MONASH University

25 years of open source forecasting software

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Outline

Outline

Early R forecasting (c.2000)

`ts` package (now `stats` package):

- `HoltWinters()`: point forecasts only, with optional multiplicative seasonality (written by David Meyer).
- `arima()`: state space formulation of ARIMA models (written by Brian Ripley).
- `structTS()`: Basic structural models as per Harvey (written by Brian Ripley).

Early R forecasting (c.2000)

`ts` package (now `stats` package):

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- `structTS()`: Basic structural models as per Harvey (written by Brian Ripley).

- Each had a `predict()` method, but output was inconsistent.
- `HoltWinters` did not produce prediction intervals.

forecast package for R: motivation

- Consistent output for existing methods by introducting new S3 generic `forecast()` and new S3 class `forecast`.
- New methods including `ets()`, `thetaf()`, `auto.arima()`.
- Modelling functions can be swapped while leaving code unchanged.
- Easy plotting tools with new `plot.forecast()` method.
- New forecasting tools such as `accuracy()` calculations.

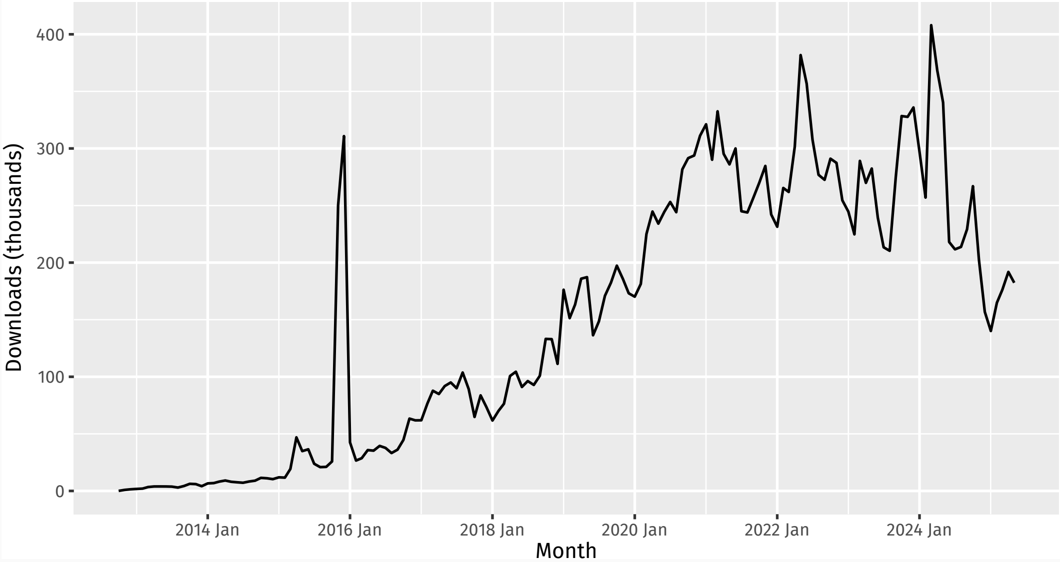
forecast package for R: history

Date	Event
Pre 2003	Collection of functions used for consulting projects
July/August 2003	`ets()` and `thetaf()` added
August 2006	**v1.0** available on CRAN
May 2007	`auto.arima()` added
July 2008	JSS paper (Hyndman & Khandakar)
September 2009	**v2.0**. Unbundled from Mcomp, fma & expsmooth
May 2010	`arfima()` added
Feb/March 2011	`tslm()`, `stlf()`, `naive()`, `snaive()` added
August 2011	**v3.0**. Box Cox transformations added
December 2011	`tbats()` added

