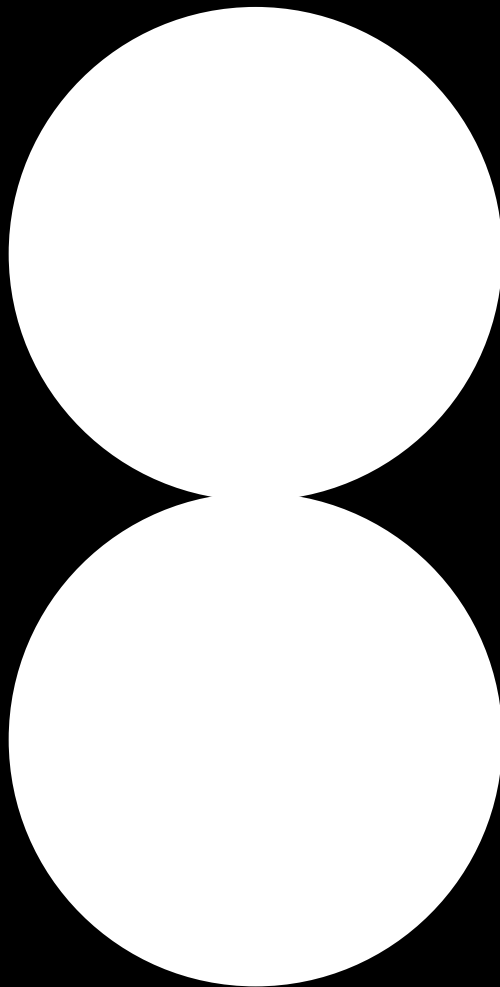




Darts for Time Series Forecasting

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- Darts core contributor



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- Darts core contributor



1 Intro to Forecasting & Darts

2 Basic forecasting using Darts

3 More advanced features

4 Conclusions & next steps

Why Forecasting?

Retail



How can we ensure that the consumer demand for every product is met without overspending and creating waste?

Energy



How can much energy should we produce?

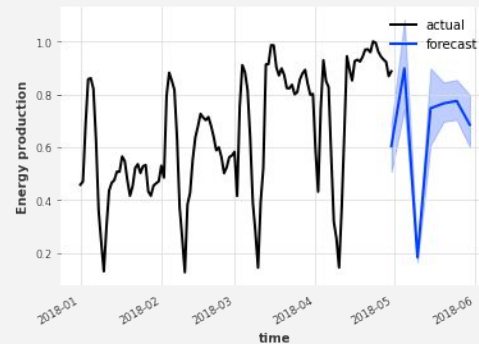
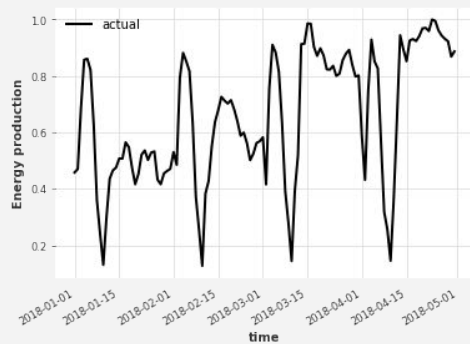
How much energy will we produce given a certain setup?

Telecommunications



Will our current infrastructure support the traffic in the near and far future?

Time Series Forecasting



Future = $f(\text{history} + \text{external data})$

Consideration: Do we have a valuable signal in the data?



Darts

Darts is a Python library for **easy** manipulation and **forecasting** of **time series**.



Immutable **TimeSeries** class as basic building block.



Unified `fit()`, `predict()` interface.

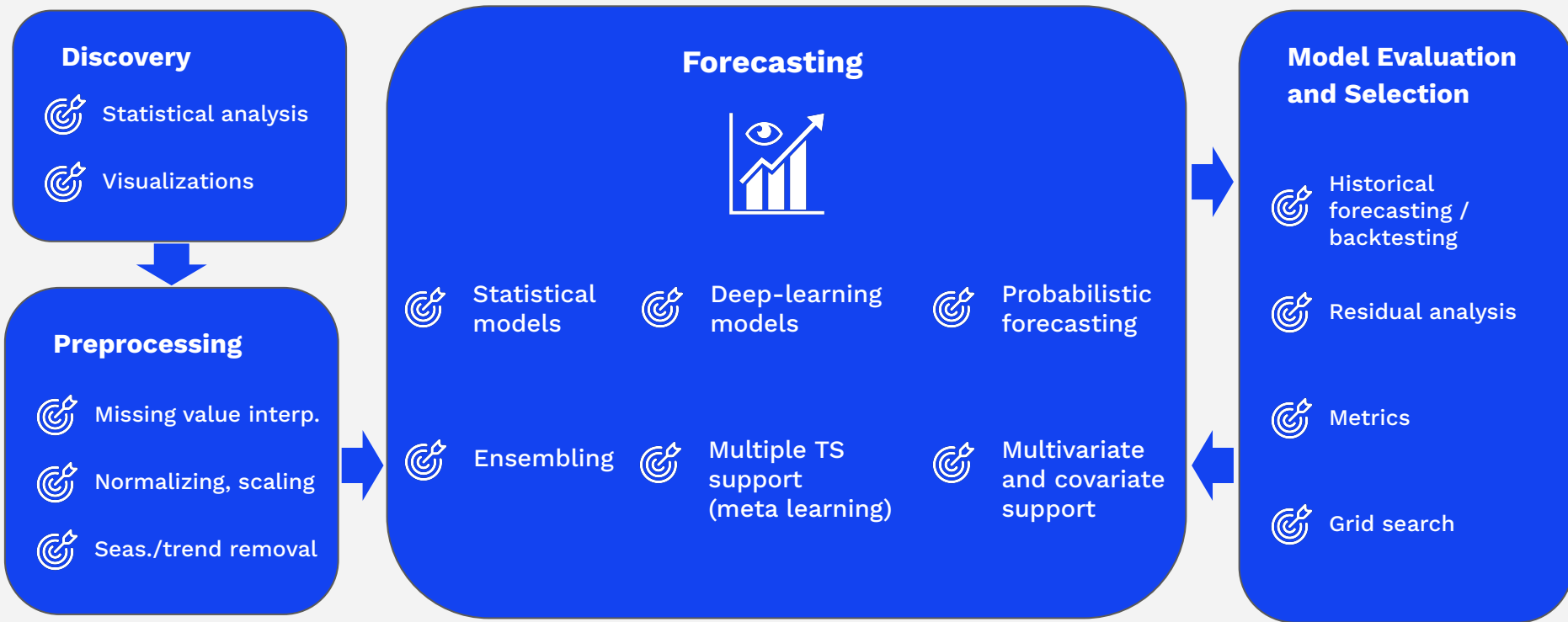


Classical models & state-of-the-art ML approaches.



