Package 'pinnEV'

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Type Package

Title Partially-Interpretable Neural Networks for Extreme Value modelling

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Description Methodology for fitting marginal extreme value (and associated) models using partially-interpretable neural networks. Networks are trained using the R interface to Keras with custom loss functions taken to be penalised versions of the negative log-likelihood for associated models.

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Encoding UTF-8

Depends R (>= 3.4)

Imports reticulate, keras, stats, evd, fields

RoxygenNote 7.3.1

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R topics documented:

AusWild *Australian Wildfire data*

Description

Data used by Cisneros et al. (2023+) for modelling extreme wildfires in Australia with eGPD graph convolutional neural networks

Usage

```
data(AusWild)
```

Format

A list with 6 elements:

BA An array with dimension (235, 7901), corresponding to the monthly burnt area response data.

a.s A vector of length (7901), giving the area of each spatial polygon.

X A list with 4 elements:

- **X.met** An array with dimension (235, 7901, 10) corresponding to the meterological predictors described below.
- **X.NDVI** An array with dimension (235, 7901, 1) corresponding to NDVI as described below.
- **X.topo** An array with dimension (235, 7901, 2) corresponding to the topographical predictors described below.

times A vector of length (235) giving the observation indices. Format is "year-month". Corresponds to first dimension of BA.

coords A matrix of dimension (7901, 2) giving the longitude/latitude coordinate for the second dimension of BA.

Details

The response data BA are observations of monthly aggregated burnt area (km^2) over 7901 artificially constructed spatial polygons that discretise Australia and Tasmania. These polygons were constructed using Statistical Area level-1 and level-2 (SA1/SA2) census regions (ABS, 2011) to ensure that the polygons have comparable population density. The observation period covers June 1999 to December 2018, inclusive, leaving 235 observed spatial fields. Observations are derived from historical reported bushfire boundaries (Lizundia-Loiola et al., 2020). Alongside monthly values of BA, we provide the area of each polygon; this is given in `a.s`, which is equivalent to $a(s)$ in Cisneros et al. (2023), and can be specified as an offset term in eGPD.NN. The boundaries of the polygons are provided separately, see `help("AusWild_geom")`.

Values of BA are missing in the Northern territories and have been set to `-1e10`; this leaves 7590 polygons with observed `BA >= 0`. Stored in X are the thirteen model predictors used by Cisneros et al. (2023). For BA and entries to X, the first two dimensions correspond to time $\times$ location with their respective ordinate values given in `times` and `coords`; `coords` is a 7901 by 2 matrix correspond to the longitude and latitude coordinates of the centroid of each polygon.

We have three types of predictor variables in X: meteorological (`X.met`), NDVI (`X.NDVI`) and topographical (`X.topo`).

Ten meteorological variables are considered and given as monthly maxima and means in `X.met`. These were provided by the ERA5-reanalysis monthly land averages (Muñoz-Sabater, 2019), available through the COPERNICUS Climate Data Service. The variables are ordered as followed: the first five variables are maximum evaporation (m of water equiv.), precipitation (m), temperature at a 2m altitude (K), and both eastern (U) and northern (V) components of wind velocity at a 10m altitude (m/s); these are followed by the corresponding mean values.

Average NDVI (unitless) is provided in `X.NDVI` and taken from the Tier-1 orthorectified Landsat-7 scenes converted to the top of atmosphere reflectance (Chander et al., 2009).

Two topographical predictors are given in `X.topo`: the average slope (◦) and aspect (◦) of each polygon, which were derived from the Shuttle Radar Topography Mission digital elevation model (Farr et al., 2000). Note that whilst these variables are static, we have stacked them into an array to have the same dimension as `X.met` and `X.NDVI`.

See Cisneros et al. (2023+) for details on the construction of this dataset. Note that the example code describes the fitting of the eGPD-GCNN model used by these authors. This model exploits the graph convolutional neural network (GCNN) of Kipf and Welling (2016), with trainable skip connection (see GCSConv layer of https://graphneural.network/layers/convolution/).

References

Farr, T. G. and Kobrick, M. (2000). *Shuttle radar topography mission produces a wealth of data.* Eos, Transactions American Geophysical Union, 81(48):583–585. (doi).

Chander, G., Markham, B. L., and Helder, D. L. (2009). *Summary of current radiometric calibration coefficients for landsat MSS, TM, ETM+, and EO-1 ALI sensors.* Remote sensing of environment, 113(5):893–903. (doi).

Australian Bureau of Statistics (ABS, 2011). *Australian statistical geography standard (ASGS): Volume 5–remoteness structure.* (Link).

Kipf, T. N. and Welling, M. (2016). *Semi-supervised classification with graph convolutional networks*. (arXiv:1412.6980).

Muñoz-Sabater, J. (2019).*ERA5-land monthly averaged data from 1981 to present, Copernicus climate change service (C3S) climate data store (CDS).* Earth Syst. Sci. Data, 55:5679–5695. (doi).

Cisneros, D., Richards, J., Dahal, A., Lombardo, L., and Huser, R. (2023+), *Deep learning-based graphical regression for jointly moderate and extreme Australian wildfires.*. (In draft).

Examples

```
data("AusWild")


#Create adjacency matrix
require(fields)
h <- rdist.earth(AusWild$coords,miles=F) #Distance matrix

range.par <- 650
A <- exp(-(h/range.par)^2)  # or alternatively, exp(-h/range.par)

cut.off.dist <- 700

A[h>cut.off.dist] <- 0 #Induce sparsity by setting values with h < cut.off.dist to zero

diag(A) <- 0 #Remove self-loops
```

```
#Make response
Y<-sqrt(AusWild$BA) # Square-root average BA per fire
Y[is.na(Y)] <- -1e10 # Any NA values set to -1e10. These are removed from evaluation of the loss function

#Make covariates
X <- array(dim=c(dim(Y),15))

X[,,1:10] <- AusWild$X$X.met
X[,,11] <- AusWild$X$X.NDVI
X[,,12:13] <- AusWild$X$X.topo
#We also add the coordinates
for(i in 1:dim(X)[1]){
  X[i,,14]=AusWild$coords[,1]
  X[i,,15]=AusWild$coords[,2]
}
#Normalise inputs
for(i in 1:dim(X)[3]){
  m=mean( X[,,i][Y > 0],na.rm=T)
  s=sd( X[,,i][Y > 0 ],na.rm=T)
  X[,,i]=( X[,,i]-m)/s
}

#We replicate the polygon areas to have the same dimension as Y. Note that we use the square root area as the offs
offset <- matrix(rep(sqrt(AusWild$a.s),nrow(Y)),nrow=nrow(Y),ncol=ncol(Y),byrow=T)

#Subset into validation and training data
valid.inds=sample(1:length(Y),length(Y)/5)
Y.train<-Y.valid<-Y
Y.train[valid.inds]=-1e10
Y.valid[-valid.inds]=-1e10


# Set inital parameters
init.xi<- 0.3; init.kappa <- 0.85; init.scale <- 50/mean(AusWild$a.s) #We scale the latter by the area

#Define architecture
widths <- c(8,8,8)

# Define predictors for sigma/scale parameter. Note that we do not use the PINN framework of Richard and Huser (2
# so we set interpetable components to NULL values.
X.s=list("X.nn.s"=X,
         "X.lin.s"=NULL, "X.add.basis.s"=NULL)


#Fit the eGPD model.
NN.fit<-eGPD.NN.train(Y.train, Y.valid,X.s,X.k=NULL, #X.k=NULL corresponds to a stationary kappa parameters
                      type="GCNN", A=A, offset=offset,
                      n.ep=3500, batch.size=235,
                      init.scale=init.scale, init.kappa=init.kappa,init.xi=init.xi,
                      widths=widths, seed=1)


preds<-eGPD.NN.predict(X.s=X.s,X.k=NULL,NN.fit$model, offset)

print("Plot scale parameter estimates")
hist(preds$pred.sigma, xlab=expression(sigma),main="")
```

```
print(paste0("kappa = ", round(preds$pred.kappa[1,1],3)))
print(paste0("xi = ", round(preds$pred.xi[1,1],3)))

# To plot a map using the geometry file. See help(AusWild_geom):
#-----------------------------------------------------------------------
# require(ggplot2)
# require(viridis)
# data("AusWild_geom")
# plot.df <- AusWild_geom
# plot.df$plot.spread <- preds$pred.sigma[1,] #Plot first month of sigma estimates

# ggplot(data = plot.df) + xlab("")+ylab("")+
#   geom_sf(mapping = aes_string(fill="plot.spread"), color = "black",size = 0.1 ) +
#   scale_fill_viridis(name="",option = "F",direction=-1,alpha=.7)
```

`AusWild_geom` *Geometry file for Australian Wildfire data*

Description

Data used by Cisneros et al. (2023+) for modelling extreme wildfires in Australia with eGPD graph convolutional neural networks

Usage

```
data(AusWild_geom)
```

Format

AusWild_geom A sf data frame containing the geometry of the (7901) polygons that make up the spatial domain.

Details

See `help("AusWild")` for relevant response and covariates.

References

Cisneros, D., Richards, J., Dahal, A., Lombardo, L., and Huser, R. (2023+), *Deep learning-based graphical regression for jointly moderate and extreme Australian wildfires.*. (In draft).

Examples

```
data("AusWild_geom")
```

bGEV *The blended-GEV distribution*

Description

Distribution function, quantile function and random generation for the blended generalised extreme value (bGEV) distribution with location equal to `q_alpha`, spread equal to `s_beta` and shape equal to `xi`. Note that unlike similar functions in package `stats`, these functions accept only scalar inputs, rather than vectors, for the parameters.

Usage

```
pbGEV(y, q_alpha, s_beta, xi, alpha = 0.5, beta = 0.5, p_a = 0.05,
  p_b = 0.2, c1 = 5, c2 = 5, log = F)

qbGEV(prob, q_alpha, s_beta, xi, alpha = 0.5, beta = 0.5, p_a = 0.05,
  p_b = 0.2, c1 = 5, c2 = 5)

rbGEV(n, q_alpha, s_beta, xi, alpha = 0.5, beta = 0.5, p_a = 0.05,
  p_b = 0.2, c1 = 5, c2 = 5)
```

Arguments

`y`	scalar quantile.
`q_alpha`	scalar location parameter.
`s_beta`	scalar spread parameter.
`xi`	scalar shape parameter.
`alpha, beta, p_a, p_b, c1, c2`	hyper-parameters for the bGEV distribution, see details. Defaults set to those proposed by Castro-Camilo et al. (2021).
`log`	logical; if `TRUE`, probabilities are given as `log(prob)`.
`prob`	scalar probability.
`n`	number of replications.

Details

The GEV distribution function for real location μ and scale $\sigma > 0$ is

$$G(y|\mu,\sigma,\xi) = \exp[-\{1+\xi(y-\mu)/\sigma\}_+^{-1/\xi}]$$

for $\xi > 0$ and

$$G(y|\mu,\sigma,\xi) = \exp\{-\exp(-(y-\mu)/\sigma)\}$$

for $\xi = 0$, where $\{x\}_+ = \max\{0, x\}$. It can be re-parameterised in terms of a location parameter q_α for $\alpha \in (0,1)$, denoting the GEV α-quantile, and a spread parameter $s_\beta = q_{1-\beta/2} - q_{\beta/2}$ for $\beta \in (0,1)$. This is achieved using the following one-to-one mapping; if $\xi > 0$, then

$$\mu = q_\alpha - s_\beta(l_{\alpha,\xi} - 1)/(l_{1-\beta/2,\xi} - l_{\beta/2,\xi})$$

and

$$\sigma = \xi s_\beta/(l_{1-\beta/2,\xi} - l_{\beta/2,\xi})$$

where $l_{x,\xi} = (-\log(x))^{-\xi}$; if $\xi = 0$, then

$$\mu = q_\alpha + s_\beta l_\alpha / (l_{\beta/2} - l_{1-\beta/2})$$

and

$$\sigma = s_\beta / (l_{\beta/2} - l_{1-\beta/2})$$

where $l_x = \log(-\log(x))$.

By Castro-Camilo et al. (2021), the blended-GEV has distribution function

$$F(y|q_\alpha, s_\beta, \xi, a, b) = G(y|\tilde{q}_\alpha, \tilde{s}_\beta, \xi = 0)^{1-p(y;a,b)} G(y|_\alpha, s_\beta, \xi)^{p(y;a,b)},$$

for real q_α, $s_\beta > 0$ and $\xi > 0$. The weight function p is defined by $p(y; a, b) = F_{beta}((y-a)/(b-a)|c_1, c_2)$, the distribution function of a beta random variable with shape parameters $c_1 > 3, c_2 > 3$. For continuity of G, we set $a = G^{-1}(p_a|q_\alpha, s_\beta, \xi)$ and $b = G^{-1}(p_b|q_\alpha, s_\beta, \xi)$ for small $0 < p_a < p_b < 1$ and let $\tilde{q}_\alpha = a - (b-a)(l_\alpha - l_{p_a})/(l_{p_a} - l_{p_b})$ and $\tilde{s}_\beta = (b-a)(l_{\beta/2} - l_{1-\beta/2})/(l_{p_a} - l_{p_b})$.

Value

`pbGEV` gives the distribution function; `qbGEV` gives the quantile function; `rbGEV` generates random deviates.

References

Castro-Camilo, D., Huser, R., and Rue, H. (2021), *Practical strategies for generalized extreme value-based regression models for extremes*, Environmetrics, e274. (doi)

`bGEV.NN` *blended-GEV PINN*

Description

Build and train a partially-interpretable neural network for fitting a bGEV model

Usage

```
bGEV.NN.train(Y.train, Y.valid = NULL, X.q, X.s, type = "MLP",
  link.loc = "identity", n.ep = 100, batch.size = 100, init.loc = NULL,
  init.spread = NULL, init.xi = NULL, widths = c(6, 3),
  filter.dim = c(3, 3), seed = NULL, init.wb_path = NULL, alpha = 0.5,
  beta = 0.5, p_a = 0.05, p_b = 0.2, c1 = 5, c2 = 5,
  S_lambda = NULL)

bGEV.NN.predict(X.q, X.s, model)
```

Arguments

`Y.train, Y.valid`

a 2 or 3 dimensional array of training or validation real response values. Missing values can be handled by setting corresponding entries to `Y.train` or `Y.valid` to `-1e10`. The first dimension should be the observation indices, e.g., time.

If `type=="CNN"`, then `Y.train` and `Y.valid` must have three dimensions with the latter two corresponding to an M by N regular grid of spatial locations. If `Y.valid==NULL`, no validation loss will be computed and the returned model will be that which minimises the training loss over `n.ep` epochs.