forecast package for R: history

Date	Event
April 2012	Package moved to github
November 2012	**v4.0**. `nnetar()` added
June 2013	Major speed-up of `ets()`
January 2014	**v5.0**. `tsoutliers()` and `tsclean()` added
May 2015	**v6.0**. Added several new plots
February 2016	**v7.0**. Added ggplot2 graphics & bias adjustment
March 2017	**v8.0**. Added `tsCV()` & `baggedETS()`
April 2018	**v8.3**. Added `mstl()`, and revised `auto.arima()`
April 2025	**v8.24**. Last update

forecast package for R



forecast package for R

- `auto.arima` + `forecast`
- `ets` + `forecast`
- `tbats` + `forecast`
- `bats` + `forecast`
- `arfima` + `forecast`
- `nnetar` + `forecast`
- `stlm` + `forecast`
- `meanf`
- `rwf`, `naive`
- `thetaf`
- `dshw`, `hw`, `holt`, `ses`
- `splinef`
- `croston`

All produce an object of class `forecast`

forecast package for R

- `auto.arima` + `forecast`
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- `stlm` + `forecast`
- `meanf`
- `rwf`, `naive`
- `thetaf`
- `dshw`, `hw`, `holt`, `ses`
- `splinef`
- `croston`

All produce an object of class `forecast`

v9.0 will have new model functions:

- `mean_model()`
- `rw_model()`
- `theta_model()`
- `spline_model()`
- `croston_model`

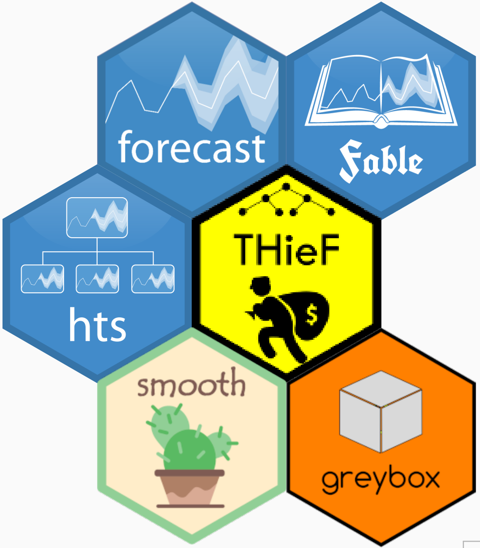
CRAN Task View Time Series

CRAN Task View: Time Series Analysis

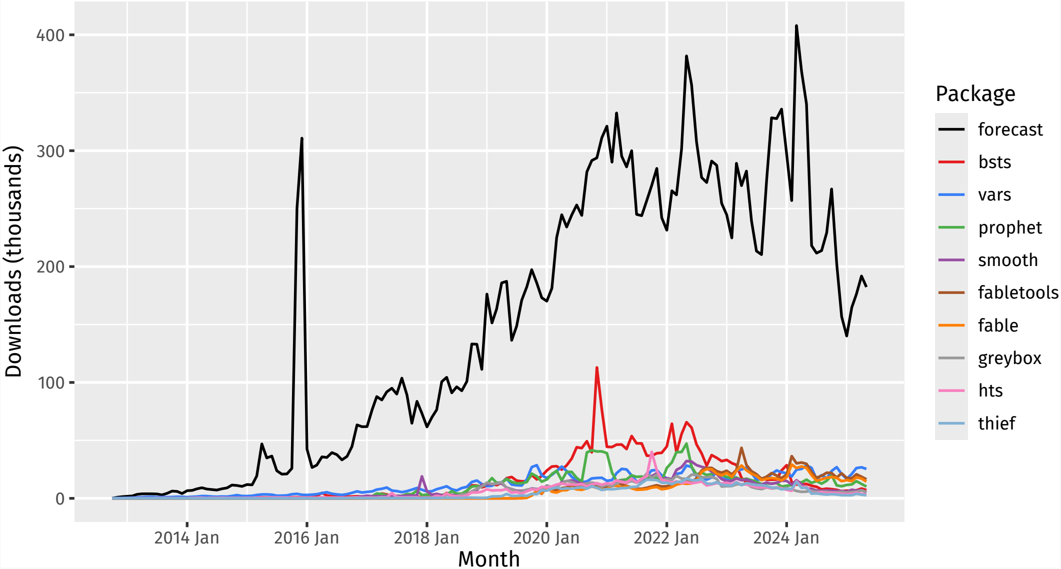
Maintainer:	Rob J Hyndman, Rebecca Killick
Contact:	Rob.Hyndman at monash.edu
Version:	2025-05-17
URL:	https://CRAN.R-project.org/view=TimeSeries
Source:	https://github.com/cran-task-views/TimeSeries/
Contributions:	Suggestions and improvements for this task view are very welcome and can be made through issues or pull requests on GitHub or via e-mail to the maintainer address. For further details see the Contributing guide.
Citation:	Rob J Hyndman, Rebecca Killick (2025). CRAN Task View: Time Series Analysis. Version 2025-05-17. URL https://CRAN.R-project.org/view=TimeSeries.
Installation:	The packages from this task view can be installed automatically using the ctv package. For example, `ctv::install.views("TimeSeries", coreOnly = TRUE)` installs all the core packages or `ctv::update.views("TimeSeries")` installs all packages that are not yet installed and up-to-date. See the CRAN Task View Initiative for more details.