User-friendliness: intuitive API and reasonable defaults.





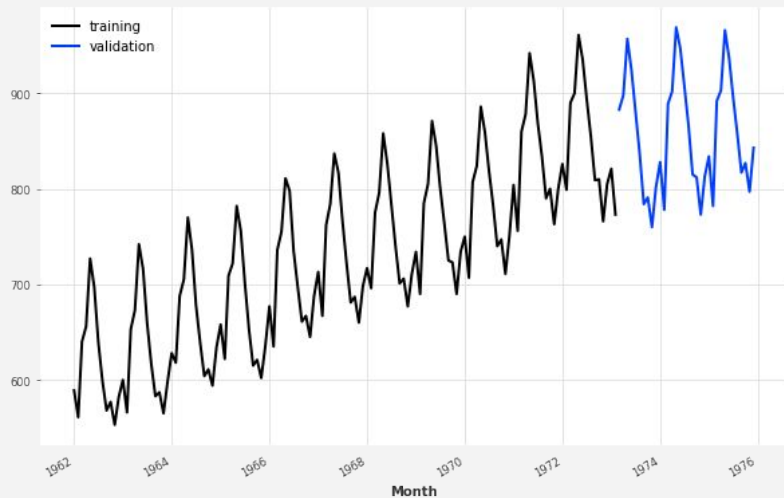
1 Intro to Forecasting & Darts

2 Basic forecasting using Darts

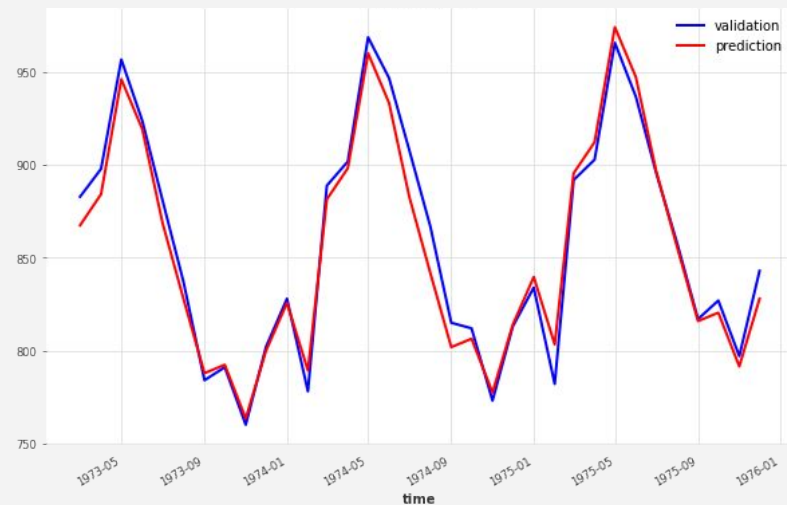
3 More advanced features

4 Conclusions & next steps

Darts Overview



Goal



TimeSeries

Forecasting

Evaluating

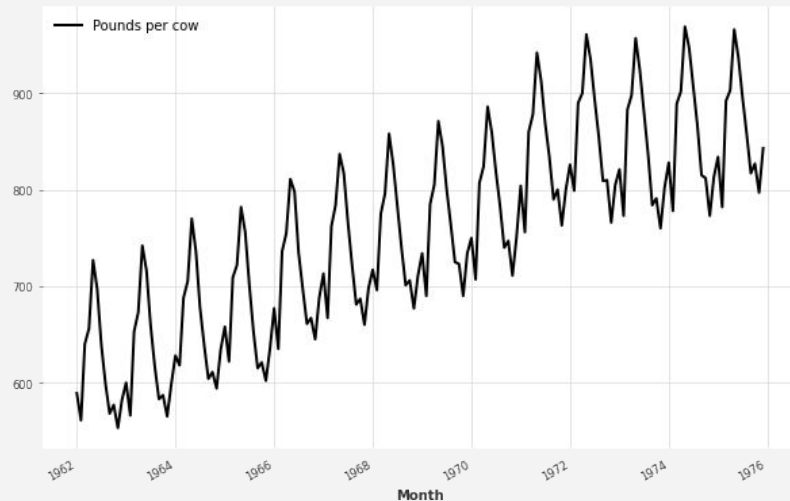
Tuning

The `TimeSeries` object



```
from darts import TimeSeries

series = TimeSeries.from_csv('monthly-milk.csv', time_col='Month')
series.plot()
```



TimeSeries

Forecasting

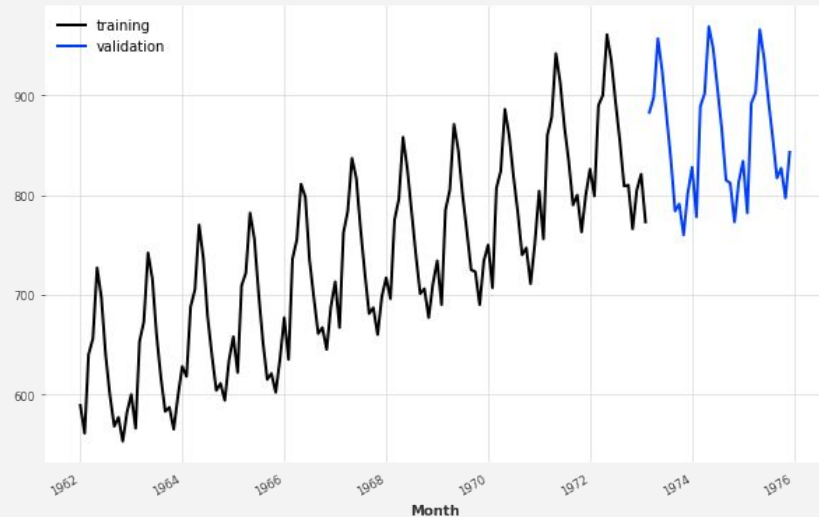
Evaluating

Tuning

Training / validation **split**



```
training, validation = series.split_after(0.8)
```