`X.q` list of arrays corresponding to complementary subsets of the $d \geq 1$ predictors which are used for modelling the location parameter q_α. Must contain at least one of the following three named entries:

- `X.lin.q` A 3 or 4 dimensional array of "linear" predictor values. One more dimension than `Y.train`. If `NULL`, a model without the linear component is built and trained. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $l_1 \geq 0$ 'linear' predictor values.
- `X.add.basis.q` A 4 or 5 dimensional array of basis function evaluations for the "additive" predictor values. The first 2/3 dimensions should be equal to that of `Y.train`; the penultimate dimensions corresponds to the chosen $a_1 \geq 0$ 'linear' predictor values and the last dimension is equal to the number of knots used for estimating the splines. See example. If `NULL`, a model without the additive component is built and trained.
- `X.nn.q` A 3 or 4 dimensional array of "non-additive" predictor values. If `NULL`, a model without the NN component is built and trained; if this is the case, then `type` has no effect. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $d - l_1 - a_1 \geq 0$ 'non-additive' predictor values.

Note that `X.q` and `X.s` are the predictors for both `Y.train` and `Y.valid`. If `is.null(X.q)`, then q_α will be treated as fixed over the predictors.

`X.s` similarly to `X.q`, but for modelling the scale parameter $s_\beta > 0$. Note that we require at least one of `!is.null(X.q)` or `!is.null(X.s)`, otherwise the formulated model will be fully stationary and will not be fitted.

`type` string defining the type of network to be built. If `type=="MLP"`, the network will have all densely connected layers; if `type=="CNN"`, the network will have all convolutional layers. Defaults to an MLP. (Currently the same network is used for all parameters, may change in future versions)

`n.ep` number of epochs used for training. Defaults to 1000.

`batch.size` batch size for stochastic gradient descent. If larger than `dim(Y.train)[1]`, i.e., the number of observations, then regular gradient descent used.

`init.loc, init.spread, init.xi`
sets the initial q_α, s_β and $\xi \in (0, 1)$ estimates across all dimensions of `Y.train`. Overridden by `init.wb_path` if `!is.null(init.wb_path)`, but otherwise the initial parameters must be supplied.

`widths` vector of widths/filters for hidden dense/convolution layers. Number of layers is equal to `length(widths)`. Defaults to (6,3).

`filter.dim` if `type=="CNN"`, this 2-vector gives the dimensions of the convolution filter kernel; must have odd integer inputs. Note that filter.dim=c(1,1) is equivalent to `type=="MLP"`. The same filter is applied for each hidden layer across all parameters with NN predictors.

`seed` seed for random initial weights and biases.

`init.wb_path` filepath to a `keras` model which is then used as initial weights and biases for training the new model. The original model must have the exact same architecture and trained with the same input data as the new model. If `NULL`, then initial weights and biases are random (with seed `seed`) but the final layer has zero initial weights to ensure that the initial location, spread and shape estimates are `init.loc`, `init.spread` and `init.xi`, respectively, across all dimensions.

`alpha, beta, p_a, p_b`
: hyper-parameters associated with the bGEV distribution. Defaults to those used by Castro-Camilo, D., et al. (2021). Require `alpha >= p_b` and `beta/2 >= p_b`.

`S_lambda`
: list of smoothing penalty matrices for the splines modelling the effects of `X.add.basis.q` and `X.add.basis.s` on their respective parameters; each element only used if `!is.null(X.add.basis.q)` and `!is.null(X.add.basis.s)`, respectively. If `is.null(S_lambda[[1]])`, then no smoothing penalty used for q_α; similarly for the second element and s_β.

`model`
: fitted `keras` model. Output from `bGEVPP.NN.train`.

`loc.link`
: string defining the link function used for the location parameter, see h_1 below. If `link=="exp"`, then $h_1 = \exp(x)$; if `link=="identity"`, then $h_1(x) = x$.

Details

Consider a real-valued random variable Y and let $\mathbf{X}$ denote a d-dimensional predictor set with observations $\mathbf{x}$. For $i = 1, 2$, we define integers $l_i \geq 0, a_i \geq 0$ and $0 \leq l_i + a_i \leq d$, and let $\mathbf{X}_L^{(i)}, \mathbf{X}_A^{(i)}$ and $\mathbf{X}_N^{(i)}$ be distinct sub-vectors of $\mathbf{X}$, with observations of each component denoted $\mathbf{x}_L^{(i)}, \mathbf{x}_A^{(i)}$ and $\mathbf{x}_N^{(i)}$, respectively; the lengths of the sub-vectors are l_i, a_i and $d_i - l_i - a$, respectively. For a fixed threshold $u(\mathbf{x})$, dependent on predictors, we model $Y|\mathbf{X} = \mathbf{x} \sim \text{bGEV}(q_\alpha(\mathbf{x}), s_\beta(\mathbf{x}), \xi)$ for $\xi \in (0, 1)$ with

$$q_\alpha(\mathbf{x}) = h_1\{\eta_0^{(1)} + m_L^{(1)}(\mathbf{x}_L^{(1)}) + m_A^{(1)}(x_A^{(1)}) + m_N^{(1)}(\mathbf{x}_N^{(1)})\}$$

and

$$s_\beta(\mathbf{x}) = \exp\{\eta_0^{(2)} + m_L^{(2)}(\mathbf{x}_L^{(2)}) + m_A^{(2)}(x_A^{(2)}) + m_N^{(2)}(\mathbf{x}_N^{(2)})\}$$

where h_1 is some link-function and $\eta_0^{(1)}, \eta_0^{(2)}$ are constant intercepts. The unknown functions $m_L^{(1)}, m_L^{(2)}$ and $m_A^{(1)}, m_A^{(2)}$ are estimated using linear functions and splines, respectively, and are both returned as outputs by `bGEV.NN.predict`; $m_N^{(1)}, m_N^{(2)}$ are estimated using neural networks (currently the same architecture is used for both parameters). Note that $\xi > 0$ is fixed across all predictors; this may change in future versions.

For details of the bGEV distribution, see `help(pbGEV)`.

The model is fitted by minimising the negative log-likelihood associated with the bGEV model plus some smoothing penalty for the additive functions (determined by `S_lambda`; see Richards and Huser, 2022); training is performed over `n.ep` training epochs. Although the model is trained by minimising the loss evaluated for `Y.train`, the final returned model may minimise some other loss. The current state of the model is saved after each epoch, using `keras::callback_model_checkpoint`, if the value of some criterion subcedes that of the model from the previous checkpoint; this criterion is the loss evaluated for validation set `Y.valid` if `!is.null(Y.valid)` and for `Y.train`, otherwise.

Value

`bGEV.NN.train` returns the fitted `model`. `bGEV.NN.predict` is a wrapper for `keras::predict` that returns the predicted parameter estimates, and, if applicable, their corresponding linear regression coefficients and spline bases weights.

References

Castro-Camilo, D., Huser, R., and Rue, H. (2021), *Practical strategies for generalized extreme value-based regression models for extremes*, Environmetrics, e274. (doi)

Richards, J. and Huser, R. (2022), *Regression modelling of spatiotemporal extreme U.S. wildfires via partially-interpretable neural networks*. (arXiv:2208.07581).

Examples

```
# Build and train a simple MLP for toy data

set.seed(1)

# Create  predictors
preds<-rnorm(prod(c(200,10,10,8)))

#Re-shape to a 4d array. First dimension corresponds to observations,
#last to the different components of the predictor set.
#Other dimensions correspond to indices of predictors, e.g., a grid of locations.
dim(preds)=c(200,10,10,8)
#We have 200 observations of eight predictors on a 10 by 10 grid.

#Split predictors into linear, additive and nn. Different for the location and scale parameters.
X.nn.q=preds[,,,1:4] #Four nn predictors for q_\alpha
X.lin.q=preds[,,,5:6] #Two additive predictors for q_\alpha
X.add.q=preds[,,,7:8] #Two additive predictors for q_\alpha

X.nn.s=preds[,,,1:2] #Two nn predictors for s_\beta
X.lin.s=preds[,,,3] #One linear predictor for s_\beta
dim(X.lin.s)=c(dim(X.lin.s),1) #Change dimension so consistent
X.add.s=preds[,,,4] #One additive predictor for s_\beta
dim(X.add.s)=c(dim(X.add.s),1) #Change dimension so consistent


# Create toy response data

#Contribution to location parameter
#Linear contribution
m_L_1 = 0.3*X.lin.q[,,,1]+0.6*X.lin.q[,,,2]

# Additive contribution
m_A_1 = 0.1*X.add.q[,,,1]^3+0.2*X.add.q[,,,1]-
 0.1*X.add.q[,,,2]^3+0.5*X.add.q[,,,2]^2

#Non-additive contribution - to be estimated by NN
m_N_1 = 0.5*exp(-3+X.nn.q[,,,4]+X.nn.q[,,,1])+
 sin(X.nn.q[,,,1]-X.nn.q[,,,2])*(X.nn.q[,,,4]+X.nn.q[,,,2])-
 cos(X.nn.q[,,,4]-X.nn.q[,,,1])*(X.nn.q[,,,3]+X.nn.q[,,,1])

q_alpha=1+m_L_1+m_A_1+m_N_1 #Identity link

#Contribution to scale parameter
#Linear contribution
m_L_2 = 0.5*X.lin.s[,,,1]

# Additive contribution
m_A_2 = 0.1*X.add.s[,,,1]^2+0.2*X.add.s[,,,1]

#Non-additive contribution - to be estimated by NN
m_N_2 = 0.2*exp(-4+X.nn.s[,,,2]+X.nn.s[,,,1])+
 sin(X.nn.s[,,,1]-X.nn.s[,,,2])*(X.nn.s[,,,1]+X.nn.s[,,,2])

s_beta=0.2*exp(m_L_2+m_A_2+m_N_2) #Exponential link
```

```
xi=0.1 # Set xi

theta=array(dim=c(dim(s_beta),3))
theta[,,,1]=q_alpha; theta[,,,2] = s_beta; theta[,,,3]=xi
#We simulate data from the bGEV distribution

Y=apply(theta,1:3,function(x) rbGEV(1,q_alpha=x[1],s_beta=x[2],xi=x[3]))

#Create training and validation, respectively.
#We mask 20% of the Y values and use this for validation
#Masked values must be set to -1e10 and are treated as missing whilst training

mask_inds=sample(1:length(Y),size=length(Y)*0.8)

Y.train<-Y.valid<-Y #Create training and validation, respectively.
Y.train[-mask_inds]=-1e10
Y.valid[mask_inds]=-1e10



#To build a model with an additive component, we require an array of evaluations of
#the basis functions for each pre-specified knot and entry to X.add.q and X.add.s

rad=function(x,c){ #Define a basis function. Here we use the radial bases
  out=abs(x-c)^2*log(abs(x-c))
  out[(x-c)==0]=0
 return(out)
}

n.knot.q = 5; n.knot.s = 4 # set number of knots.
#Must be the same for each additive predictor,
#but can differ between the parameters q_\alpha and s_\beta

#Get knots for q_\alpha predictors
knots.q=matrix(nrow=dim(X.add.q)[4],ncol=n.knot.q)

#We set knots to be equally-spaced marginal quantiles
for( i in 1:dim(X.add.q)[4]){
knots.q[i,]=quantile(X.add.q[,,,i],probs=seq(0,1,length=n.knot.q))
}
#Evaluate radial basis functions for q_\alpha predictors
X.add.basis.q<-array(dim=c(dim(X.add.q),n.knot.q))
for( i in 1:dim(X.add.q)[4]) {
  for(k in 1:n.knot.q) {
    X.add.basis.q[,,,i,k]= rad(x=X.add.q[,,,i],c=knots.q[i,k])
    #Evaluate rad at all entries to X.add.q and for all knots
  }}

  #'#Create smoothing penalty matrix for the two q_alpha additive functions

# Set smoothness parameters for two functions
 lambda = c(0.1,0.2)

S_lambda.q=matrix(0,nrow=n.knot.q*dim(X.add.q)[4],ncol=n.knot.q*dim(X.add.q)[4])
for(i in 1:dim(X.add.q)[4]){
 for(j in 1:n.knot.q){
  for(k in 1:n.knot.q){
```

```
    S_lambda.q[(j+(i-1)*n.knot.q),(k+(i-1)*n.knot.q)]=lambda[i]*rad(knots.q[i,j],knots.q[i,k])
  }
}
}

#Get knots for s_\beta predictor
knots.s=matrix(nrow=dim(X.add.s)[4],ncol=n.knot.s)
for( i in 1:dim(X.add.s)[4]){
 knots.s[i,]=quantile(X.add.s[,,,i],probs=seq(0,1,length=n.knot.s))
}

#Evaluate radial basis functions for s_\beta predictor
X.add.basis.s<-array(dim=c(dim(X.add.s),n.knot.s))
for( i in 1:dim(X.add.s)[4]) {
  for(k in 1:n.knot.s) {
    X.add.basis.s[,,,i,k]= rad(x=X.add.s[,,,i],c=knots.s[i,k])
    #Evaluate rad at all entries to X.add.q and for all knots
  }}

#Create smoothing penalty matrix for the s_beta additive function

# Set smoothness parameter
 lambda = c(0.2)

S_lambda.s=matrix(0,nrow=n.knot.s*dim(X.add.s)[4],ncol=n.knot.s*dim(X.add.s)[4])
for(i in 1:dim(X.add.s)[4]){
 for(j in 1:n.knot.s){
  for(k in 1:n.knot.s){
   S_lambda.s[(j+(i-1)*n.knot.s),(k+(i-1)*n.knot.s)]=lambda[i]*rad(knots.s[i,j],knots.s[i,k])
  }
}
}

#Join in one list
S_lambda =list("S_lambda.q"=S_lambda.q, "S_lambda.s"=S_lambda.s)


#lin+GAM+NN models defined for both location and scale parameters
X.q=list("X.nn.q"=X.nn.q, "X.lin.q"=X.lin.q,
               "X.add.basis.q"=X.add.basis.q) #Predictors for q_\alpha
X.s=list("X.nn.s"=X.nn.s, "X.lin.s"=X.lin.s,
               "X.add.basis.s"=X.add.basis.s) #Predictors for s_\beta


#Fit the bGEV model. Note that training is not run to completion.
NN.fit<-bGEV.NN.train(Y.train, Y.valid,X.q,X.s, type="MLP",link.loc="identity",
                      n.ep=500, batch.size=50,init.loc=2, init.spread=5,init.xi=0.1,
                      widths=c(6,3),seed=1,S_lambda=S_lambda)
out<-bGEV.NN.predict(X.q=X.q,X.s=X.s,NN.fit$model)

print("q_alpha linear coefficients: "); print(round(out$lin.coeff_q,2))
print("s_beta linear coefficients: "); print(round(out$lin.coeff_s,2))

# Note that this is a simple example that can be run in a personal computer.
# Whilst the q_alpha functions are well estimated, more data/larger n.ep are required for more accurate
# estimation of s_beta functions and xi
```

```
#To save model, run
#NN.fit$model %>% save_model_tf("model_bGEV")
#To load model, run
# model  <- load_model_tf("model_bGEV",
#  custom_objects=list(
#    "bgev_loss_alpha__beta__p_a__p_b__c1__c2__S_lambda___S_lambda_"=
#        bgev_loss(S_lambda=S_lambda))
#        )

#Note that bGEV_loss() can take custom alpha,beta, p_a and p_b arguments if defaults not used


# Plot splines for the additive predictors

#Location predictors
n.add.preds_q=dim(X.add.q)[length(dim(X.add.q))]
par(mfrow=c(1,n.add.preds_q))
for(i in 1:n.add.preds_q){
 plt.x=seq(from=min(knots.q[i,]),to=max(knots.q[i,]),length=1000) #Create sequence for x-axis

  tmp=matrix(nrow=length(plt.x),ncol=n.knot.q)
  for(j in 1:n.knot.q){
   tmp[,j]=rad(plt.x,knots.q[i,j]) #Evaluate radial basis function of plt.x and all knots
  }
  plt.y=tmp%*%out$gam.weights_q[i,]
 plot(plt.x,plt.y,type="l",main=paste0("q_alpha spline: predictor ",i),xlab="x",ylab="f(x)")
  points(knots.q[i,],rep(mean(plt.y),n.knot.q),col="red",pch=2)
  #Adds red triangles that denote knot locations

}

#Spread predictors
n.add.preds_s=dim(X.add.s)[length(dim(X.add.s))]
par(mfrow=c(1,n.add.preds_s))
for(i in 1:n.add.preds_s){
 plt.x=seq(from=min(knots.s[i,]),to=max(knots.s[i,]),length=1000) #Create sequence for x-axis

  tmp=matrix(nrow=length(plt.x),ncol=n.knot.s)
  for(j in 1:n.knot.s){
   tmp[,j]=rad(plt.x,knots.s[i,j]) #Evaluate radial basis function of plt.x and all knots
  }
  plt.y=tmp%*%out$gam.weights_s[i,]
 plot(plt.x,plt.y,type="l",main=paste0("s_beta spline: predictor ",i),xlab="x",ylab="f(x)")
  points(knots.s[i,],rep(mean(plt.y),n.knot.s),col="red",pch=2)
  #Adds red triangles that denote knot locations

}
```