Top ten downloaded forecasting packages on CRAN

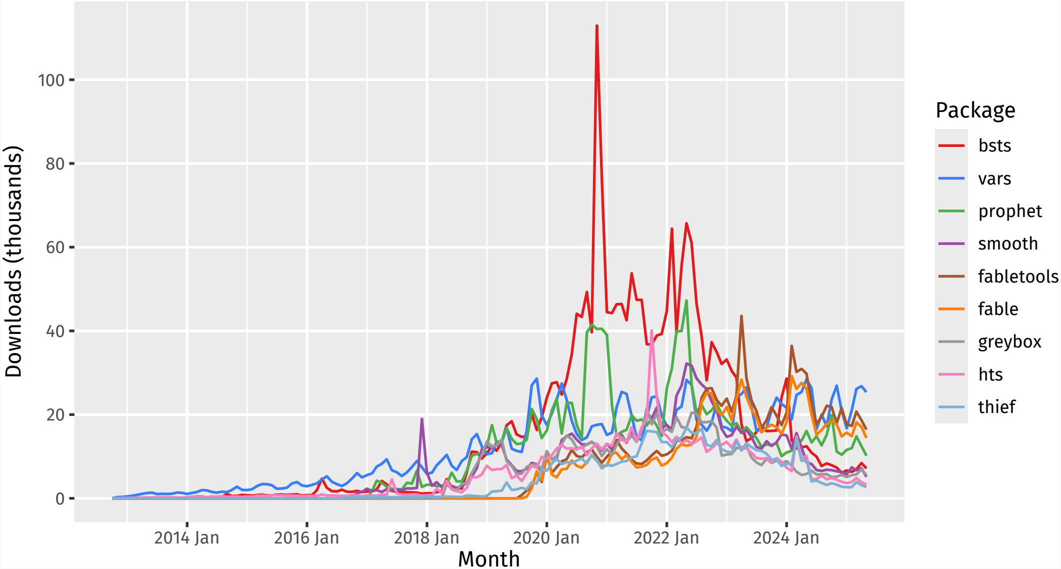
Package	Downloads ('000)
forecast	22783
bsts	2322
vars	1851
prophet	1578
smooth	1159
fabletools	1134
fable	982
greybox	910
hts	896
thief	673