TimeSeries

Forecasting

Evaluating

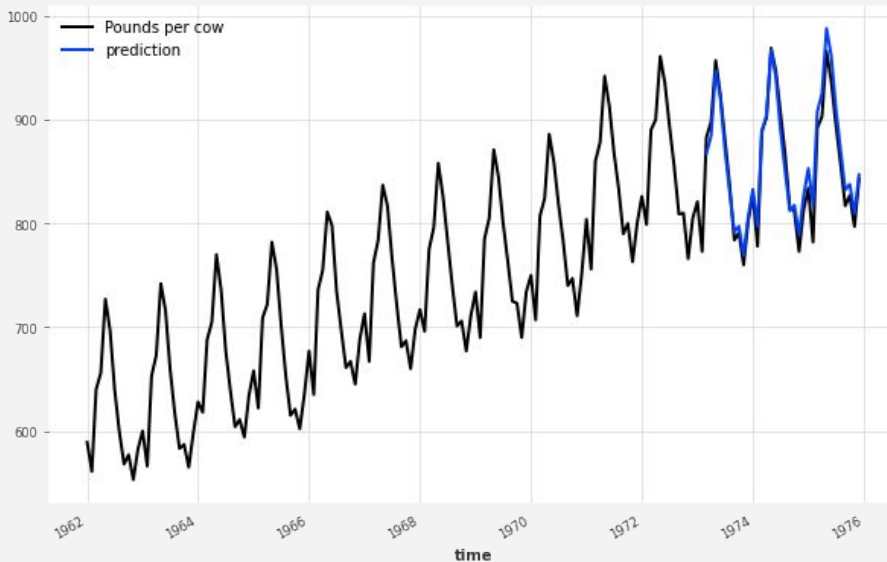
Tuning

Forecasting – Exponential Smoothing



```
from darts.models import ExponentialSmoothing

model = ExponentialSmoothing()
model.fit(training)
pred = model.predict(len(validation))
```



TimeSeries

Forecasting

Evaluating

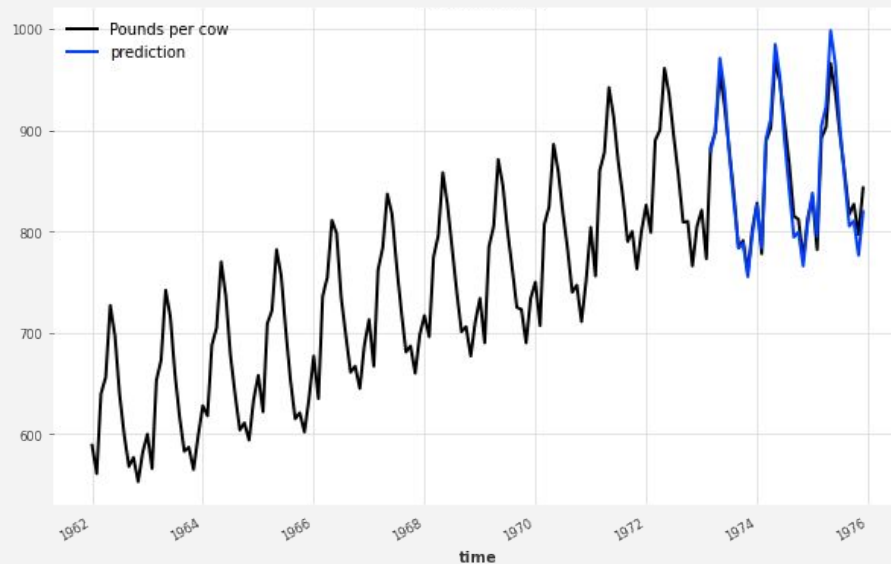
Tuning

Forecasting – Theta



```
from darts.models import Theta

model = Theta()
model.fit(training)
pred = model.predict(len(validation))
```



TimeSeries

Forecasting

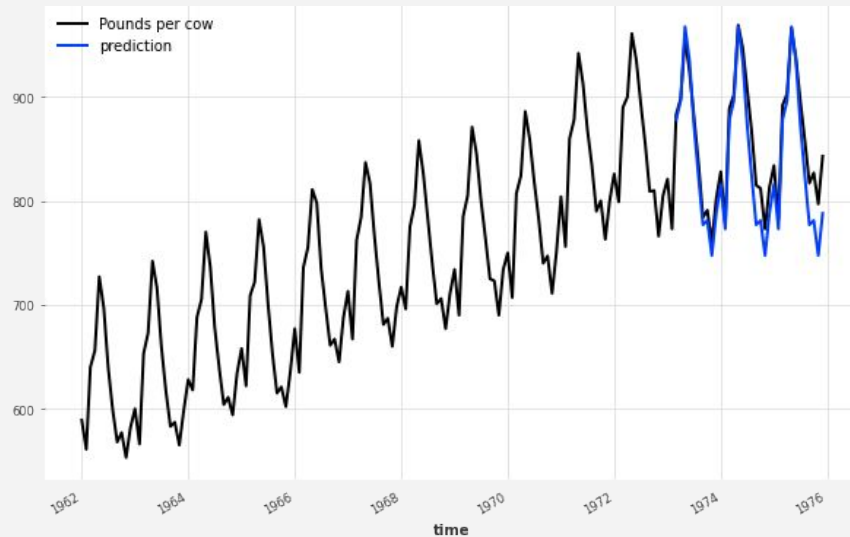
Evaluating

Tuning

Specifying parameters



```
model = Theta(theta=1)
model.fit(training)
pred = model.predict(len(validation))
```