---

bGEVPP.NN *blended-GEV point process PINN*

Description

Build and train a partially-interpretable neural network for fitting a bGEV point-process model

Usage

```
bGEVPP.NN.train(Y.train, Y.valid = NULL, X.q, X.s, u = NULL,
  type = "MLP", link.loc = "identity", n.ep = 100, batch.size = 100,
  init.loc = NULL, init.spread = NULL, init.xi = NULL, widths = c(6,
  3), filter.dim = c(3, 3), seed = NULL, init.wb_path = NULL,
  alpha = 0.5, beta = 0.5, p_a = 0.05, p_b = 0.2, c1 = 5, c2 = 5,
  n_b = 1, S_lambda = NULL)

bGEVPP.NN.predict(X.q, X.s, u, model)
```

Arguments

`Y.train`, `Y.valid`

a 2 or 3 dimensional array of training or validation real response values. Missing values can be handled by setting corresponding entries to `Y.train` or `Y.valid` to `-1e10`. The first dimension should be the observation indices, e.g., time.

If `type=="CNN"`, then `Y.train` and `Y.valid` must have three dimensions with the latter two corresponding to an M by N regular grid of spatial locations. If `Y.valid==NULL`, no validation loss will be computed and the returned model will be that which minimises the training loss over `n.ep` epochs.

`X.q` list of arrays corresponding to complementary subsets of the $d \geq 1$ predictors which are used for modelling the location parameter q_α. Must contain at least one of the following three named entries:

`X.lin.q` A 3 or 4 dimensional array of "linear" predictor values. One more dimension than `Y.train`. If `NULL`, a model without the linear component is built and trained. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $l_1 \geq 0$ 'linear' predictor values.

`X.add.basis.q` A 4 or 5 dimensional array of basis function evaluations for the "additive" predictor values. The first 2/3 dimensions should be equal to that of `Y.train`; the penultimate dimensions corresponds to the chosen $a_1 \geq 0$ 'linear' predictor values and the last dimension is equal to the number of knots used for estimating the splines. See example. If `NULL`, a model without the additive component is built and trained.

`X.nn.q` A 3 or 4 dimensional array of "non-additive" predictor values. If `NULL`, a model without the NN component is built and trained; if this is the case, then `type` has no effect. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $d - l_1 - a_1 \geq 0$ 'non-additive' predictor values.

Note that `X.q` and `X.s` are the predictors for both `Y.train` and `Y.valid`. If `is.null(X.q)`, then q_α will be treated as fixed over the predictors.

`X.s` similarly to `X.q`, but for modelling the scale parameter $s_\beta > 0$. Note that we require at least one of `!is.null(X.q)` or `!is.null(X.s)`, otherwise the formulated model will be fully stationary and will not be fitted.

`u` an array with the same dimension as `Y.train`. Gives the threshold above which the bGEV-PP model is fitted, see below. Note that `u` is applied to both `Y.train` and `Y.valid`.

`type` string defining the type of network to be built. If `type=="MLP"`, the network will have all densely connected layers; if `type=="CNN"`, the network will have all convolutional layers. Defaults to an MLP. (Currently the same network is used for all parameters, may change in future versions)

`n.ep` number of epochs used for training. Defaults to 1000.

`batch.size` batch size for stochastic gradient descent. If larger than `dim(Y.train)[1]`, i.e., the number of observations, then regular gradient descent used.

`init.loc, init.spread, init.xi`
sets the initial q_α, s_β and $\xi \in (0,1)$ estimates across all dimensions of `Y.train`. Overridden by `init.wb_path` if `!is.null(init.wb_path)`, but otherwise the initial parameters must be supplied.

`widths` vector of widths/filters for hidden dense/convolution layers. Number of layers is equal to `length(widths)`. Defaults to (6,3).

`filter.dim` if `type=="CNN"`, this 2-vector gives the dimensions of the convolution filter kernel; must have odd integer inputs. Note that filter.dim=c(1,1) is equivalent to `type=="MLP"`. The same filter is applied for each hidden layer across all parameters with NN predictors.

`seed` seed for random initial weights and biases.

`init.wb_path` filepath to a `keras` model which is then used as initial weights and biases for training the new model. The original model must have the exact same architecture and trained with the same input data as the new model. If `NULL`, then initial weights and biases are random (with seed `seed`) but the final layer has zero initial weights to ensure that the initial location, spread and shape estimates are `init.loc`, `init.spread` and `init.xi`, respectively, across all dimensions.

`alpha, beta, p_a, p_b, c1, c2`
hyper-parameters associated with the bGEV distribution. Defaults to those used by Castro-Camilo, D., et al. (2021). Require `alpha >= p_b` and `beta/2 >= p_b`.

`n_b` number of observations per block, e.g., if observations correspond to months and the interest is annual maxima, then `n_b=12`.

`S_lambda` List of smoothing penalty matrices for the splines modelling the effects of `X.add.basis.q` and `X.add.basis.s` on their respective parameters; each element only used if `!is.null(X.add.basis.q)` and `!is.null(X.add.basis.s)`, respectively. If `is.null(S_lambda[[1]])`, then no smoothing penalty is used for q_α; similarly for the second element and s_β.

`model` fitted `keras` model. Output from `bGEVPP.NN.train`.

`loc.link` string defining the link function used for the location parameter, see h_1 below. If `link=="exp"`, then $h_1 = \exp(x)$; if `link=="identity"`, then $h_1(x) = x$.

Details

Consider a real-valued random variable Y and let $\mathbf{X}$ denote a d-dimensional predictor set with observations $\mathbf{x}$. For $i = 1, 2$, we define integers $l_i \geq 0, a_i \geq 0$ and $0 \leq l_i + a_i \leq d$, and let $\mathbf{X}_L^{(i)}, \mathbf{X}_A^{(i)}$ and $\mathbf{X}_N^{(i)}$ be distinct sub-vectors of $\mathbf{X}$, with observations of each component denoted $\mathbf{x}_L^{(i)}, \mathbf{x}_A^{(i)}$ and $\mathbf{x}_N^{(i)}$, respectively; the lengths of the sub-vectors are l_i, a_i and $d_i - l_i - a$, respectively. For a fixed threshold $u(\mathbf{x})$, dependent on predictors, we model $Y|\mathbf{X} = \mathbf{x} \sim$ bGEV-PP$(q_\alpha(\mathbf{x}), s_\beta(\mathbf{x}), \xi; u(\mathbf{x}))$ for $\xi \in (0,1)$ with

$$q_\alpha(\mathbf{x}) = h_1\{\eta_0^{(1)} + m_L^{(1)}(\mathbf{x}_L^{(1)}) + m_A^{(1)}(x_A^{(1)}) + m_N^{(1)}(\mathbf{x}_N^{(1)})\}$$

and

$$s_\beta(\mathbf{x}) = \exp\{\eta_0^{(2)} + m_L^{(2)}(\mathbf{x}_L^{(2)}) + m_A^{(2)}(x_A^{(2)}) + m_N^{(2)}(\mathbf{x}_N^{(2)})\}$$

where h_1 is some link-function and $\eta_0^{(1)}, \eta_0^{(2)}$ are constant intercepts. The unknown functions $m_L^{(1)}, m_L^{(2)}$ and $m_A^{(1)}, m_A^{(2)}$ are estimated using linear functions and splines, respectively, and are

both returned as outputs by `bGEVPP.NN.predict`; $m_N^{(1)}, m_N^{(2)}$ are estimated using neural networks (currently the same architecture is used for both parameters). Note that $\xi > 0$ is fixed across all predictors; this may change in future versions.

Note that for sufficiently large u that $Y \sim$ bGEV-PP$(q_\alpha, s_\beta, \xi; u)$ implies that $\max_{i=1,\ldots,n_b}\{Y_i\} \sim$ bGEV(q_α, s_β, ξ), i.e., the n_b-block maxima of independent realisations of Y follow a bGEV distribution (see `help(pbGEV)`). The size of the block can be specified by the parameter `n_b`.

The model is fitted by minimising the negative log-likelihood associated with the bGEV-PP model plus some smoothing penalty for the additive functions (determined by `S_lambda`; see Richards and Huser, 2022); training is performed over `n.ep` training epochs. Although the model is trained by minimising the loss evaluated for `Y.train`, the final returned model may minimise some other loss. The current state of the model is saved after each epoch, using `keras::callback_model_checkpoint`, if the value of some criterion subcedes that of the model from the previous checkpoint; this criterion is the loss evaluated for validation set `Y.valid` if `!is.null(Y.valid)` and for `Y.train`, otherwise.

Value

`bGEVPP.NN.train` returns the fitted `model`. `bGEVPP.NN.predict` is a wrapper for `keras::predict` that returns the predicted parameter estimates, and, if applicable, their corresponding linear regression coefficients and spline bases weights.

References

Castro-Camilo, D., Huser, R., and Rue, H. (2021), *Practical strategies for generalized extreme value-based regression models for extremes*, Environmetrics, e274. (doi)

Richards, J. and Huser, R. (2022), *Regression modelling of spatiotemporal extreme U.S. wildfires via partially-interpretable neural networks*. (arXiv:2208.07581).