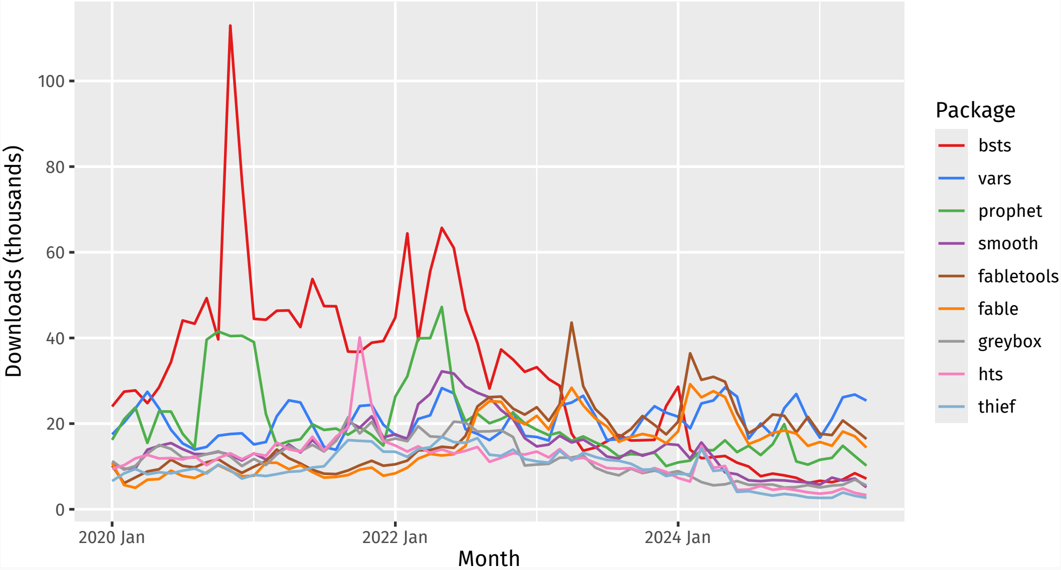
Top ten downloaded forecasting packages on CRAN



Top ten downloaded forecasting packages on CRAN



Top ten downloaded forecasting packages on CRAN



ETS

Function	PIntervals	Automatic	Covariates
`stats::HoltWinters()`	No	No	No
`forecast::ets()`	Yes	Yes	No
`fable::ETS()`	Yes	Yes	No
`smooth::es()`	Yes	Yes	Yes

forecast::ets()

```r
ets(AirPassengers)
```

```
ETS(M,Ad,M)

Call:
ets(y = AirPassengers)

  Smoothing parameters:
    alpha = 0.7096
    beta  = 0.0204
    gamma = 1e-04
    phi   = 0.98

  Initial states:
    l = 120.9939
    b = 1.7705
    s = 0.8944 0.7993 0.9217 1.059 1.22 1.232
           1.111 0.9786 0.9804 1.011 0.8869 0.9059
```

forecast::ets()

```r
ets(AirPassengers) |> forecast(h = 10)
```

```
         Point Forecast Lo 80 Hi 80 Lo 95 Hi 95
Jan 1961          441.8 419.6 464.0 407.9 475.7
Feb 1961          434.1 407.2 461.1 392.9 475.3
Mar 1961          496.6 460.6 532.6 441.6 551.7
Apr 1961          483.2 443.6 522.9 422.6 543.8
May 1961          484.0 440.0 528.0 416.7 551.2
Jun 1961          551.0 496.3 605.7 467.4 634.7
Jul 1961          613.2 547.4 679.0 512.6 713.8
Aug 1961          609.4 539.2 679.5 502.1 716.6
Sep 1961          530.5 465.5 595.6 431.0 630.0
Oct 1961          463.0 402.8 523.2 371.0 555.1
```

fable::ETS()

```r
as_tsibble(AirPassengers) |>
  model(ets = ETS(value)) |>
  report()
```

```
Series: value
Model: ETS(M,Ad,M)
  Smoothing parameters:
    alpha = 0.7096
    beta  = 0.02041
    gamma = 0.0001005
    phi   = 0.98

  Initial states:
 l[0]  b[0]   s[0]  s[-1]  s[-2] s[-3] s[-4] s[-5] s[-6]  s[-7]  s[-8] s[-
9] s[-10]
  121 1.771 0.8944 0.7993 0.9217 1.059  1.22 1.232 1.111 0.9786 0.9804 1.011 0.8869
 s[-11]
 0.9059
```