TimeSeries

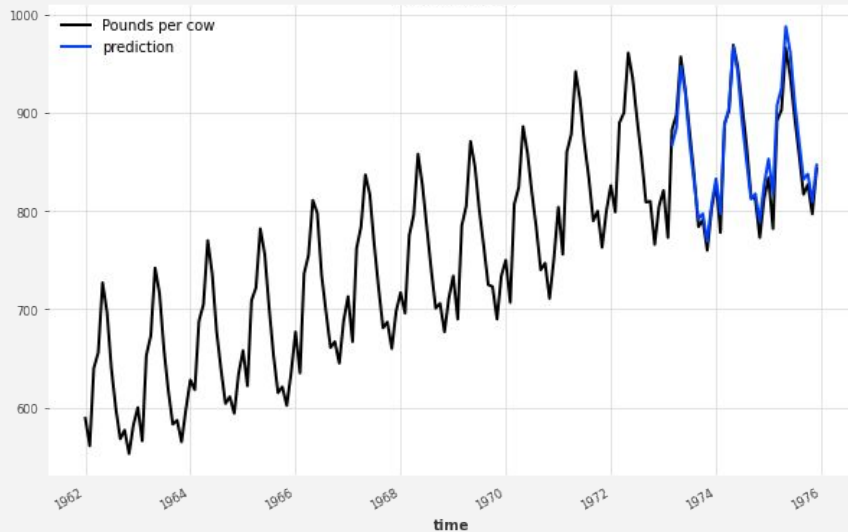
Forecasting

Evaluating

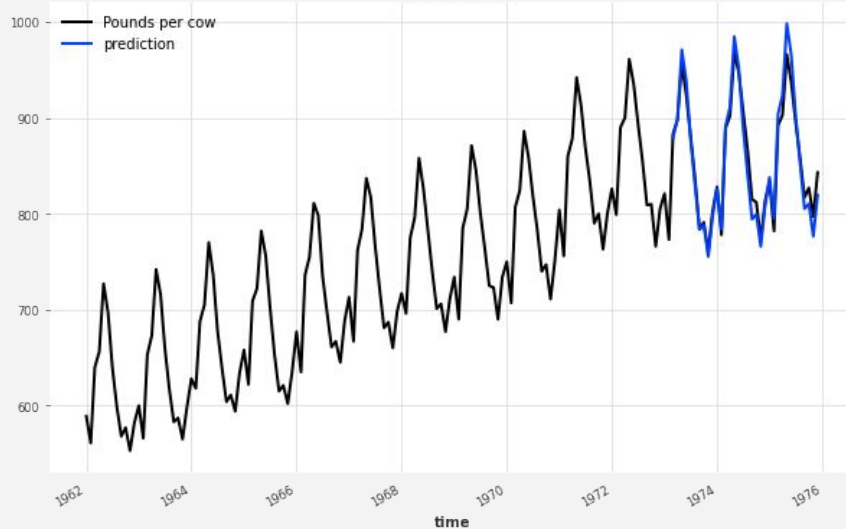
Tuning

Evaluating predictions – Which one is better?

Exponential Smoothing



Theta



TimeSeries

Forecasting

Evaluating

Tuning

Metrics

Many different scores can be computed – Darts lets you import the one you need.



```
from darts.metrics import mape  
  
score = mape(validation, pred)
```



```
from darts.metrics import mase  
  
score = mase(validation, pred, training)
```

TimeSeries

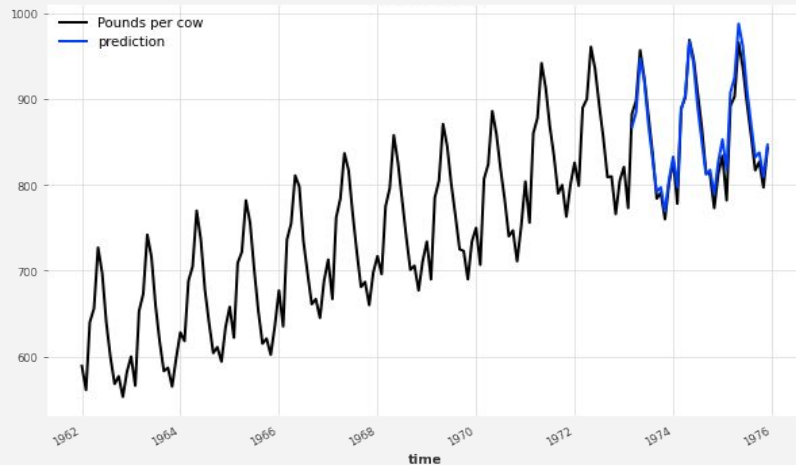
Forecasting

Evaluating

Tuning

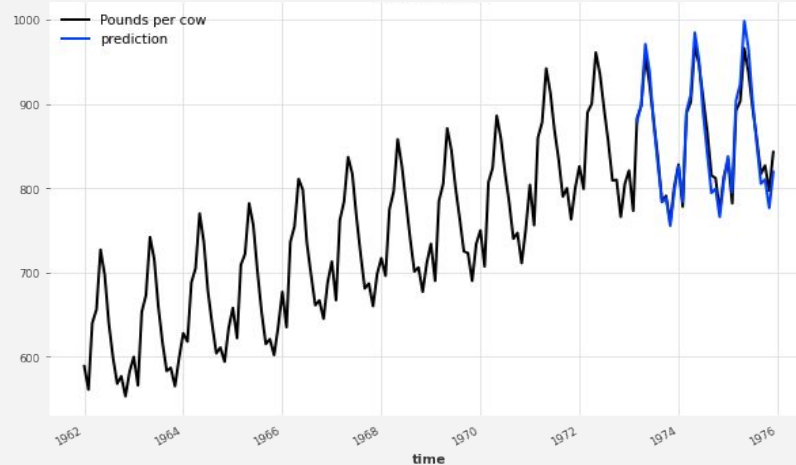
Which one is better?