Examples

```
# Build and train a simple MLP for toy data

set.seed(1)

# Create  predictors
preds<-rnorm(prod(c(200,10,10,8)))

#Re-shape to a 4d array. First dimension corresponds to observations,
#last to the different components of the predictor set.
#Other dimensions correspond to indices of predictors, e.g., a grid of locations. Can be just a 1D grid.
dim(preds)=c(200,10,10,8)
#We have 200 observations of eight predictors on a 10 by 10 grid.

#Split predictors into linear, additive and nn. Different for the location and scale parameters.
X.nn.q=preds[,,,1:4] #Four nn predictors for q_\alpha
X.lin.q=preds[,,,5:6] #Two additive predictors for q_\alpha
X.add.q=preds[,,,7:8] #Two additive predictors for q_\alpha

X.nn.s=preds[,,,1:2] #Two nn predictors for s_\beta
X.lin.s=preds[,,,3] #One linear predictor for s_\beta
dim(X.lin.s)=c(dim(X.lin.s),1) #Change dimension so consistent
X.add.s=preds[,,,4] #One additive predictor for s_\beta
dim(X.add.s)=c(dim(X.add.s),1) #Change dimension so consistent

# Create toy response data
```

```
#Contribution to location parameter
#Linear contribution
m_L_1 = 0.3*X.lin.q[,,,1]+0.6*X.lin.q[,,,2]

# Additive contribution
m_A_1 = 0.1*X.add.q[,,,1]^3+0.2*X.add.q[,,,1]-
 0.1*X.add.q[,,,2]^3+0.5*X.add.q[,,,2]^2

#Non-additive contribution - to be estimated by NN
m_N_1 = 0.5*exp(-3+X.nn.q[,,,4]+X.nn.q[,,,1])+
 sin(X.nn.q[,,,1]-X.nn.q[,,,2])*(X.nn.q[,,,4]+X.nn.q[,,,2])-
 cos(X.nn.q[,,,4]-X.nn.q[,,,1])*(X.nn.q[,,,3]+X.nn.q[,,,1])

q_alpha=1+m_L_1+m_A_1+m_N_1 #Identity link

#Contribution to scale parameter
#Linear contribution
m_L_2 = 0.5*X.lin.s[,,,1]

# Additive contribution
m_A_2 = 0.1*X.add.s[,,,1]^2+0.2*X.add.s[,,,1]

#Non-additive contribution - to be estimated by NN
m_N_2 = 0.2*exp(-4+X.nn.s[,,,2]+X.nn.s[,,,1])+
 sin(X.nn.s[,,,1]-X.nn.s[,,,2])*(X.nn.s[,,,1]+X.nn.s[,,,2])

s_beta=0.2*exp(m_L_2+m_A_2+m_N_2) #Exponential link

xi=0.1 # Set xi

theta=array(dim=c(dim(s_beta),3))
theta[,,,1]=q_alpha; theta[,,,2] = s_beta; theta[,,,3]=xi
#We simulate data from the extreme value point process model with u take as the 80% quantile

#Gives the 80% quantile of Y
u<-apply(theta,1:3,function(x) qPP(prob=0.8,loc=x[1],scale=x[2],xi=x[3],re.par = T))

#Simulate from re-parametrised point process model using same u as given above
Y=apply(theta,1:3,function(x) rPP(1,u.prob=0.8,loc=x[1],scale=x[2],xi=x[3],re.par=T))

# Note that the point process model is only valid for Y > u. If Y < u, then rPP gives NA.
# We can set NA values to some c < u as these do not contribute to model fitting.
Y[is.na(Y)]=u[is.na(Y)]-1



#Create training and validation, respectively.
#We mask 20% of the Y values and use this for validation
#Masked values must be set to -1e10 and are treated as missing whilst training

mask_inds=sample(1:length(Y),size=length(Y)*0.8)

Y.train<-Y.valid<-Y #Create training and validation, respectively.
Y.train[-mask_inds]=-1e10
Y.valid[mask_inds]=-1e10
```

```
#To build a model with an additive component, we require an array of evaluations of
#the basis functions for each pre-specified knot and entry to X.add.q and X.add.s

rad=function(x,c){ #Define a basis function. Here we use the radial bases
  out=abs(x-c)^2*log(abs(x-c))
  out[(x-c)==0]=0
 return(out)
}

n.knot.q = 5; n.knot.s = 4 # set number of knots.
#Must be the same for each additive predictor,
#but can differ between the parameters q_\alpha and s_\beta

#Get knots for q_\alpha predictors
knots.q=matrix(nrow=dim(X.add.q)[4],ncol=n.knot.q)

#We set knots to be equally-spaced marginal quantiles
for( i in 1:dim(X.add.q)[4]){
 knots.q[i,]=quantile(X.add.q[,,,i],probs=seq(0,1,length=n.knot.q))
}

#Evaluate radial basis functions for q_\alpha predictors
X.add.basis.q<-array(dim=c(dim(X.add.q),n.knot.q))
for( i in 1:dim(X.add.q)[4]) {
  for(k in 1:n.knot.q) {
    X.add.basis.q[,,,i,k]= rad(x=X.add.q[,,,i],c=knots.q[i,k])
    #Evaluate rad at all entries to X.add.q and for all knots
  }}

  #'#Create smoothing penalty matrix for the two q_alpha additive functions

# Set smoothness parameters for two functions
 lambda = c(0.1,0.2)

S_lambda.q=matrix(0,nrow=n.knot.q*dim(X.add.q)[4],ncol=n.knot.q*dim(X.add.q)[4])
for(i in 1:dim(X.add.q)[4]){
 for(j in 1:n.knot.q){
  for(k in 1:n.knot.q){
   S_lambda.q[(j+(i-1)*n.knot.q),(k+(i-1)*n.knot.q)]=lambda[i]*rad(knots.q[i,j],knots.q[i,k])
  }
}
}

#Get knots for s_\beta predictor
knots.s=matrix(nrow=dim(X.add.s)[4],ncol=n.knot.s)
for( i in 1:dim(X.add.s)[4]){
 knots.s[i,]=quantile(X.add.s[,,,i],probs=seq(0,1,length=n.knot.s))
}

#Evaluate radial basis functions for s_\beta predictor
X.add.basis.s<-array(dim=c(dim(X.add.s),n.knot.s))
for( i in 1:dim(X.add.s)[4]) {
  for(k in 1:n.knot.s) {
    X.add.basis.s[,,,i,k]= rad(x=X.add.s[,,,i],c=knots.s[i,k])
    #Evaluate rad at all entries to X.add.q and for all knots
```

```
  }}

#Create smoothing penalty matrix for the s_beta additive function

# Set smoothness parameter
 lambda = c(0.2)

S_lambda.s=matrix(0,nrow=n.knot.s*dim(X.add.s)[4],ncol=n.knot.s*dim(X.add.s)[4])
for(i in 1:dim(X.add.s)[4]){
 for(j in 1:n.knot.s){
  for(k in 1:n.knot.s){
   S_lambda.s[(j+(i-1)*n.knot.s),(k+(i-1)*n.knot.s)]=lambda[i]*rad(knots.s[i,j],knots.s[i,k])
  }
}
}

#Join in one list
S_lambda =list("S_lambda.q"=S_lambda.q, "S_lambda.s"=S_lambda.s)

#lin+GAM+NN models defined for both location and scale parameters
X.q=list("X.nn.q"=X.nn.q, "X.lin.q"=X.lin.q,
               "X.add.basis.q"=X.add.basis.q) #Predictors for q_\alpha
X.s=list("X.nn.s"=X.nn.s, "X.lin.s"=X.lin.s,
               "X.add.basis.s"=X.add.basis.s) #Predictors for s_\beta

#We treat u as fixed and known. In an application, u can be estimated using quant.NN.train.

#Fit the bGEV-PP model using u. Note that training is not run to completion.
NN.fit<-bGEVPP.NN.train(Y.train, Y.valid,X.q,X.s, u, type="MLP",link.loc="identity",
                        n.ep=500, batch.size=50,init.loc=2, init.spread=2,init.xi=0.1,
                        widths=c(6,3),seed=1, n_b=12,S_lambda=S_lambda)
out<-bGEVPP.NN.predict(X.q=X.q,X.s=X.s,u=u,NN.fit$model)

print("q_alpha linear coefficients: "); print(round(out$lin.coeff_q,2))
print("s_beta linear coefficients: "); print(round(out$lin.coeff_s,2))

# Note that this is a simple example that can be run in a personal computer.
# Whilst the q_alpha functions are well estimated, more data/larger n.ep are required for more accurate
# estimation of s_beta functions and xi

#To save model, run
#model %>% NN.fit$save_model_tf("model_bGEVPP")
#To load model, run
# model  <- load_model_tf("model_bGEVPP",
#  custom_objects=list(
#    "bgev_PP_loss_alpha__beta__p_a__p_b__c1__c2__n_b__S_lambda___S_lambda_"=
#      bgev_PP_loss(n_b=12,S_lambda=S_lambda))
#        )

#Note that bGEV_PP_loss() can take custom alpha,beta, p_a, p_b, c1 and c2 arguments if defaults not used.


# Plot splines for the additive predictors

#Location predictors
n.add.preds_q=dim(X.add.q)[length(dim(X.add.q))]
par(mfrow=c(1,n.add.preds_q))
```

```
for(i in 1:n.add.preds_q){
 plt.x=seq(from=min(knots.q[i,]),to=max(knots.q[i,]),length=1000) #Create sequence for x-axis

  tmp=matrix(nrow=length(plt.x),ncol=n.knot.q)
  for(j in 1:n.knot.q){
   tmp[,j]=rad(plt.x,knots.q[i,j]) #Evaluate radial basis function of plt.x and all knots
  }
  plt.y=tmp%*%out$gam.weights_q[i,]
 plot(plt.x,plt.y,type="l",main=paste0("q_alpha spline: predictor ",i),xlab="x",ylab="f(x)")
  points(knots.q[i,],rep(mean(plt.y),n.knot.q),col="red",pch=2)
  #Adds red triangles that denote knot locations

}

#Spread predictors
n.add.preds_s=dim(X.add.s)[length(dim(X.add.s))]
par(mfrow=c(1,n.add.preds_s))
for(i in 1:n.add.preds_s){
 plt.x=seq(from=min(knots.s[i,]),to=max(knots.s[i,]),length=1000) #Create sequence for x-axis

  tmp=matrix(nrow=length(plt.x),ncol=n.knot.s)
  for(j in 1:n.knot.s){
   tmp[,j]=rad(plt.x,knots.s[i,j]) #Evaluate radial basis function of plt.x and all knots
  }
  plt.y=tmp%*%out$gam.weights_s[i,]
 plot(plt.x,plt.y,type="l",main=paste0("s_beta spline: predictor ",i),xlab="x",ylab="f(x)")
  points(knots.s[i,],rep(mean(plt.y),n.knot.s),col="red",pch=2)
  #Adds red triangles that denote knot locations

}
```

---

eGPD *The extended GPD distribution*

Description

Distribution function, quantile function and random generation for the extended generalised Pareto distribution (eGPD) with scale `sigma` > `0` and shapes `kappa` > `0` and `xi` > `0`. Note that unlike similar functions in package `stats`, these functions accept only scalar inputs, rather than vectors, for the parameters.

Usage

```
peGPD(y, sigma, kappa, xi, log = F)

qeGPD(prob, sigma, kappa, xi)

reGPD(n, sigma, kappa, xi)
```

Arguments

`y`	scalar quantile.
`sigma`	scalar scale parameter.

kappa	scalar location parameter.
xi	scalar shape parameter.
log	logical; if TRUE, probabilities are given as log(prob).
prob	scalar probability.
n	number of replications.

Details

Originally proposed by Papastathopoulos and Tawn (2013), the first family of the eGPD (as named by Naveau et al., 2016) has distribution function

$$G(y|\sigma,\kappa,\xi) = [\{1+\xi(y-\mu)/\sigma\}_+^{-1/\xi}]^\kappa$$

for scale $\sigma > 0$ and shapes $\kappa > 0$ and $\xi > 0$.

Value

peGPD gives the distribution function; qeGPD gives the quantile function; reGPD generates random deviates.

References

Papastathopoulos, I. and Tawn, J. A. (2013), *xtended generalised Pareto models for tail estimation*, Journal of Statistical Planning and Inference, 43(1):131–1439. (doi)

Naveau, P., Huser, R., Ribereau, P., and Hannart, A. (2016), *Modeling jointly low, moderate, and heavy rainfall intensities without a threshold selection*, Water Resources Research, 2(4):2753–2769. (doi)

---

eGPD.NN *eGPD PINN*

Description

Build and train a partially-interpretable neural network for fitting an eGPD model

Usage

```
eGPD.NN.train(Y.train, Y.valid = NULL, X.s, X.k, type = "MLP",
  offset = NULL, A = NULL, n.ep = 100, batch.size = 100,
  init.scale = NULL, init.kappa = NULL, init.xi = NULL, widths = c(6,
  3), filter.dim = c(3, 3), seed = NULL, init.wb_path = NULL,
  S_lambda = NULL)

eGPD.NN.predict(X.s, X.k, model, offset = NULL)
```

Arguments

`Y.train, Y.valid`

a 2 or 3 dimensional array of training or validation real response values. Missing values can be handled by setting corresponding entries to `Y.train` or `Y.valid` to `-1e10`. The first dimension should be the observation indices, e.g., time.

If `type=="CNN"`, then `Y.train` and `Y.valid` must have three dimensions with the latter two corresponding to an M by N regular grid of spatial locations. If `type=="GCNN"`, then `Y.train` and `Y.valid` must have two dimensions with the latter corresponding to M spatial locations. If `Y.valid==NULL`, no validation loss will be computed and the returned model will be that which minimises the training loss over `n.ep` epochs.

`X.s`

list of arrays corresponding to complementary subsets of the $d \geq 1$ predictors which are used for modelling the scale parameter $sigma$. Must contain at least one of the following three named entries:

`X.lin.s` A 3 or 4 dimensional array of "linear" predictor values. One more dimension than `Y.train`. If `NULL`, a model without the linear component is built and trained. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $l_1 \geq 0$ 'linear' predictor values.

`X.add.basis.s` A 4 or 5 dimensional array of basis function evaluations for the "additive" predictor values. The first 2/3 dimensions should be equal to that of `Y.train`; the penultimate dimensions corresponds to the chosen $a_1 \geq 0$ 'linear' predictor values and the last dimension is equal to the number of knots used for estimating the splines. See example. If `NULL`, a model without the additive component is built and trained.

`X.nn.s` A 3 or 4 dimensional array of "non-additive" predictor values. If `NULL`, a model without the NN component is built and trained; if this is the case, then `type` has no effect. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $d - l_1 - a_1 \geq 0$ 'non-additive' predictor values.

Note that `X.s` and `X.k` are the predictors for both `Y.train` and `Y.valid`. If `is.null(X.s)`, then σ will be treated as fixed over the predictors.

`X.k`

similarly to `X.s`, but for modelling the shape parameter $\kappa > 0$. Note that we require at least one of `!is.null(X.s)` or `!is.null(X.k)`, otherwise the formulated model will be fully stationary and will not be fitted.

`type`

string defining the type of network to be built. If `type=="MLP"`, the network will have all densely connected layers; if `type=="CNN"`, the network will have all convolutional layers. If `type=="GCNN"`, then a graph convolutional neural network (with skip connections) is used and require `!is.null(A)`. Defaults to an MLP (currently the same network is used for all parameters, may change in future versions).

`offset`

an array of strictly positive scalars the same dimension as `Y.train`, containing the offset values used in modelling the scale parameter. If `offset=NULL`, then no offset is used in the scale parameter (equivalently, `offset` is populated with ones). Defaults to `NULL`.

`A`

$M \times M$ adjacency matrix used if and only if `type=="GCNN"`. Must be supplied, defaults to `NULL`.

`n.ep`

number of epochs used for training. Defaults to 1000.

`batch.size`

batch size for stochastic gradient descent. If larger than `dim(Y.train)[1]`, i.e., the number of observations, then regular gradient descent used.

`init.scale, init.kappa, init.xi`
: sets the initial σ, κ and ξ estimates across all dimensions of `Y.train`. Overridden by `init.wb_path` if `!is.null(init.wb_path)`, but otherwise the initial parameters must be supplied.

`widths`
: vector of widths/filters for hidden layers. Number of layers is equal to `length(widths)`. Defaults to (6,3).

`filter.dim`
: if `type=="CNN"`, this 2-vector gives the dimensions of the convolution filter kernel; must have odd integer inputs. Note that filter.dim=c(1,1) is equivalent to `type=="MLP"`. The same filter is applied for each hidden layer across all parameters with NN predictors.

`seed`
: seed for random initial weights and biases.

`init.wb_path`
: filepath to a `keras` model which is then used as initial weights and biases for training the new model. The original model must have the exact same architecture and trained with the same input data as the new model. If `NULL`, then initial weights and biases are random (with seed `seed`) but the final layer has zero initial weights to ensure that the initial scale, kappa and shape estimates are `init.scale, init.kappa` and `init.xi`, respectively, across all dimensions.

`S_lambda`
: list of smoothing penalty matrices for the splines modelling the effects of `X.add.basis.s` and `X.add.basis.k` on their respective parameters; each element only used if `!is.null(X.add.basis.s)` and `!is.null(X.add.basis.k)`, respectively. If `is.null(S_lambda[[1]])`, then no smoothing penalty used for σ; similarly for the second element and κ.

`model`
: fitted `keras` model. Output from `bGEVPP.NN.train`.