fable::ETS()

```r
as_tsibble(AirPassengers) |>
  model(ets = ETS(value)) |>
  forecast(h = 10)
```

```
# A fable: 10 x 4 [1M]
# Key:     .model [1]
   .model    index          value .mean
   <chr>     <mth>         <dist> <dbl>
 1 ets    1961 Jan  N(442, 299)  442.
 2 ets    1961 Feb  N(434, 442)  434.
 3 ets    1961 Mar  N(497, 789)  497.
 4 ets    1961 Apr  N(483, 956)  483.
 5 ets    1961 May N(484, 1177)  484.
 6 ets    1961 Jun N(551, 1821)  551.
 7 ets    1961 Jul N(613, 2636)  613.
 8 ets    1961 Aug N(609, 2994)  609.
 9 ets    1961 Sep N(531, 2577)  531.
10 ets    1961 Oct N(463, 2205)  463.
```

smooth::es()

```r
es(AirPassengers)
```

```
Time elapsed: 1.45 seconds
Model estimated using es() function: ETS(MMdM)
With optimal initialisation
Distribution assumed in the model: Normal
Loss function type: likelihood; Loss function value: 526.8
Persistence vector g:
 alpha   beta  gamma
0.3536 0.0000 0.4560
Damping parameter: 0.9991
Sample size: 144
Number of estimated parameters: 18
Number of degrees of freedom: 126
Information criteria:
 AIC AICc  BIC BICc
1090 1095 1143 1157
```

smooth::es()

```r
es(AirPassengers) |> forecast(h = 10, interval = "parametric")
```

```
         Point forecast Lower bound (2.5%) Upper bound (97.5%)
Jan 1961          450.9              413.5               488.9
Feb 1961          426.4              388.9               464.9
Mar 1961          483.2              438.4               529.8
Apr 1961          506.7              458.1               556.4
May 1961          521.8              470.1               575.1
Jun 1961          597.4              536.3               662.7
Jul 1961          689.0              614.4               765.1
Aug 1961          681.8              607.6               761.4
Sep 1961          566.8              503.2               634.1
Oct 1961          504.8              445.2               566.2
```

Benchmarks

```r
bench::mark(
  forecast = ets(AirPassengers) |> forecast(h = 10),
  fable = as_tsibble(AirPassengers) |> model(ETS(value)) |> forecast(h = 10),
  smooth = es(AirPassengers) |> forecast(h = 10, interval = "parametric"),
  check = FALSE
)
```

expression	min	median	itr/sec	mem_alloc
forecast	673.96ms	673.96ms	1.48	43.6MB
fable	729.2ms	729.2ms	1.37	37.5MB
smooth	1.61s	1.61s	0.62	221.9MB

ARIMA

Function	PIntervals	Automatic	Covariates
`stats::arima()`	Yes	No	Yes
`forecast::Arima()`	Yes	No	Yes
`forecast::auto.arima()`	Yes	Yes	Yes
`fable::ARIMA()`	Yes	Yes	Yes
`smooth::ssarima()`	Yes	No	Yes
`smooth::auto.ssarima()`	Yes	Yes	Yes

forecast::auto.arima()

```r
auto.arima(AirPassengers, lambda = 0)
```

```
Series: AirPassengers
ARIMA(0,1,1)(0,1,1)[12]
Box Cox transformation: lambda= 0

Coefficients:
          ma1    sma1
       -0.402  -0.557
s.e.    0.090   0.073

sigma^2 = 0.00137:  log likelihood = 244.7
AIC=-483.4   AICc=-483.2   BIC=-474.8
```