Exponential Smoothing



MAPE: ~1.39%

Theta



MAPE: ~1.28%



TimeSeries

Forecasting

Evaluating

Tuning

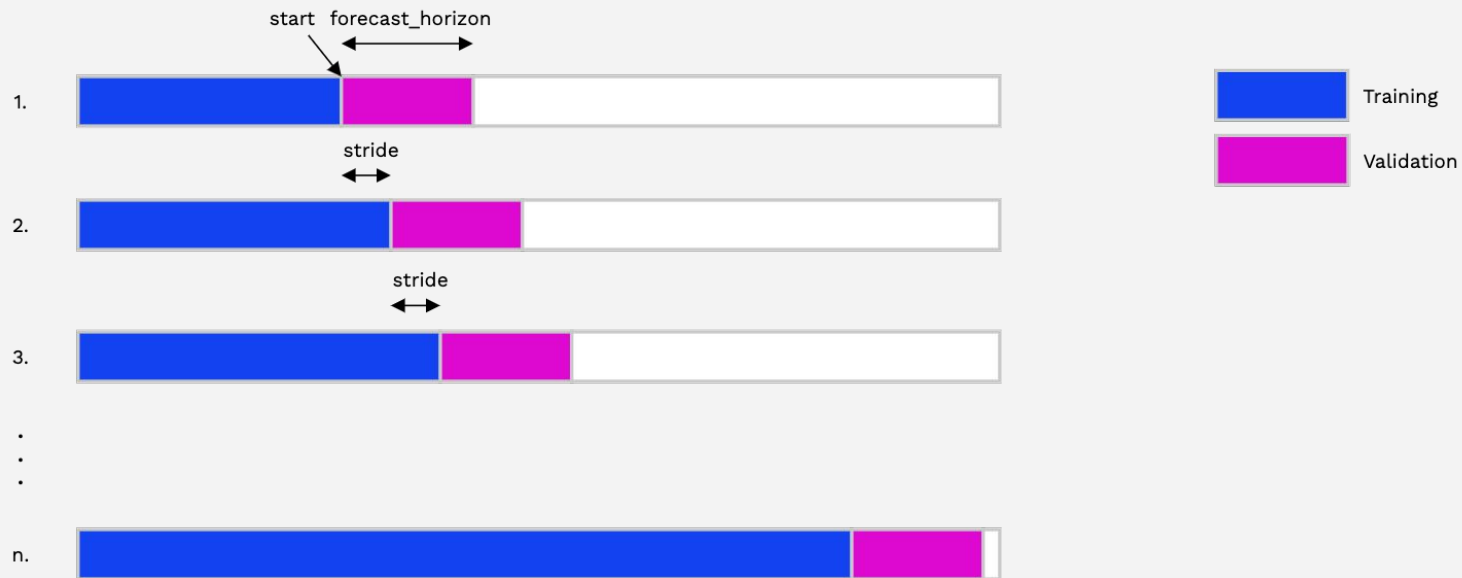
Evaluating model performance

`historical_forecasts()` and `backtest()`

Simulate how a model **would have performed**
if it had been historically used to forecast a time series.



Predicting historical forecasts



TimeSeries

Forecasting

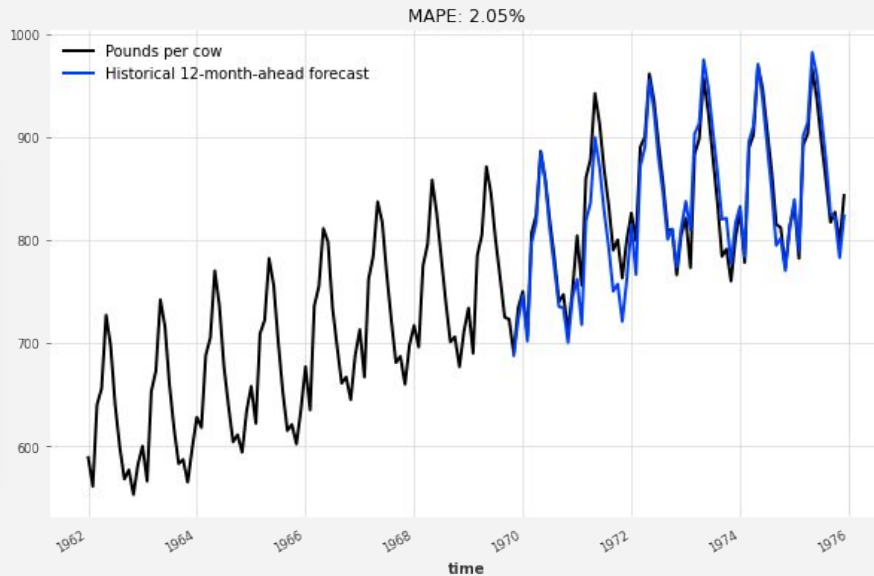
Evaluating

Tuning

Historical forecasts



```
historical_forecast = model.historical_forecasts(  
    series=series,  
    start=0.5,  
    forecast_horizon=12  
)
```



TimeSeries

Forecasting

Evaluating

Tuning

From evaluating to optimizing

How can we find the **best hyperparameters** to maximize accuracy ?



Gridsearch

```
parameters = {  
    'theta': [0.5, 1, 1.5, 2, 2.5],  
    'season_mode': [SeasonalityMode.MULTIPLICATIVE,  
                    SeasonalityMode.ADDITIVE]  
}  
  
best_model, best_parameters = Theta.gridsearch(  
    parameters=parameters,  
    series=training,  
    start=0.5,  
    forecast_horizon=12  
)
```

TimeSeries

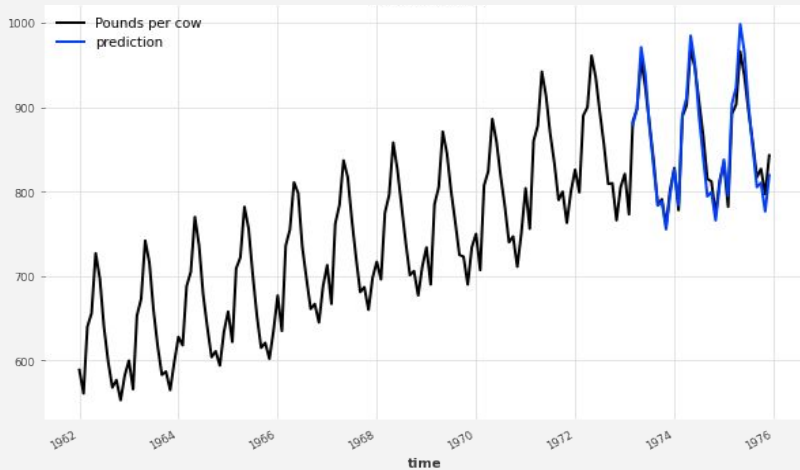
Forecasting

Evaluating

Tuning

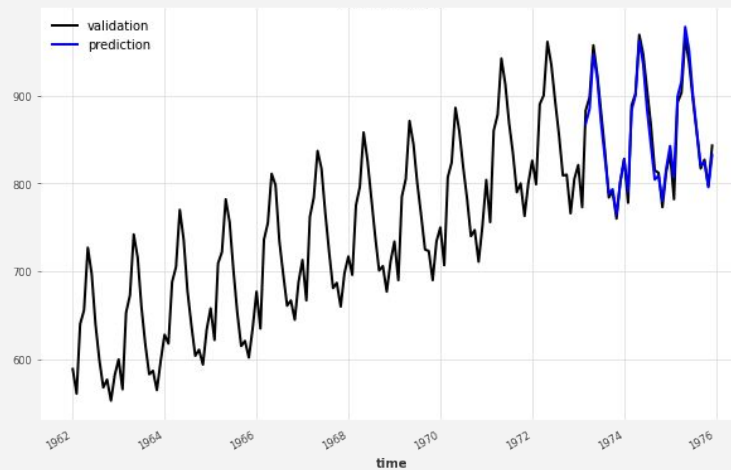
Gridsearch


Theta(theta=2, season_mode=MULTIPLICATIVE)