Details

Consider a real-valued random variable Y and let $\mathbf{X}$ denote a d-dimensional predictor set with observations $\mathbf{x}$. For $i = 1, 2$, we define integers $l_i \geq 0, a_i \geq 0$ and $0 \leq l_i + a_i \leq d$, and let $\mathbf{X}_L^{(i)}, \mathbf{X}_A^{(i)}$ and $\mathbf{X}_N^{(i)}$ be distinct sub-vectors of $\mathbf{X}$, with observations of each component denoted $\mathbf{x}_L^{(i)}, \mathbf{x}_A^{(i)}$ and $\mathbf{x}_N^{(i)}$, respectively; the lengths of the sub-vectors are l_i, a_i and $d_i - l_i - a$, respectively. We model $Y|\mathbf{X} = \mathbf{x} \sim \text{eGPD}(\sigma(\mathbf{x}), \kappa(\mathbf{x}), \xi)$ for $\xi > 0$ with

$$\sigma(\mathbf{x}) = C(\mathbf{x}) \exp\{\eta_0^{(1)} + m_L^{(1)}(\mathbf{x}_L^{(1)}) + m_A^{(1)}(x_A^{(1)}) + m_N^{(1)}(\mathbf{x}_N^{(1)})\}$$

and

$$\kappa(\mathbf{x}) = \exp\{\eta_0^{(2)} + m_L^{(2)}(\mathbf{x}_L^{(2)}) + m_A^{(2)}(x_A^{(2)}) + m_N^{(2)}(\mathbf{x}_N^{(2)})\}$$

where $\eta_0^{(1)}, \eta_0^{(2)}$ are constant intercepts and $C(\mathbf{x}) > 0$ is a fixed offset term. The unknown functions $m_L^{(1)}, m_L^{(2)}$ and $m_A^{(1)}, m_A^{(2)}$ are estimated using linear functions and splines, respectively, and are both returned as outputs by `eGPD.NN.predict`; $m_N^{(1)}, m_N^{(2)}$ are estimated using neural networks (currently the same architecture is used for both parameters). The offset term is, by default, $C(\mathbf{x}) = 1$ for all $\mathbf{x}$; if `!is.null(offset)`, then `offset` determines $C(\mathbf{x})$ (see Cisneros et al., 2023). Note that $\xi > 0$ is fixed across all predictors; this may change in future versions. Note that $\xi > 0$ is fixed across all predictors; this may change in future versions.

For details of the eGPD distribution, see `help(peGPD)`.

The model is fitted by minimising the negative log-likelihood associated with the bGEV model plus some smoothing penalty for the additive functions (determined by `S_lambda`; see Richards and Huser, 2022); training is performed over `n.ep` training epochs. Although the model is trained by minimising the loss evaluated for `Y.train`, the final returned model may minimise some other loss. The current state of the model is saved after each epoch, using `keras::callback_model_checkpoint`,

if the value of some criterion subcedes that of the model from the previous checkpoint; this criterion is the loss evaluated for validation set `Y.valid` if `!is.null(Y.valid)` and for `Y.train`, otherwise.

A non-interpretable version of this model was exploited by Cisneros et al. (2023). Equivalence with their model is achieved by setting `X.k=NULL`, `X.lin.s=NULL`, `X.add.basis.s=NULL` and `type="GCNN"`. See `help(AusWild)`.

Value

`eGPD.NN.train` returns the fitted `model`. `eGPD.NN.predict` is a wrapper for `keras::predict` that returns the predicted parameter estimates, and, if applicable, their corresponding linear regression coefficients and spline bases weights.

References

Papastathopoulos, I. and Tawn, J. A. (2013), *xtended generalised Pareto models for tail estimation*, Journal of Statistical Planning and Inference, 43(1):131–1439. (doi)

Naveau, P., Huser, R., Ribereau, P., and Hannart, A. (2016), *Modeling jointly low, moderate, and heavy rainfall intensities without a threshold selection*, Water Resources Research, 2(4):2753–2769. (doi)

Richards, J. and Huser, R. (2022), *Regression modelling of spatiotemporal extreme U.S. wildfires via partially-interpretable neural networks*. (arXiv:2208.07581).

Cisneros, D., Richards, J., Dahal, A., Lombardo, L., and Huser, R. (2023), *Deep learning-based graphical regression for jointly moderate and extreme Australian wildfires.*. (In draft).

Examples

```
set.seed(1)

# Create  predictors
preds<-rnorm(prod(c(2500,10,8)))


#Re-shape to a 3d array. First dimension corresponds to observations,
#last to the different components of the predictor set.
#Other dimensions correspond to indices of predictors, e.g., a grid of locations. Can be a 1D or 2D grid.
dim(preds)=c(2500,10,8)
#We have 2000 observations of eight predictors at 10 sites.


#Split predictors into linear, additive and nn. Different for kappa and scale parameters.
X.nn.k=preds[,,1:4] #Four nn predictors for kappa
X.lin.k=preds[,,5:6] #Two additive predictors for kappa
X.add.k=preds[,,7:8] #Two additive predictors for kappa

X.nn.s=preds[,,1:2] #Two nn predictors for sigma
X.lin.s=preds[,,3] #One linear predictor for sigma
dim(X.lin.s)=c(dim(X.lin.s),1) #Change dimension so consistent
X.add.s=preds[,,4] #One additive predictor for sigma
dim(X.add.s)=c(dim(X.add.s),1) #Change dimension so consistent

# Create toy response data

#Contribution to scale parameter
#Linear contribution
```

```
m_L_1 = 0.2*X.lin.s[,,1]

# Additive contribution
m_A_1 = 0.1*X.add.s[,,1]^2+0.2*X.add.s[,,1]

plot(X.add.s[,,1],m_A_1)

#Non-additive contribution - to be estimated by NN
m_N_1 = 0.2*exp(-4+X.nn.s[,,2]+X.nn.s[,,1])+
  0.1*sin(X.nn.s[,,1]-X.nn.s[,,2])*(X.nn.s[,,1]+X.nn.s[,,2])

sigma=0.4*exp(0.5+m_L_1+m_A_1+m_N_1+1) #Exponential link


#Contribution to kappa parameter
#Linear contribution
m_L_2 = 0.1*X.lin.k[,,1]-0.02*X.lin.k[,,2]

# Additive contribution
m_A_2 = 0.1*X.add.k[,,1]^2+0.1*X.add.k[,,1]-
  0.025*X.add.k[,,2]^3+0.025*X.add.k[,,2]^2

#Non-additive contribution - to be estimated by NN
m_N_2 = 0.5*exp(-3+X.nn.k[,,4]+X.nn.k[,,1])+
  sin(X.nn.k[,,1]-X.nn.k[,,2])*(X.nn.k[,,4]+X.nn.k[,,2])-
  cos(X.nn.k[,,4]-X.nn.k[,,1])*(X.nn.k[,,3]+X.nn.k[,,1])

kappa=exp(m_L_2+m_A_2+0.05 *m_N_2)  #Exponential link


xi=0.1 # Set xi

theta=array(dim=c(dim(sigma),3))
theta[,,1]=sigma; theta[,,2] = kappa; theta[,,3]=xi
#We simulate data from an eGPD model

#Simulate from eGPD model using same u as given above
Y=apply(theta,1:2,function(x) reGPD(1,sigma=x[1],kappa=x[2],xi=x[3]))



#Create training and validation, respectively.
#We mask 20% of the Y values and use this for validation
#Masked values must be set to -1e10 and are treated as missing whilst training

mask_inds=sample(1:length(Y),size=length(Y)*0.8)

Y.train<-Y.valid<-Y #Create training and validation, respectively.
Y.train[-mask_inds]=-1e10
Y.valid[mask_inds]=-1e10



#To build a model with an additive component, we require an array of evaluations of
#the basis functions for each pre-specified knot and entry to X.add.k and X.add.s

rad=function(x,c){ #Define a basis function. Here we use the radial bases
```

```
  out=abs(x-c)^2*log(abs(x-c))
  out[(x-c)==0]=0
  return(out)
}

n.knot.s = 4; n.knot.k = 5# set number of knots.
#Must be the same for each additive predictor,
#but can differ between the parameters sigma and kappa


#Get knots for sigma predictor
knots.s=matrix(nrow=dim(X.add.s)[3],ncol=n.knot.s)
for( i in 1:dim(X.add.s)[3]){
  knots.s[i,]=quantile(X.add.s[,,i],probs=seq(0,1,length=n.knot.s))
}

#Evaluate radial basis functions for s_\beta predictor
X.add.basis.s<-array(dim=c(dim(X.add.s),n.knot.s))
for( i in 1:dim(X.add.s)[3]) {
  for(k in 1:n.knot.s) {
    X.add.basis.s[,,i,k]= rad(x=X.add.s[,,i],c=knots.s[i,k])
    #Evaluate rad at all entries to X.add.k and for all knots
  }}




#Create smoothing penalty matrix for the sigma additive function

# Set smoothness parameter
lambda = c(0.2)

S_lambda.s=matrix(0,nrow=n.knot.s*dim(X.add.s)[3],ncol=n.knot.s*dim(X.add.s)[3])
for(i in 1:dim(X.add.s)[3]){
  for(j in 1:n.knot.s){
    for(k in 1:n.knot.s){
    S_lambda.s[(j+(i-1)*n.knot.s),(k+(i-1)*n.knot.s)]=lambda[i]*rad(knots.s[i,j],knots.s[i,k])
    }
  }
}
#Get knots for kappa predictors
knots.k=matrix(nrow=dim(X.add.k)[3],ncol=n.knot.k)

#We set knots to be equally-spaced marginal quantiles
for( i in 1:dim(X.add.k)[3]){
  knots.k[i,]=quantile(X.add.k[,,i],probs=seq(0,1,length=n.knot.k))
}


#Evaluate radial basis functions for kappa predictors
X.add.basis.k<-array(dim=c(dim(X.add.k),n.knot.k))
for( i in 1:dim(X.add.k)[3]) {
  for(k in 1:n.knot.k) {
    X.add.basis.k[,,i,k]= rad(x=X.add.k[,,i],c=knots.k[i,k])
    #Evaluate rad at all entries to X.add.k and for all knots
  }}
```

```
#'#Create smoothing penalty matrix for the two kappa additive functions

# Set smoothness parameters for two functions
lambda = c(0.1,0.2)

S_lambda.k=matrix(0,nrow=n.knot.k*dim(X.add.k)[3],ncol=n.knot.k*dim(X.add.k)[3])
for(i in 1:dim(X.add.k)[3]){
  for(j in 1:n.knot.k){
    for(k in 1:n.knot.k){
    S_lambda.k[(j+(i-1)*n.knot.k),(k+(i-1)*n.knot.k)]=lambda[i]*rad(knots.k[i,j],knots.k[i,k])
    }
  }
}


#Join in one list
S_lambda =list("S_lambda.k"=S_lambda.k, "S_lambda.s"=S_lambda.s)

#lin+GAM+NN models defined for both scale and kappa parameters
X.s=list("X.nn.s"=X.nn.s, "X.lin.s"=X.lin.s,
         "X.add.basis.s"=X.add.basis.s) #Predictors for sigma
X.k=list("X.nn.k"=X.nn.k, "X.lin.k"=X.lin.k,
         "X.add.basis.k"=X.add.basis.k) #Predictors for kappa


#Fit the eGPD model. Note that training is not run to completion.
NN.fit<-eGPD.NN.train(Y.train, Y.valid,X.s,X.k, type="MLP",
                      n.ep=50, batch.size=50,init.scale=1, init.kappa=1,init.xi=0.1,
                      widths=c(6,3),seed=1,S_lambda=S_lambda)
out<-eGPD.NN.predict(X.s=X.s,X.k=X.k,NN.fit$model)

print("sigma linear coefficients: "); print(round(out$lin.coeff_s,2))
print("kappa linear coefficients: "); print(round(out$lin.coeff_k,2))

# Note that this is a simple example that can be run in a personal computer.


# #To save model, run
# NN.fit$model %>% save_model_tf("model_eGPD")
# #To load model, run
#  model  <- load_model_tf("model_eGPD",
#   custom_objects=list(
#     "eGPD_loss_S_lambda___S_lambda_"=
#       eGPD_loss(S_lambda=S_lambda))
#         )


# Plot splines for the additive predictors



#Sigma predictors
n.add.preds_s=dim(X.add.s)[length(dim(X.add.s))]
par(mfrow=c(1,n.add.preds_s))
for(i in 1:n.add.preds_s){
 plt.x=seq(from=min(knots.s[i,]),to=max(knots.s[i,]),length=1000) #Create sequence for x-axis
```

```
  tmp=matrix(nrow=length(plt.x),ncol=n.knot.s)
  for(j in 1:n.knot.s){
   tmp[,j]=rad(plt.x,knots.s[i,j]) #Evaluate radial basis function of plt.x and all knots
  }
  plt.y=tmp%*%out$gam.weights_s[i,]
 plot(plt.x,plt.y,type="l",main=paste0("sigma spline: predictor ",i),xlab="x",ylab="f(x)")
  points(knots.s[i,],rep(mean(plt.y),n.knot.s),col="red",pch=2)
  #Adds red triangles that denote knot locations

}

#Kappa predictors
n.add.preds_k=dim(X.add.k)[length(dim(X.add.k))]
par(mfrow=c(1,n.add.preds_k))
for(i in 1:n.add.preds_k){
 plt.x=seq(from=min(knots.k[i,]),to=max(knots.k[i,]),length=1000) #Create sequence for x-axis

  tmp=matrix(nrow=length(plt.x),ncol=n.knot.k)
  for(j in 1:n.knot.k){
   tmp[,j]=rad(plt.x,knots.k[i,j]) #Evaluate radial basis function of plt.x and all knots
  }
  plt.y=tmp%*%out$gam.weights_k[i,]
 plot(plt.x,plt.y,type="l",main=paste0("kappa spline: predictor ",i),xlab="x",ylab="f(x)")
  points(knots.k[i,],rep(mean(plt.y),n.knot.k),col="red",pch=2)
  #Adds red triangles that denote knot locations

}
```

---

evPP *The extreme value point process*

Description

Quantile function and random generation for the extreme value point process with location equal to `loc`, scale equal to `scale` and shape equal to `xi >= 0`. Note that unlike similar functions in package `stats`, these functions accept only scalar inputs, rather than vectors, for the parameters.