forecast::auto.arima()

```r
auto.arima(AirPassengers, lambda = 0) |> forecast(h = 10)
```

```
         Point Forecast Lo 80 Hi 80 Lo 95 Hi 95
Jan 1961          450.4 429.5 472.3 418.9 484.3
Feb 1961          425.7 402.8 449.9 391.2 463.3
Mar 1961          479.0 450.1 509.7 435.6 526.8
Apr 1961          492.4 459.9 527.2 443.5 546.7
May 1961          509.1 472.7 548.2 454.6 570.0
Jun 1961          583.3 538.9 631.5 516.8 658.5
Jul 1961          670.0 615.9 728.9 589.1 762.1
Aug 1961          667.1 610.4 729.1 582.3 764.2
Sep 1961          558.2 508.5 612.8 484.0 643.8
Oct 1961          497.2 451.0 548.1 428.3 577.2
```

fable::ARIMA()

```r
as_tsibble(AirPassengers) |>
  model(arima = ARIMA(log(value))) |>
  report()
```

```
Series: value
Model: ARIMA(2,0,0)(0,1,1)[12] w/ drift
Transformation: log(value)

Coefficients:
         ar1     ar2     sma1  constant
      0.5754  0.2614  -0.5553    0.0193
s.e.  0.0843  0.0842   0.0771    0.0015

sigma^2 estimated as 0.001323:  log likelihood=249.7
AIC=-489.3   AICc=-488.8   BIC=-474.9
```

fable::ARIMA()

```r
as_tsibble(AirPassengers) |>
  model(arima = ARIMA(log(value))) |>
  forecast(h = 10)
```

```
# A fable: 10 x 4 [1M]
# Key:     .model [1]
   .model    index                 value .mean
   <chr>     <mth>                <dist> <dbl>
 1 arima  1961 Jan t(N(6.1, 0.0013))  453.
 2 arima  1961 Feb t(N(6.1, 0.0018))  430.
 3 arima  1961 Mar t(N(6.2, 0.0022))  486.
 4 arima  1961 Apr t(N(6.2, 0.0025))  502.
 5 arima  1961 May t(N(6.3, 0.0028))  522.
 6 arima  1961 Jun  t(N(6.4, 0.003))  600.
 7 arima  1961 Jul t(N(6.5, 0.0031))  691.
 8 arima  1961 Aug t(N(6.5, 0.0032))  690.
 9 arima  1961 Sep t(N(6.4, 0.0033))  579.
10 arima  1961 Oct t(N(6.2, 0.0034))  516.
```

smooth::auto.ssarima()

```r
auto.ssarima(log(AirPassengers))
```

```
Time elapsed: 2.63 seconds
Model estimated: SARIMA(0,1,3)[1](0,1,3)[12]
Matrix of MA terms:
        Lag 1  Lag 12
MA(1) -0.4157 -0.7397
MA(2)  0.0313  0.1145
MA(3) -0.1255  0.0747
Initial values were produced using backcasting.

Loss function type: likelihood; Loss function value: -287.9556
Error standard deviation: 0.0336
Sample size: 144
Number of estimated parameters: 7
Number of degrees of freedom: 137
Information criteria:
   AIC   AICc    BIC   BICc
-561.9 -561.1 -541.1 -539.1
```

smooth::auto.ssarima()

```r
auto.ssarima(log(AirPassengers)) |> forecast(h = 10)
```

```
         Point forecast Lower bound (2.5%) Upper bound (97.5%)
Jan 1961          6.104              6.039               6.169
Feb 1961          6.049              5.973               6.124
Mar 1961          6.181              6.096               6.266
Apr 1961          6.185              6.094               6.276
May 1961          6.224              6.128               6.321
Jun 1961          6.372              6.271               6.474
Jul 1961          6.506              6.399               6.612
Aug 1961          6.512              6.401               6.623
Sep 1961          6.324              6.209               6.440
Oct 1961          6.201              6.082               6.321
```