MAPE: ~1.28%

Theta(theta=3, season_mode=ADDITIVE)



MAPE: ~0.98% 

TimeSeries

Forecasting

Evaluating

Tuning

1 Intro to Forecasting & Darts

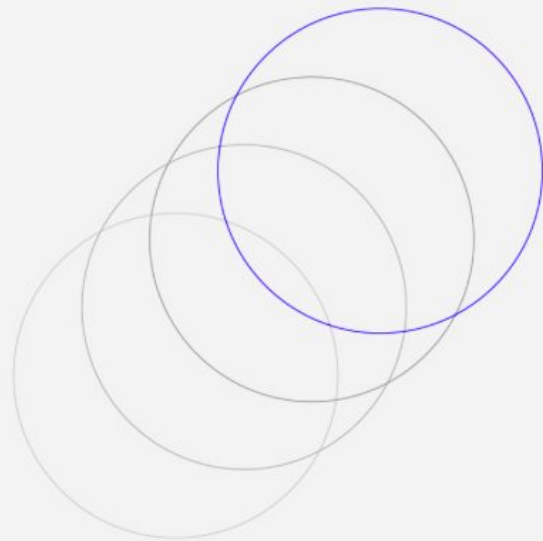
2 Basic forecasting using Darts

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4 Conclusions & next steps

Modern Machine Learning for Time Series

- Classical ML & deep learning
- Training on multiple series & large datasets
- Support for multi-dimensional series
- Including external past & future data
- Probabilistic forecasting



Meta-learning on 48,000 monthly series (M4 dataset)



Meta-learning with N-BEATS



```
from darts.models import NBEATSModel

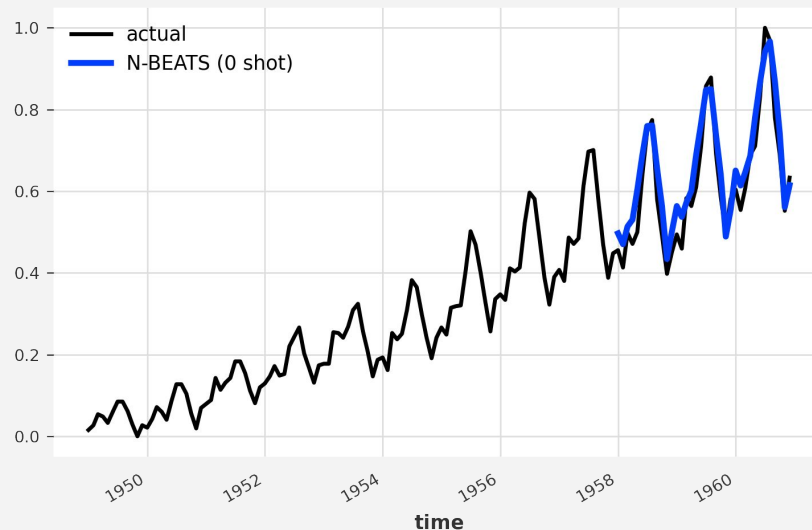
model = NBEATSModel(**kwargs)
model.fit(all_train_series)

pred = model.predict(n=36, series=air_train)
```

Sequence of 48,000 TimeSeries

Zero shot forecasting

Inference on a series **never seen during training** (takes a few ms)