Usage

```
qPP(prob, loc, scale, xi, n_b = 1, re.par = F, alpha = 0.5, beta = 0.5,
  tol = 1e-04, qMax = 10000)

rPP(n, u.prob, loc, scale, xi, n_b = 1, re.par = F, alpha = 0.5,
  beta = 0.5, tol = 1e-04, qMax = 10000)
```

Arguments

`prob`	scalar probability.
`loc`	location parameter. If `re.par==FALSE`, then `loc` corresponds to μ; otherwise, `loc` corresponds to q_α.
`scale`	scale parameter. If `re.par==FALSE`, then `scale` corresponds to σ; otherwise, `scale` corresponds to s_β.
`xi`	shape parameter. Require `xi >= 0`.

n_b	number of observations per block, e.g., if observations correspond to months and the interest is annual maxima, then n_b=12. See details.
re.par	logical; if TRUE, then the corresponding GEV used the alternative parameterisation.
alpha, beta	hyper-parameters for the reparameterisation, see details. Defaults set both to 0.5. Only used if re.par==TRUE.
tol	tolerance for the numerical solver. Defaults to 1e-4.
qMax	finite upper and lower bounds used by the numerical solver. If the absolute value of the output from qPP or maximum output from rPP is close to qMax, then qMax needs increasing at the cost of computation time. Defaults to 1e4.
n	number of replications.
u.prob	exceedance probability for threshold u.

Details

Following Coles (2001), consider a sequence of independent random variables $Y_1, \ldots, Y_n$ with common distribution function F. For n_b-block-maxima $M_{n_b} = \max\{Y_1, \ldots, Y_{n_b}\}$; if there exists sequences $\{a_n > 0\}$ and $\{b_n\}$ such that

$$\Pr\{(M_{n_b} - b_n)/a_n \leq z\} \to G(z) \text{ as } n_b \to \infty,$$

for non-degenerate G, then G is the generalised extreme value GEV(μ, σ, ξ) distribution function, see help{pbGEV}. If $\xi > 0$, then G has finite lower-endpoint $z_- = \mu - \sigma/\xi$; if $\xi = 0$, then the lower-endpoint is infinite.

Assume that the above limit holds and $\xi \geq 0$. Then for any $u > z_-$, the sequence of point processes $N_n = \{(i/(n+1), (Y_i - b_n)/a_n) : i = 1, \ldots, n\}$ converges on regions $(0,1) \times (u, \infty)$ as $n \to \infty$ to a Poisson point process with intensity measure Λ of the form $\Lambda(A) = -(n/n_b)(t_2 - t_1)\log G(z)$, where $A = [t_1, t_2] \times [z, \infty)$ for $0 \leq t_1 \leq t_2 \leq 1$. We consider unit inter-arrival times and so set $t_2 - t_1 = 1$. Here the functions qPP and rPP give the quantile function and random generation of Y assuming that the Poisson process limit holds for Y above u. The threshold u is taken to be the u.prob quantile of Y.

Castro-Camilo et al. (2021) propose a reparameterisation of the GEV distribution in terms of a location parameter q_α for $\alpha \in (0,1)$, denoting the GEV α-quantile, and a spread parameter $s_\beta = q_{1-\beta/2} - q_{\beta/2}$ for $\beta \in (0,1)$; for the full mapping, see help{pbGEV}. If re.par==TRUE, then the input loc and scale correspond to q_α and s_β, rather than μ and σ.

Distribution function inversion is performed numerically using the bisection method.

Value

qPP gives the quantile function and rPP generates n random deviates. Any simulated values subceding the threshold u are treated as censored and set to NA.

References

Coles, S. G. (2001), *An Introduction to Statistical Modeling of Extreme Values*. Volume 208, Springer. (doi)

Castro-Camilo, D., Huser, R., and Rue, H. (2021), *Practical strategies for generalized extreme value-based regression models for extremes*, Environmetrics, e274. (doi)

Examples

```
set.seed(1)
loc<-3; scale<-4; xi<-0.2 #Parameter values

u<-qPP(prob=0.9,loc,scale,xi) #Gives the 90% quantile of Y

#Create 1000 realisations of Y with exceedance threshold equal to u.
#Note that the input to rPP is the exceedance probability u.prob, not the threshold itself
Y<-rPP(1000,u.prob=0.9,loc,scale,xi)
hist(Y)
#Note that values Y<u are censored and set to NA
```

GPD.NN *GPD PINN*

Description

Build and train a partially-interpretable neural network for fitting a GPD model to threshold exceedances

Usage

```
GPD.NN.train(Y.train, Y.valid = NULL, X, u = NULL, type = "MLP",
  offset = NULL, re.par = F, n.ep = 100, batch.size = 100,
  init.scale = NULL, init.xi = NULL, widths = c(6, 3),
  filter.dim = c(3, 3), seed = NULL, init.wb_path = NULL,
  S_lambda = NULL)

GPD.NN.predict(X, u, model, offset = NULL)
```

Arguments

`Y.train, Y.valid`

a 2 or 3 dimensional array of training or validation real response values. Missing values can be handled by setting corresponding entries to `Y.train` or `Y.valid` to `-1e10`. The first dimension should be the observation indices, e.g., time.

If `type=="CNN"`, then `Y.train` and `Y.valid` must have three dimensions with the latter two corresponding to an M by N regular grid of spatial locations. If `Y.valid==NULL`, no validation loss will be computed and the returned model will be that which minimises the training loss over `n.ep` epochs.

`X` list of arrays corresponding to complementary subsets of the $d \geq 1$ predictors which are used for modelling the scale parameter σ_u (or σ if `re.par==TRUE`). Must contain at least one of the following three named entries:

`X.lin` A 3 or 4 dimensional array of "linear" predictor values. One more dimension then `Y.train`. If `NULL`, a model without the linear component is built and trained. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $l \geq 0$ 'linear' predictor values.

`X.add.basis` A 4 or 5 dimensional array of basis function evaluations for the "additive" predictor values. The first 2/3 dimensions should be equal to that of `Y.train`; the penultimate dimensions corresponds to the chosen $a \geq 0$ 'linear' predictor values and the last dimension is equal to the number of knots used for estimating the splines. See example. If `NULL`, a model without the additive component is built and trained.

`X.nn` A 3 or 4 dimensional array of "non-additive" predictor values. If `NULL`, a model without the NN component is built and trained; if this is the case, then `type` has no effect. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $d - l - a \geq 0$ 'non-additive' predictor values.

Note that `X` is the predictors for both `Y.train` and `Y.valid`.

`u` an array with the same dimension as `Y.train`. Gives the threshold used to create exceedances of `Y.train`, see below. Note that `u` is applied to both `Y.train` and `Y.valid`.

`type` string defining the type of network to be built. If `type=="MLP"`, the network will have all densely connected layers; if `type=="CNN"`, the network will have all convolutional layers. Defaults to an MLP. (Currently the same network is used for all parameters, may change in future versions)

`offset` an array of strictly positive scalars the same dimension as `Y.train`, containing the offset values used in modelling the scale parameter. If `offset=NULL`, then no offset is used in the scale parameter (equivalently, `offset` is populated with ones). Defaults to `NULL`.

`re.par` if `TRUE`, uses the re-parameterised version of the GPD. Defaults to `FALSE`.

`n.ep` number of epochs used for training. Defaults to 1000.

`batch.size` batch size for stochastic gradient descent. If larger than `dim(Y.train)[1]`, i.e., the number of observations, then regular gradient descent used.

`init.scale, init.xi`

sets the initial σ_u (or σ) and $\xi \in (0, 1)$ estimates across all dimensions of `Y.train`. Overridden by `init.wb_path` if `!is.null(init.wb_path)`, but otherwise the initial parameters must be supplied. Note that if `!is.null(offset)`, then the initial scale parameter array will be `init.scale*offset`.

`widths` vector of widths/filters for hidden dense/convolution layers. Number of layers is equal to `length(widths)`. Defaults to (6,3).

`filter.dim` if `type=="CNN"`, this 2-vector gives the dimensions of the convolution filter kernel; must have odd integer inputs. Note that filter.dim=c(1,1) is equivalent to `type=="MLP"`. The same filter is applied for each hidden layer across all parameters with NN predictors.

`seed` seed for random initial weights and biases.

`init.wb_path` filepath to a `keras` model which is then used as initial weights and biases for training the new model. The original model must have the exact same architecture and trained with the same input data as the new model. If `NULL`, then initial weights and biases are random (with seed `seed`) but the final layer has zero initial weights to ensure that the initial scale and shape estimates are `init.scale` and `init.xi`, respectively, across all dimensions.

`model` fitted `keras` model. Output from `GPD.NN.train`.

`S_lamda` smoothing penalty matrix for the splines modelling the effect of `X.add.basis` on $\log(\sigma_u)$ (or $\log(\sigma)$); only used if `!is.null(X.add.basis)`. If `is.null(S_lambda)`, then no smoothing penalty is used.

Details

Consider a real-valued random variable Y and let $\mathbf{X}$ denote a d-dimensional predictor set with observations $\mathbf{x}$. For integers $l \geq 0, a \geq 0$ and $0 \leq l + a \leq d$, let $\mathbf{X}_L, \mathbf{X}_A$ and $\mathbf{X}_N$ be distinct sub-vectors of $\mathbf{X}$, with observations of each component denoted $\mathbf{x}_L, \mathbf{x}_A$ and $\mathbf{x}_N$, respectively; the lengths of the sub-vectors are l, a and $d - l - a$, respectively. For a fixed threshold $u(\mathbf{x})$, dependent on predictors, we model $\{Y - u(\mathbf{x})\}|\mathbf{X} = \mathbf{x} \sim \text{GPD}\{\sigma_u(\mathbf{x}), \xi; u(\mathbf{x})\}$ for $\xi \in (0, 1)$ with $\sigma_u(\mathbf{x})$ dependent on predictors $\mathbf{x}$. If `re.par==FALSE`, then we model

$$\sigma_u(\mathbf{x}) = C(\mathbf{x}) \exp\{\eta_0 + m_L(\mathbf{x}_L) + m_A(\mathbf{x}_A) + m_N(\mathbf{x}_N)\},$$

where η_0 is a constant intercept and $C(\mathbf{x}) > 0$ is a fixed offset term; if `re.par==TRUE`, we use the re-parameterisation proposed by Richards et al. (2022), and instead model

$$\sigma(\mathbf{x}) = C(\mathbf{x}) \exp\{\eta_0 + m_L(\mathbf{x}_L) + m_A(\mathbf{x}_A) + m_N(\mathbf{x}_N)\},$$

and set $\sigma_u(\mathbf{x}) = \sigma(\mathbf{x}) + u(\mathbf{x})\xi$. The unknown functions m_L and m_A are estimated using linear functions and splines, respectively, and are both returned as outputs by `GPD.NN.predict`; m_N is estimated using a neural network (currently the same architecture is used for both parameters). The offset term is, by default, $C(\mathbf{x}) = 1$ for all $\mathbf{x}$; if `!is.null(offset)`, then `offset` determines $C(\mathbf{x})$ (see Richards et al., 2022). Note that $\xi > 0$ is fixed across all predictors; this may change in future versions.

For details of the generalised Pareto distribution, see `help(pgpd)`. Note we use the parameterisation $u = a$, $\sigma_u = b$ and $\xi = s$.

The model is fitted by minimising the negative log-likelihood associated with the GPD model over `n.ep` training epochs. Although the model is trained by minimising the loss evaluated for `Y.train`, the final returned model may minimise some other loss. The current state of the model is saved after each epoch, using `keras::callback_model_checkpoint`, if the value of some criterion subcedes that of the model from the previous checkpoint; this criterion is the loss evaluated for validation set `Y.valid` if `!is.null(Y.valid)` and for `Y.train`, otherwise.

Value

`bGEVPP.NN.train` returns the fitted `model`. `bGEVPP.NN.predict` is a wrapper for `keras::predict` that returns the predicted parameter estimates, and, if applicable, their corresponding linear regression coefficients and spline bases weights.

References

Coles, S. G. (2001), *An Introduction to Statistical Modeling of Extreme Values*. Volume 208, Springer. (doi)

Richards, J. and Huser, R. (2022), *Regression modelling of spatiotemporal extreme U.S. wildfires via partially-interpretable neural networks*. (arXiv:2208.07581)

Richards, J., Huser, R., Bevacqua, E., Zscheischler, J, (2022), *Insights into the drivers and spatio-temporal trends of extreme Mediterranean wildfires with statistical deep-learning.* (arXiv:2212.01796)

