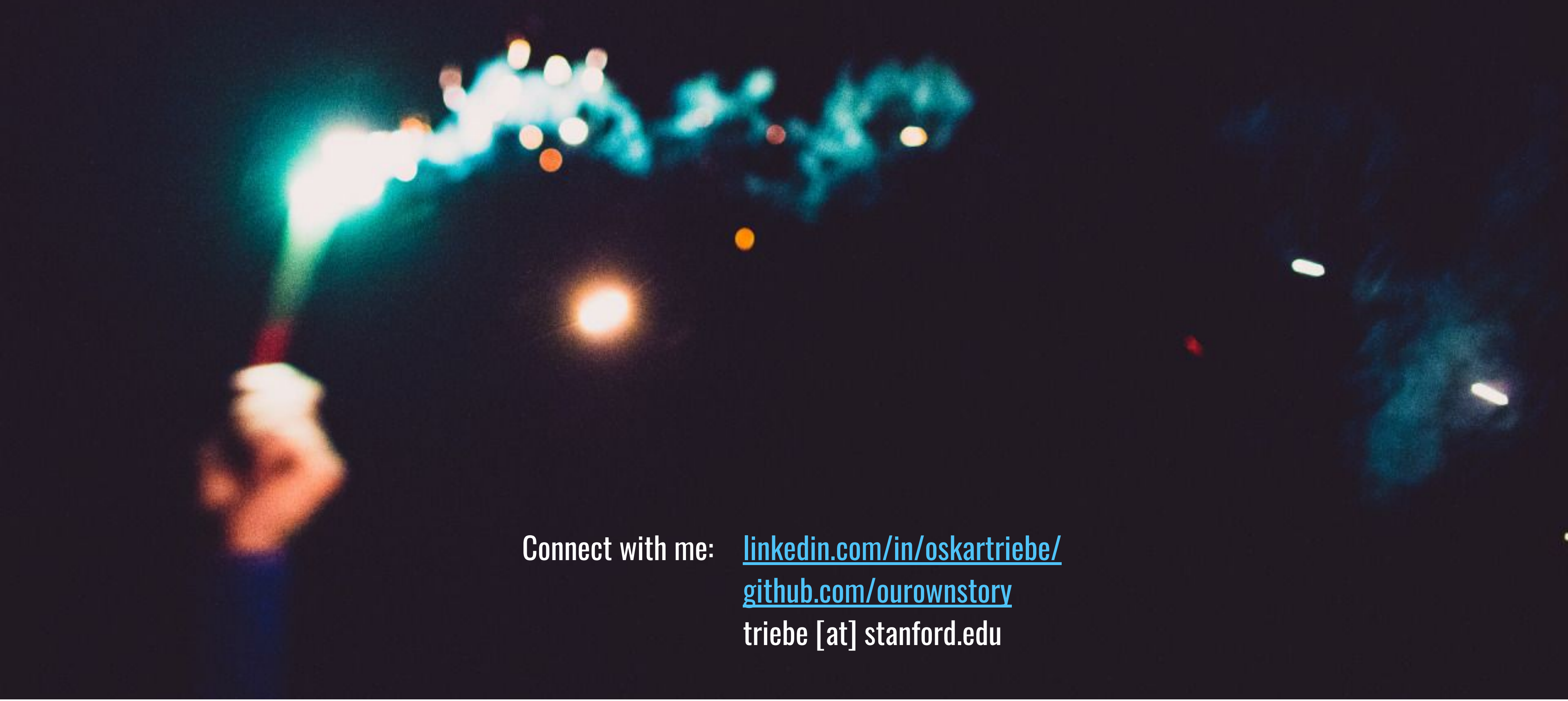

Christoph Bergmeir

facebook

TOTAL

Stanford University

MONASH University



Connect with me: linkedin.com/in/oskartriebe/
github.com/ourownstory
triebe [at] stanford.edu

Thank You