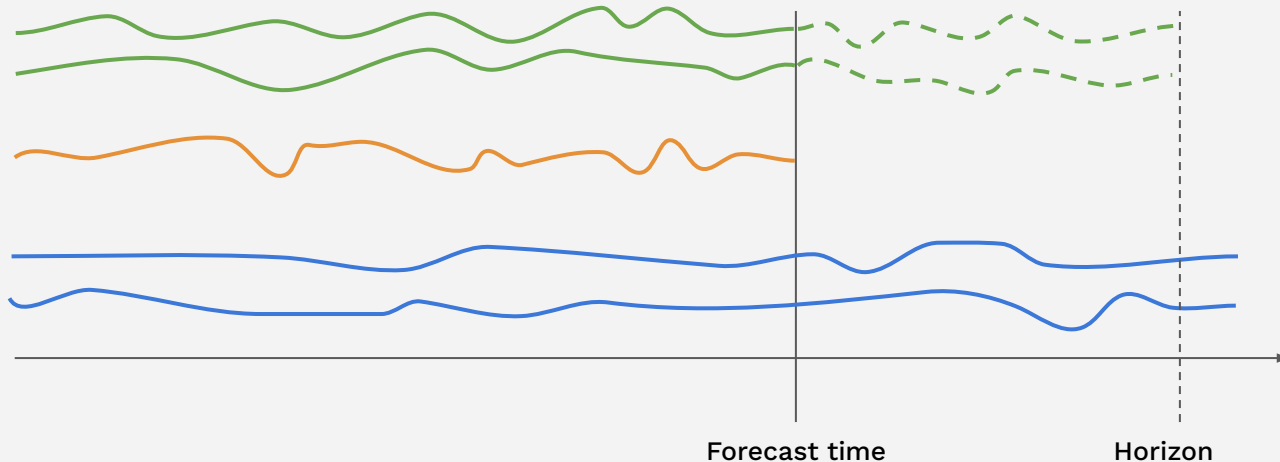


Including Past & Future External Data

Target series: what we want to forecast

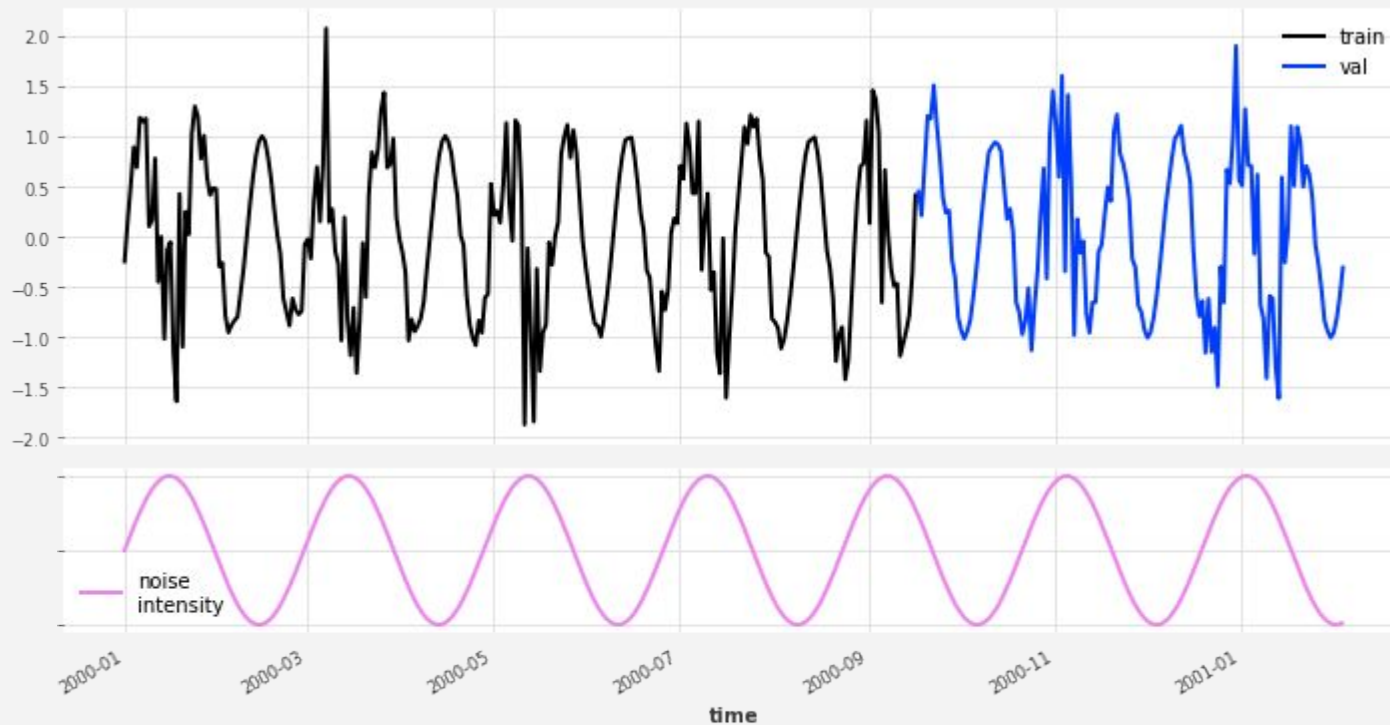
Past covariates:
Unknown into the future
e.g. measurements

Future covariates:
Known into the future
e.g. calendar, weather forecasts, actions



- `fit()` and `predict()` can accept `past_covariates` and/or `future_covariates`, depending on model.
- If `future_covariates` are given, future values will be required at inference time.
- Alignment of covariates with target is automatic.

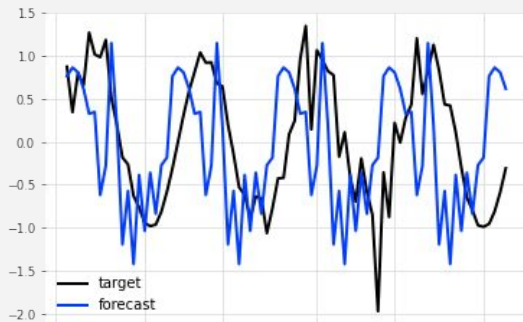
Probabilistic Forecasts



Capturing Series Stochasticity

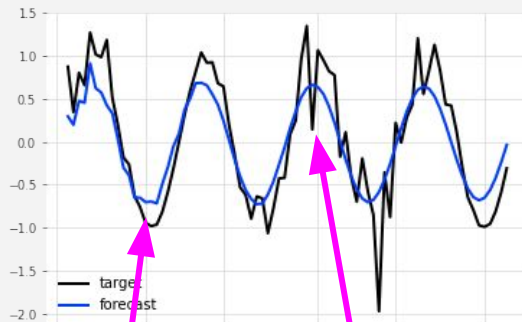
Attempt 1

```
model = NaiveSeasonal(seasonal_period)
model.fit(train)
pred = model.predict(n)
```



Attempt 2

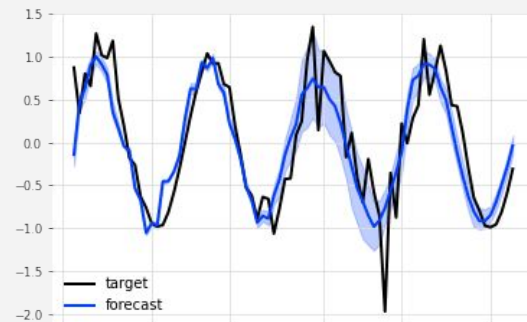
```
model = ARIMA(seasonal_period, 0, 0)
model.fit(train)
pred = model.predict(n)
```