Examples

```
#Apply model to toy data

set.seed(1)
# Create  predictors
 preds<-rnorm(prod(c(200,10,10,8)))
```

```
#Re-shape to a 4d array. First dimension corresponds to observations,
#last to the different components of the predictor set.
#Other dimensions correspond to indices of predictors, e.g., a grid of locations. Can be just a 1D grid.
dim(preds)=c(200,10,10,8)
#We have 200 observations of eight predictors on a 10 by 10 grid.

#Split predictors into linear, additive and nn.

X.nn=preds[,,,1:4] #Four nn predictors
X.lin=preds[,,,5:6] #Two linear predictors
X.add=preds[,,,7:8] #Two additive predictors


# Create response data

#Contribution to scale parameter
#Linear contribution
m_L = 0.5*X.lin[,,,1]-0.3*X.lin[,,,2]

# Additive contribution
m_A = 0.2*X.add[,,,1]^2+0.05*X.add[,,,1]-0.1*X.add[,,,2]^2+
0.1*X.add[,,,2]^3

#Non-additive contribution - to be estimated by NN
m_N =0.5*(exp(-4+X.nn[,,,2]+X.nn[,,,3])+
            sin(X.nn[,,,1]-X.nn[,,,2])*(X.nn[,,,1]+X.nn[,,,2])-
            cos(X.nn[,,,3]-X.nn[,,,4])*(X.nn[,,,2]))

sigma=2*exp(-2+m_L+m_A+m_N) #Exponential link
xi=0.2 # Set xi

#We simulate data as exceedances above some random positive threshold u.
u<-apply(sigma,1:3,function(x) rgpd(n=1,loc=0,scale=1,shape=0.1) ) #Random threshold

theta=array(dim=c(dim(sigma),3))
theta[,,,1]=sigma; theta[,,,2]  =xi; theta[,,,3]  =u

#If u were the true 80% quantile, say,  of the response, then only 20% of the data should exceed u.
#We achieve this by simulating a Bernoulli variable to determine if Y exceeds u

require(evd)
Y=apply(theta,1:3,function(x){
  if(rbinom(1,1,0.8)==1) rgpd(n=1,loc=x[3],scale=x[1],shape=x[2]) else  runif(1,0,x[3])
}
) #Simulate GPD exceedances above u as given above


#Create training and validation, respectively.
#We mask 20% of the Y values and use this for validation
#Masked values must be set to -1e10 and are treated as missing whilst training

mask_inds=sample(1:length(Y),size=length(Y)*0.8)

Y.train<-Y.valid<-Y #Create training and validation, respectively.
Y.train[-mask_inds]=-1e10
Y.valid[mask_inds]=-1e10
```

```
#To build a model with an additive component, we require an array of evaluations of
#the basis functions for each pre-specified knot and entry to X.add

rad=function(x,c){ #Define a basis function. Here we use the radial bases
  out=abs(x-c)^2*log(abs(x-c))
  out[(x-c)==0]=0
  return(out)
}

n.knot = 5 # set number of knots. Must be the same for each additive predictor

knots=matrix(nrow=dim(X.add)[4],ncol=n.knot)

#We set knots to be equally-spaced marginal quantiles
for( i in 1:dim(X.add)[4]){
 knots[i,]=quantile(X.add[,,,i],probs=seq(0,1,length=n.knot))
}

X.add.basis<-array(dim=c(dim(X.add),n.knot))
for( i in 1:dim(X.add)[4]) {
  for(k in 1:n.knot) {
    X.add.basis[,,,i,k]= rad(x=X.add[,,,i],c=knots[i,k])
    #Evaluate rad at all entries to X.add and for all knots
  }}

#Create smoothing penalty matrix for the two sigma additive functions

# Set smoothness parameters for the two functions
lambda = c(0.1,0.2)

S_lambda=matrix(0,nrow=n.knot*dim(X.add)[4],ncol=n.knot*dim(X.add)[4])
for(i in 1:dim(X.add)[4]){
 for(j in 1:n.knot){
  for(k in 1:n.knot){
     S_lambda[(j+(i-1)*n.knot),(k+(i-1)*n.knot)]=lambda[i]*rad(knots[i,j],knots[i,k])
  }
}
}

#lin+GAM+NN models defined for scale parameter
X=list("X.nn"=X.nn, "X.lin"=X.lin,
             "X.add.basis"=X.add.basis)

#We treat u as fixed and known. In an application, u can be estimated using quant.NN.train.

#Fit the GPD model for exceedances above u. Note that training is not run to completion.
NN.fit<-GPD.NN.train(Y.train, Y.valid,X, u, type="MLP", re.par=F,
                     n.ep=500, batch.size=50,init.scale=1, init.xi=0.1,
                     widths=c(6,3),seed=1,S_lambda=S_lambda)
out<-GPD.NN.predict(X=X,u=u,model=NN.fit$model)
hist(out$pred.sigma) #Plot histogram of predicted sigma
print("sigma linear coefficients: "); print(round(out$lin.coeff_sigma,2))

#To save model, run
#NN.fit$model %>% save_model_tf("model_GPD")
```

```
#To load model, run
#model  <- load_model_tf("model_GPD",
#custom_objects=list(
#"GPD_loss_S_lambda___S_lambda__re_par___re_par_"=GPD_loss(S_lambda=S_lambda,re.par=F))
#)


# Plot splines for the additive predictors
n.add.preds=dim(X.add)[length(dim(X.add))]
par(mfrow=c(1,n.add.preds))
for(i in 1:n.add.preds){
 plt.x=seq(from=min(knots[i,]),to=max(knots[i,]),length=1000) #Create sequence for x-axis

  tmp=matrix(nrow=length(plt.x),ncol=n.knot)
  for(j in 1:n.knot){
    tmp[,j]=rad(plt.x,knots[i,j]) #Evaluate radial basis function of plt.x and all knots
  }
  plt.y=tmp%*%out$gam.weights_sigma[i,]
 plot(plt.x,plt.y,type="l",main=paste0("sigma spline: predictor ",i),xlab="x",ylab="f(x)")
  points(knots[i,],rep(mean(plt.y),n.knot),col="red",pch=2)
  #Adds red triangles that denote knot locations

}
```

`logistic.NN` *Logistic regression PINN*

Description

Build and train a partially-interpretable neural network for a logistic regression model

Usage

```
logistic.NN.train(Y.train, Y.valid = NULL, X, type = "MLP", A = NULL,
  n.ep = 100, batch.size = 100, init.p = NULL, widths = c(6, 3),
  filter.dim = c(3, 3), seed = NULL, init.wb_path = NULL,
  S_lambda = NULL)

logistic.NN.predict(X, model)
```

Arguments

`Y.train`, `Y.valid`

a 2 or 3 dimensional array of training or validation response values, with entries of 0/1 for failure/success. Missing values can be handled by setting corresponding entries to `Y.train` or `Y.valid` to `-1e10`. The first dimension should be the observation indices, e.g., time.

If `type=="CNN"`, then `Y.train` and `Y.valid` must have three dimensions with the latter two corresponding to an M by N regular grid of spatial locations. If `type=="GCNN"`, then `Y.train` and `Y.valid` must have two dimensions with the latter corresponding to M spatial locations. If `Y.valid==NULL`, no validation loss will be computed and the returned model will be that which minimises the training loss over `n.ep` epochs.

`X` list of arrays corresponding to complementary subsets of the $d \geq 1$ predictors which are used for modelling. Must contain at least one of the following three named entries:

- `X.lin` A 3 or 4 dimensional array of "linear" predictor values. One more dimension than `Y.train`. If `NULL`, a model without the linear component is built and trained. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $l \geq 0$ 'linear' predictor values.
- `X.add.basis` A 4 or 5 dimensional array of basis function evaluations for the "additive" predictor values. The first 2/3 dimensions should be equal to that of `Y.train`; the penultimate dimensions corresponds to the chosen $a \geq 0$ 'linear' predictor values and the last dimension is equal to the number of knots used for estimating the splines. See example. If `NULL`, a model without the additive component is built and trained.
- `X.nn` A 3 or 4 dimensional array of "non-additive" predictor values. If `NULL`, a model without the NN component is built and trained; if this is the case, then `type` has no efect. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $d - l - a \geq 0$ 'non-additive' predictor values.

Note that `X` is the predictors for both `Y.train` and `Y.valid`.

`type` string defining the type of network to be built. If `type=="MLP"`, the network will have all densely connected layers; if `type=="CNN"`, the network will have all convolutional layers. If `type=="GCNN"`, then a graph convolutional neural network (with skip connections) is used and require `!is.null(A)`. Defaults to an MLP (currently the same network is used for all parameters, may change in future versions). Defaults to an MLP.

`A` $M \times M$ adjacency matrix used if and only if `type=="GCNN"`. Must be supplied in this case.

`n.ep` number of epochs used for training. Defaults to 1000.

`batch.size` batch size for stochastic gradient descent. If larger than `dim(Y.train)[1]`, i.e., the number of observations, then regular gradient descent used.

`init.p` sets the initial probability estimate across all dimensions of `Y.train`. Defaults to empirical estimate. Overriden by `init.wb_path` if `!is.null(init.wb_path)`.

`widths` vector of widths/filters for hidden dense/convolution layers. Number of layers is equal to `length(widths)`. Defaults to (6,3).

`filter.dim` if `type=="CNN"`, this 2-vector gives the dimensions of the convolution filter kernel; must have odd integer inputs. Note that filter.dim=c(1,1) is equivalent to `type=="MLP"`. The same filter is applied for each hidden layer.

`seed` seed for random initial weights and biases.

`init.wb_path` filepath to a `keras` model which is then used as initial weights and biases for training the new model. The original model must have the exact same architecture and trained with the same input data as the new model. If `NULL`, then initial weights and biases are random (with seed `seed`) but the final layer has zero initial weights to ensure that the initial probability estimate is `init.p` across all dimensions.

`model` fitted `keras` model. Output from `logistic.NN.train`.

`S_lamda` smoothing penalty matrix for the splines modelling the effect of `X.add.basis` on logit(p); only used if `!is.null(X.add.basis)`. If `is.null(S_lambda)`, then no smoothing penalty is used.

Details

Consider a Bernoulli random variable, say $Z \sim \text{Bernoulli}(p)$, with probability mass function $\Pr(Z = 1) = p = 1 - \Pr(Z = 0) = 1 - p$. Let $Y \in \{0, 1\}$ be a univariate Boolean response and let $\mathbf{X}$ denote a d-dimensional predictor set with observations $\mathbf{x}$. For integers $l \geq 0, a \geq 0$ and $0 \leq l + a \leq d$, let $\mathbf{X}_L, \mathbf{X}_A$ and $\mathbf{X}_N$ be distinct sub-vectors of $\mathbf{X}$, with observations of each component denoted $\mathbf{x}_L, \mathbf{x}_A$ and $\mathbf{x}_N$, respectively; the lengths of the sub-vectors are l, a and $d - l - a$, respectively. We model $Y|\mathbf{X} = \mathbf{x} \sim \text{Bernoulli}(p\{\mathbf{x}\})$ with

$$p(\mathbf{x}) = h\{\eta_0 + m_L(\mathbf{x}_L) + m_A(\mathbf{x}_A) + m_N(\mathbf{x}_N)\}$$

where h is the logistic link-function and η_0 is a constant intercept. The unknown functions m_L and m_A are estimated using a linear function and spline, respectively, and are both returned as outputs by `logistic.NN.predict`; m_N is estimated using a neural network.

The model is fitted by minimising the binary cross-entropy loss plus some smoothing penalty for the additive functions (determined by `S_lambda`; see Richards and Huser, 2022) over `n.ep` training epochs. Although the model is trained by minimising the loss evaluated for `Y.train`, the final returned model may minimise some other loss. The current state of the model is saved after each epoch, using `keras::callback_model_checkpoint`, if the value of some criterion subcedes that of the model from the previous checkpoint; this criterion is the loss evaluated for validation set `Y.valid` if `!is.null(Y.valid)` and for `Y.train`, otherwise.

A non-interpretable version of this model was exploited by Cisneros et al. (2023). Equivalence with their model is achieved by setting `X.lin=NULL`, `X.add.basis=NULL` and `type="GCNN"`, and using the adjacency matrix `A` given in the example of `help(AusWild)`.

Value

`logistic.NN.train` returns the fitted `model`. `logistic.NN.predict` is a wrapper for `keras::predict` that returns the predicted probability estimates, and, if applicable, the linear regression coefficients and spline bases weights.

References

Richards, J. and Huser, R. (2022), *Regression modelling of spatiotemporal extreme U.S. wildfires via partially-interpretable neural networks*. (arXiv:2208.07581).

Examples

```
# Build and train a simple MLP for toy data

set.seed(1)

# Create  predictors
preds<-rnorm(prod(c(500,12,12,10)))

#Re-shape to a 4d array. First dimension corresponds to observations,
#last to the different components of the predictor set.
#Other dimensions correspond to indices of predictors, e.g., a grid of locations. Can be just a 1D grid.
dim(preds)=c(500,12,12,10)
#' #We have 500 observations of ten predictors on a 12 by 12 grid.

#Split predictors into linear, additive and nn.
```

```
X.nn=preds[,,,1:5] #Five nn predictors
X.lin=preds[,,,6:8] #Three linear predictors
X.add=preds[,,,9:10] #Two additive predictors

# Create toy response data

#Linear contribution
m_L = 0.3*X.lin[,,,1]+0.6*X.lin[,,,2]-0.2*X.lin[,,,3]

# Additive contribution
  m_A = 0.1*X.add[,,,1]^2+0.2*X.add[,,,1]-0.1*X.add[,,,2]^2+
0.1*X.add[,,,2]^3-0.5*X.add[,,,2]

#Non-additive contribution - to be estimated by NN
m_N = exp(-3+X.nn[,,,2]+X.nn[,,,3])+
sin(X.nn[,,,1]-X.nn[,,,2])*(X.nn[,,,4]+X.nn[,,,5])

p=0.5+0.5*tanh((m_L+m_A+m_N)/2) #Logistic link
Y=apply(p,1:3,function(x) rbinom(1,1,x))

#Create training and validation, respectively.
#We mask 20% of the Y values and use this for validation
#Masked values must be set to -1e10 and are treated as missing whilst training

mask_inds=sample(1:length(Y),size=length(Y)*0.8)

Y.train<-Y.valid<-Y #Create training and validation, respectively.
Y.train[-mask_inds]=-1e10
Y.valid[mask_inds]=-1e10



#To build a model with an additive component, we require an array of evaluations of
#the basis functions for each pre-specified knot and entry to X.add

rad=function(x,c){ #Define a basis function. Here we use the radial bases
  out=abs(x-c)^2*log(abs(x-c))
  out[(x-c)==0]=0
  return(out)
}

n.knot = 5 # set number of knots. Must be the same for each additive predictor
knots=matrix(nrow=dim(X.add)[4],ncol=n.knot)

#We set knots to be equally-spaced marginal quantiles
for( i in 1:dim(X.add)[4]) {
knots[i,]=quantile(X.add[,,,i],probs=seq(0,1,length=n.knot))}

X.add.basis<-array(dim=c(dim(X.add),n.knot))
for( i in 1:dim(X.add)[4]) {
for(k in 1:n.knot) {
X.add.basis[,,,i,k]= rad(x=X.add[,,,i],c=knots[i,k])
#Evaluate rad at all entries to X.add and for all knots
}}

 #Penalty matrix for additive functions
```

```
# Set smoothness parameters for first and second additive functions
 lambda = c(0.1,0.1)

S_lambda=matrix(0,nrow=n.knot*dim(X.add)[4],ncol=n.knot*dim(X.add)[4])
for(i in 1:dim(X.add)[4]){
 for(j in 1:n.knot){
  for(k in 1:n.knot){
     S_lambda[(j+(i-1)*n.knot),(k+(i-1)*n.knot)]=lambda[i]*rad(knots[i,j],knots[i,k])
  }
}
}

X=list("X.nn"=X.nn, "X.lin"=X.lin,
"X.add.basis"=X.add.basis)

#Build and train a two-layered "lin+GAM+NN" logistic MLP.
#Note that training is not run to completion.
NN.fit<-logistic.NN.train(Y.train, Y.valid,X,  type="MLP",n.ep=600,
                      batch.size=100,init.p=0.4, widths=c(6,3),
                      S_lambda=S_lambda)

out<-logistic.NN.predict(X,NN.fit$model)
hist(out$pred.p) #Plot histogram of predicted probability
print(out$lin.coeff)

n.add.preds=dim(X.add)[length(dim(X.add))]
par(mfrow=c(1,n.add.preds))
for(i in 1:n.add.preds){
 plt.x=seq(from=min(knots[i,]),to=max(knots[i,]),length=1000) #Create sequence for x-axis

 tmp=matrix(nrow=length(plt.x),ncol=n.knot)
 for(j in 1:n.knot){
   tmp[,j]=rad(plt.x,knots[i,j]) #Evaluate radial basis function of plt.x and all knots
 }
 plt.y=tmp%*%out$gam.weights[i,]
 plot(plt.x,plt.y,type="l",main=paste0("Quantile spline: predictor ",i),xlab="x",ylab="f(x)")
 points(knots[i,],rep(mean(plt.y),n.knot),col="red",pch=2)
 #Adds red triangles that denote knot locations
}

#To save model, run NN.fit$model %>% save_model_tf("model_Bernoulli")
#To load model, run model  <- load_model_tf("model_Bernoulli",
#custom_objects=list("bce_loss_S_lambda___S_lambda_"=bce.loss(S_lambda)))
```

`lognormal.NN` *log-normal PINN*

Description

Build and train a partially-interpretable neural network for fitting a log-normal model

Usage

```
lognormal.NN.train(Y.train, Y.valid = NULL, X.mu, X.sig, type = "MLP",
```

```
  link.loc = "identity", n.ep = 100, batch.size = 100, init.loc = NULL,
  init.sig = NULL, widths = c(6, 3), filter.dim = c(3, 3), seed = NULL,
  init.wb_path = NULL, S_lambda = NULL)

lognormal.NN.predict(X.mu, X.sig, model)
```

Arguments

`Y.train, Y.valid`
: a 2 or 3 dimensional array of training or validation real response values. Missing values can be handled by setting corresponding entries to `Y.train` or `Y.valid` to `-1e10`. The first dimension should be the observation indices, e.g., time.