Benchmarks

```r
bench::mark(
  forecast = auto.arima(AirPassengers, lambda = 0, biasadj = TRUE) |>
    forecast(h = 12),
  fable = as_tsibble(AirPassengers) |> model(ARIMA(log(value))) |>
    forecast(h = 12),
  smooth = auto.ssarima(log(AirPassengers)) |>
    forecast(h = 12, interval="parametric"),
  check = FALSE
)
```

expression	min	median	itr/sec	mem_alloc
forecast	1.92s	1.92s	0.52	402.39MB
fable	5.26s	5.26s	0.19	1.28GB
smooth	3.2s	3.2s	0.31	428.36MB

Outline

Python packages with statistical models

(Release dates)

- `statsmodels` (2016–2024)
- `pmdarima` (2017–2023)
- `sktime` (2019–2025) — includes wrapper to `pmdarima` and to some `StatsForecast` functions
- `GluonTS` (AWS, 2019–2025) — via wrapper to R forecast package
- `Darts` (2020–2025) — some wrappers to `StatsForecast`
- `Merlion` (Salesforce, 2021–2023)
- `StatsForecast` (Nixtla 2022–2025)
- `aeon` (2023–2025) — fork of `sktime`

Most complete packages

statsmodels

- ARIMA (not automated)
- ETS (not automated)
- MSTL
- Theta
- Regime switching
- ARDL
- ECM
- VARMA

sktime

- AutoARIMA
- AutoETS
- BATS/TBATS
- Theta
- STLForecaster
- Croston
- Bagged-ETS
- Prophet

StatsForecast

- AutoARIMA
- AutoETS
- AutoTBATS
- Theta
- MSTL
- Croston
- TSB, ADIDA
- ARCH/GARCH

Python packages with ML methods

(Release dates)

- `sktime` (2019–2025)
- `GluonTS` (AWS, 2019–2025)
- `Darts` (2020–2025)
- `Merlion` (Salesforce, 2021–2023)
- `MLforecast` (Nixtla 2022–2025)
- `NeuralForecast` (Nixtla 2022–2025)
- `aeon` (2023–2025) — fork of `sktime`
- `skforecast` (2021–2025)
- `NeuralProphet` (2020–2024)
- `Kats` (2021–2022)

Forecasting methods available in `NeuralForecast`

- `Autoformer`
- `BiTCN`
- `DeepAR`
- `DeepNPTS`
- `DilatedRNN`
- `FEDformer`
- `GRU`
- `HINT`
- `Informer`
- `iTransformer`
- `KAN`
- `LSTM`
- `MLP`
- `MLPMultivariate`
- `NBEATS`
- `NBEATSx`
- `NHITS`
- `NLinear`
- `PatchTST`
- `RNN`
- `SOFTS`
- `StemGNN`
- `TCN`
- `TFT`
- `TiDE`
- `TimeMixer`
- `TimeLLM`
- `TimesNet`
- `TSMixer`
- `TSMixerx`
- `VanillaTransformer`

ML forecasting methods available in `GluonTS`

- DeepAR
- DeepState
- DeepFactor
- Deep Renewal Processes
- GPForecaster
- MQ-CNN
- MQ-RNN
- N-BEATS
- Rotbaum
- Temporal Fusion Transformer
- Transformer
- WaveNet
- SimpleFeedForward
- DeepNPTS
- MQF2
- DeepVAR
- GPVAR
- LSTNet
- DeepTPP
- DeepVARHierarchical

Python reconciliation packages

- HierarchicalForecast (Nixtla)
- sktime
- pyhts
- Darts

Foundation models

- Time-LLM (Jin et al. 2023)
- TimeGPT-1 (Garza, Challu, and Mergenthaler-Canseco 2023)
- Lag-Llama (Rasul et al. 2023)
- TimesFM (Das et al. 2023)
- Tiny Time Mixers (Ekambaram et al. 2024)
- Moirai (Woo et al. 2024)
- MOMENT (Goswami et al. 2024)
- UniTS (Gao et al. 2024)
- Chronos (Ansari et al. 2024)

Outline

Julia

- `forecast`

Outline

Forecasting: principles and practice

OTexts.com