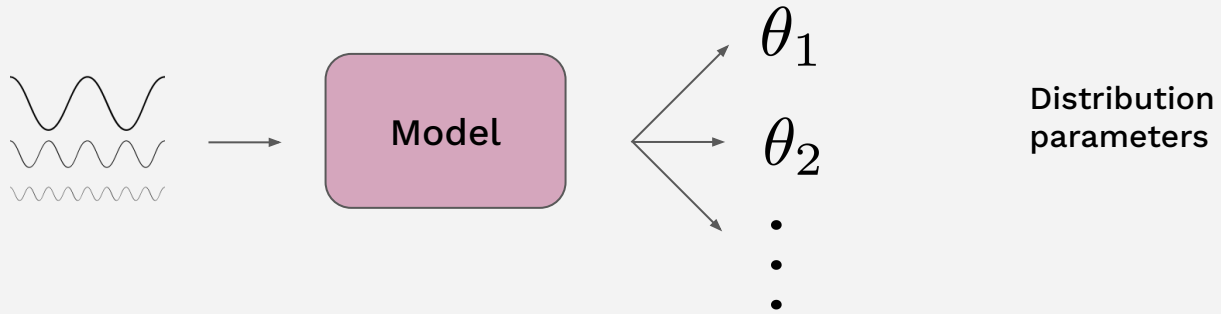
“safe” forecast uncertain forecast

Attempt 3

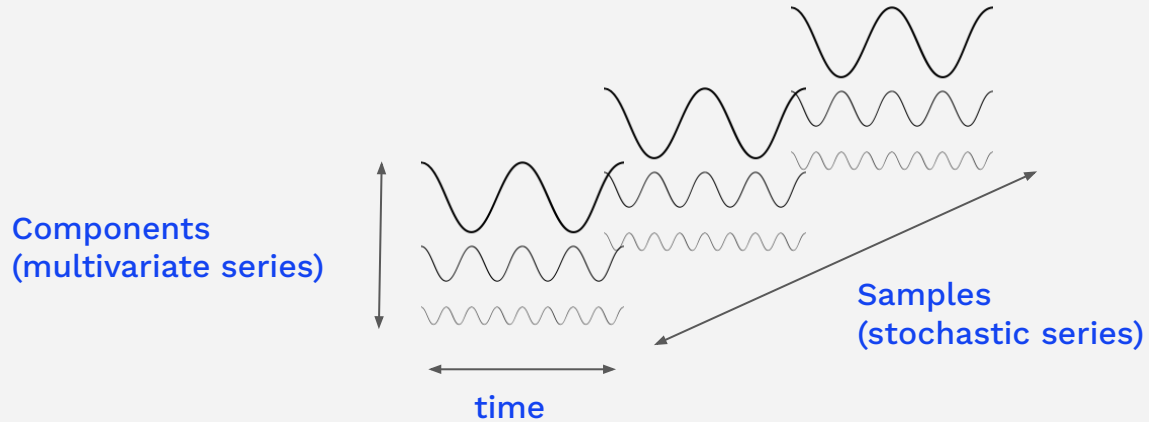
```
model = TCNModel(likelihood=GaussianLikelihood(),
                 **kwargs)
model.fit(train, past_covariates=noise_intensity)
pred = model.predict(n,
                    past_covariates=noise_intensity,
                    num_samples=100)
```



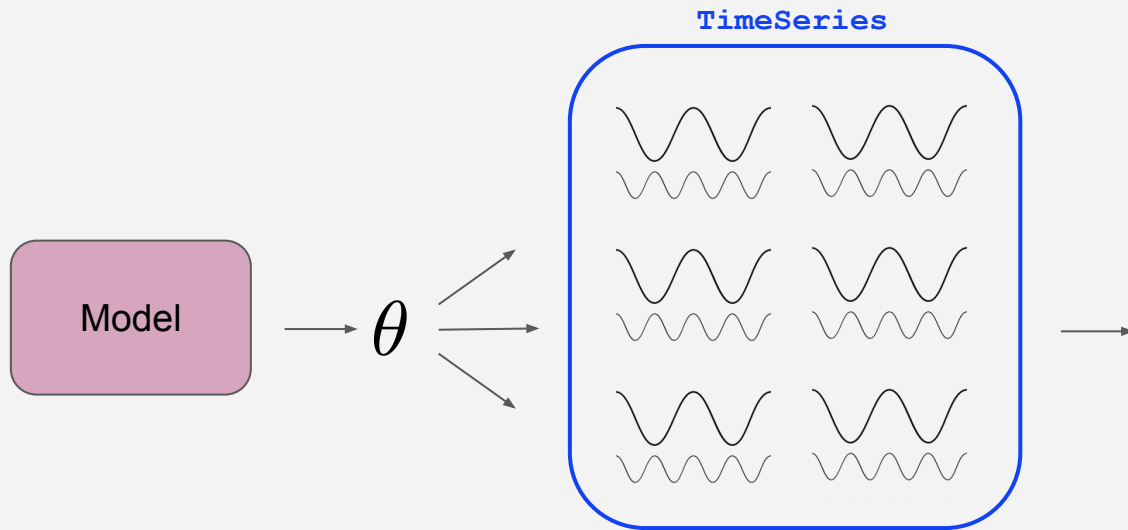
Probabilistic forecasts



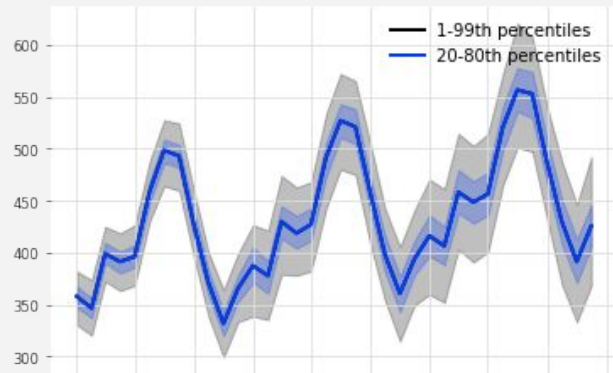
A **TimeSeries** contains 3 dimensions



Probabilistic forecasts



Probabilistic time series
(distribution-agnostic)



```
forecast.plot(low_quantile=0.01, high_quantile=0.99)  
forecast.plot(low_quantile=0.2, high_quantile=0.8)
```

Confidence intervals



Probabilistic forecasts

```
from darts.utils.likelihood_models import (GaussianLikelihood,
                                           PoissonLikelihood,
                                           NegativeBinomialLikelihood,
                                           BernoulliLikelihood,
                                           GammaLikelihood,
                                           GumbelLikelihood,
                                           LaplaceLikelihood,
                                           BetaLikelihood,
                                           ExponentialLikelihood,
                                           DirichletLikelihood,
                                           GeometricLikelihood,
                                           CauchyLikelihood,
                                           ContinuousBernoulliLikelihood,
                                           HalfNormalLikelihood,
                                           LogNormalLikelihood,
                                           WeibullLikelihood)
```

+ Priors on distributions' parameters

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Darts: User-friendly & Modern ML for Time Series

Try it out for yourself :)

- `pip install darts`
- <https://github.com/unit8co/darts/>

Some next steps:

- Anomaly detection
- Static covariates
- AutoML
- Pre-trained models
- ...



Contributions welcome



Contact: info@unit8.co. We're always happy to discuss time series problems!





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–
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**thank
you**