  If `type=="CNN"`, then `Y.train` and `Y.valid` must have three dimensions with the latter two corresponding to an M by N regular grid of spatial locations. If `Y.valid==NULL`, no validation loss will be computed and the returned model will be that which minimises the training loss over `n.ep` epochs.

`X.mu`
: list of arrays corresponding to complementary subsets of the $d \geq 1$ predictors which are used for modelling the location parameter μ. Must contain at least one of the following three named entries:

  `X.lin.mu` A 3 or 4 dimensional array of "linear" predictor values. One more dimension than `Y.train`. If `NULL`, a model without the linear component is built and trained. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $l_1 \geq 0$ 'linear' predictor values.

  `X.add.basis.mu` A 4 or 5 dimensional array of basis function evaluations for the "additive" predictor values. The first 2/3 dimensions should be equal to that of `Y.train`; the penultimate dimensions corresponds to the chosen $a_1 \geq 0$ 'linear' predictor values and the last dimension is equal to the number of knots used for estimating the splines. See example. If `NULL`, a model without the additive component is built and trained.

  `X.nn.mu` A 3 or 4 dimensional array of "non-additive" predictor values. If `NULL`, a model without the NN component is built and trained; if this is the case, then `type` has no effect. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $d - l_1 - a_1 \geq 0$ 'non-additive' predictor values.

  Note that `X.mu` and `X.sig` are the predictors for both `Y.train` and `Y.valid`. If `is.null(X.mu)`, then μ will be treated as fixed over the predictors.

`X.sig`
: similarly to `X.mu`, but for modelling the shape parameter $\sigma > 0$. Note that we require at least one of `!is.null(X.mu)` or `!is.null(X.sig)`, otherwise the formulated model will be fully stationary and will not be fitted.

`type`
: string defining the type of network to be built. If `type=="MLP"`, the network will have all densely connected layers; if `type=="CNN"`, the network will have all convolutional layers. Defaults to an MLP. (Currently the same network is used for all parameters, may change in future versions)

`n.ep`
: number of epochs used for training. Defaults to 1000.

`batch.size`
: batch size for stochastic gradient descent. If larger than `dim(Y.train)[1]`, i.e., the number of observations, then regular gradient descent used.

`init.loc, init.sig`
: sets the initial μ and σ estimates across all dimensions of `Y.train`. Overridden by `init.wb_path` if `!is.null(init.wb_path)`. Defaults to empirical estimates of mean and standard deviation, respectively, of `log(Y.train)`.

`widths` vector of widths/filters for hidden dense/convolution layers. Number of layers is equal to `length(widths)`. Defaults to (6,3).

`filter.dim` if `type=="CNN"`, this 2-vector gives the dimensions of the convolution filter kernel; must have odd integer inputs. Note that filter.dim=c(1,1) is equivalent to `type=="MLP"`. The same filter is applied for each hidden layer across all parameters with NN predictors.

`seed` seed for random initial weights and biases.

`init.wb_path` filepath to a `keras` model which is then used as initial weights and biases for training the new model. The original model must have the exact same architecture and trained with the same input data as the new model. If `NULL`, then initial weights and biases are random (with seed `seed`) but the final layer has zero initial weights to ensure that the initial location and shape estimates are `init.loc` and `init.sig`, respectively, across all dimensions.

`S_lambda` list of smoothing penalty matrices for the splines modelling the effects of `X.add.basis.mu` and `X.add.basis.sig` on their respective parameters; each element only used if `!is.null(X.add.basis.mu)` and `!is.null(X.add.basis.sig)`, respectively. If `is.null(S_lambda[[1]])`, then no smoothing penalty is used for μ; similarly for the second element and σ.

`model` fitted `keras` model. Output from `bGEVPP.NN.train`.

`loc.link` string defining the link function used for the location parameter, see h_1 below. If `link=="exp"`, then $h_1 = \exp(x)$; if `link=="identity"`, then $h_1(x) = x$.

Details

Consider a real-valued random variable Y and let $\mathbf{X}$ denote a d-dimensional predictor set with observations $\mathbf{x}$. For $i = 1, 2$, we define integers $l_i \geq 0, a_i \geq 0$ and $0 \leq l_i + a_i \leq d$, and let $\mathbf{X}_L^{(i)}, \mathbf{X}_A^{(i)}$ and $\mathbf{X}_N^{(i)}$ be distinct sub-vectors of $\mathbf{X}$, with observations of each component denoted $\mathbf{x}_L^{(i)}, \mathbf{x}_A^{(i)}$ and $\mathbf{x}_N^{(i)}$, respectively; the lengths of the sub-vectors are l_i, a_i and $d_i - l_i - a$, respectively. We model $Y|\mathbf{X} = \mathbf{x} \sim \text{Lognormal}(\mu(\mathbf{x}), \sigma(\mathbf{x}))$ with $\sigma > 0$ and

$$\mu(\mathbf{x}) = h_1\{\eta_0^{(1)} + m_L^{(1)}(\mathbf{x}_L^{(1)}) + m_A^{(1)}(x_A^{(1)}) + m_N^{(1)}(\mathbf{x}_N^{(1)})\}$$

and

$$\sigma(\mathbf{x}) = \exp\{\eta_0^{(2)} + m_L^{(2)}(\mathbf{x}_L^{(2)}) + m_A^{(2)}(x_A^{(2)}) + m_N^{(2)}(\mathbf{x}_N^{(2)})\}$$

where h_1 is some link-function and $\eta_0^{(1)}, \eta_0^{(2)}$ are constant intercepts. The unknown functions $m_L^{(1)}, m_L^{(2)}$ and $m_A^{(1)}, m_A^{(2)}$ are estimated using linear functions and splines, respectively, and are both returned as outputs by `lognormal.NN.predict`; $m_N^{(1)}, m_N^{(2)}$ are estimated using neural networks (currently the same architecture is used for both parameters).

For details of the log-normal parameterisation, see `help(Lognormal)`.

The model is fitted by minimising the negative log-likelihood associated with the lognormal distribution plus some smoothing penalty for the additive functions (determined by `S_lambda`; see Richards and Huser, 2022); training is performed over `n.ep` training epochs. Although the model is trained by minimising the loss evaluated for `Y.train`, the final returned model may minimise some other loss. The current state of the model is saved after each epoch, using `keras::callback_model_checkpoint`, if the value of some criterion subcedes that of the model from the previous checkpoint; this criterion is the loss evaluated for validation set `Y.valid` if `!is.null(Y.valid)` and for `Y.train`, otherwise.

Value

`lognormal.NN.train` returns the fitted `model`. `lognormal.NN.predict` is a wrapper for `keras::predict` that returns the predicted parameter estimates, and, if applicable, their corresponding linear regression coefficients and spline bases weights.

References

Richards, J. and Huser, R. (2022), *Regression modelling of spatiotemporal extreme U.S. wildfires via partially-interpretable neural networks*. (arXiv:2208.07581).

Examples

```
# Build and train a simple MLP for toy data

set.seed(1)

# Create  predictors
preds<-rnorm(prod(c(200,10,10,8)))

#Re-shape to a 4d array. First dimension corresponds to observations,
#last to the different components of the predictor set.
#Other dimensions correspond to indices of predictors, e.g., a grid of locations.
dim(preds)=c(200,10,10,8)
#We have 200 observations of eight predictors on a 10 by 10 grid.

#Split predictors into linear, additive and nn. Different for the location and shape parameters.
X.nn.mu=preds[,,,1:4] #Four nn predictors for mu
X.lin.mu=preds[,,,5:6] #Two additive predictors for mu
X.add.mu=preds[,,,7:8] #Two additive predictors for mu

X.nn.sig=preds[,,,1:2] #Two nn predictors for sigma
X.lin.sig=preds[,,,3] #One linear predictor for sigma
dim(X.lin.sig)=c(dim(X.lin.sig),1) #Change dimension so consistent
X.add.sig=preds[,,,4] #One additive predictor for sigma
dim(X.add.sig)=c(dim(X.add.sig),1) #Change dimension so consistent


# Create toy response data

#Contribution to location parameter
#Linear contribution
m_L_1 = 0.3*X.lin.mu[,,,1]+0.6*X.lin.mu[,,,2]

# Additive contribution
m_A_1 = 0.05*X.add.mu[,,,1]^3+0.2*X.add.mu[,,,1]-
 0.05*X.add.mu[,,,2]^3+0.5*X.add.mu[,,,2]^2

#Non-additive contribution - to be estimated by NN
m_N_1 = 0.25*exp(-3+X.nn.mu[,,,4]+X.nn.mu[,,,1])+
  sin(X.nn.mu[,,,1]-X.nn.mu[,,,2])*(X.nn.mu[,,,4]+X.nn.mu[,,,2])-
  cos(X.nn.mu[,,,4]-X.nn.mu[,,,1])*(X.nn.mu[,,,3]+X.nn.mu[,,,1])

mu=m_L_1+m_A_1+m_N_1 #Identity link

#Contribution to shape parameter
#Linear contribution
```

```
m_L_2 = 0.5*X.lin.sig[,,,1]

# Additive contribution
m_A_2 = 0.1*X.add.sig[,,,1]^2+0.2*X.add.sig[,,,1]

#Non-additive contribution - to be estimated by NN
m_N_2 = 0.1*exp(-4+X.nn.sig[,,,2]+X.nn.sig[,,,1])+
  0.1* sin(X.nn.sig[,,,1]-X.nn.sig[,,,2])*(X.nn.sig[,,,1]+X.nn.sig[,,,2])

sig=0.1*exp(m_L_2+m_A_2+m_N_2) #Exponential link


theta=array(dim=c(dim(sig),2))
theta[,,,1]=mu; theta[,,,2] = sig
#We simulate data from a lognormal distribution

Y=apply(theta,1:3,function(x) rlnorm(1,meanlog =x[1],sdlog=x[2]))

#Create training and validation, respectively.
#We mask 20% of the Y values and use this for validation
#Masked values must be set to -1e10 and are treated as missing whilst training

mask_inds=sample(1:length(Y),size=length(Y)*0.8)

Y.train<-Y.valid<-Y #Create training and validation, respectively.
Y.train[-mask_inds]=-1e10
Y.valid[mask_inds]=-1e10



#To build a model with an additive component, we require an array of evaluations of
#the basis functions for each pre-specified knot and entry to X.add.mu and X.add.sig

rad=function(x,c){ #Define a basis function. Here we use the radial bases
  out=abs(x-c)^2*log(abs(x-c))
  out[(x-c)==0]=0
 return(out)
}

n.knot.mu = 5; n.knot.sig = 4 # set number of knots.
#Must be the same for each additive predictor,
#but can differ between the parameters mu and sigma

#Get knots for mu predictors
knots.mu=matrix(nrow=dim(X.add.mu)[4],ncol=n.knot.mu)

#We set knots to be equally-spaced marginal quantiles
for( i in 1:dim(X.add.mu)[4]){
knots.mu[i,]=quantile(X.add.mu[,,,i],probs=seq(0,1,length=n.knot.mu))
}
#Evaluate radial basis functions for mu predictors
X.add.basis.mu<-array(dim=c(dim(X.add.mu),n.knot.mu))
for( i in 1:dim(X.add.mu)[4]) {
  for(k in 1:n.knot.mu) {
    X.add.basis.mu[,,,i,k]= rad(x=X.add.mu[,,,i],c=knots.mu[i,k])
    #Evaluate rad at all entries to X.add.mu and for all knots
  }}
```

```
  #'#Create smoothing penalty matrix for the two q_alpha additive functions

# Set smoothness parameters for two functions
 lambda = c(0.1,0.2)

S_lambda.mu=matrix(0,nrow=n.knot.mu*dim(X.add.mu)[4],
ncol=n.knot.mu*dim(X.add.mu)[4])

for(i in 1:dim(X.add.mu)[4]){
 for(j in 1:n.knot.mu){
  for(k in 1:n.knot.mu){
   S_lambda.mu[(j+(i-1)*n.knot.mu),(k+(i-1)*n.knot.mu)]=lambda[i]*rad(knots.mu[i,j],knots.mu[i,k])
  }
}
}

#Get knots for sigma predictor

knots.sig=matrix(nrow=dim(X.add.sig)[4],ncol=n.knot.sig)

for( i in 1:dim(X.add.sig)[4]){
 knots.sig[i,]=quantile(X.add.sig[,,,i],probs=seq(0,1,length=n.knot.sig))
}

#Evaluate radial basis functions for sigma predictor

X.add.basis.sig<-array(dim=c(dim(X.add.sig),n.knot.sig))

for( i in 1:dim(X.add.sig)[4]) {
  for(k in 1:n.knot.sig) {
    X.add.basis.sig[,,,i,k]= rad(x=X.add.sig[,,,i],c=knots.sig[i,k])
    #Evaluate rad at all entries to X.add.mu and for all knots
  }}

#Create smoothing penalty matrix for the s_beta additive function

# Set smoothness parameter
 lambda = c(0.2)

S_lambda.sig=matrix(0,nrow=n.knot.sig*dim(X.add.sig)[4],
ncol=n.knot.sig*dim(X.add.sig)[4])

for(i in 1:dim(X.add.sig)[4]){
 for(j in 1:n.knot.sig){
  for(k in 1:n.knot.sig){
   S_lambda.sig[(j+(i-1)*n.knot.sig),(k+(i-1)*n.knot.sig)]=lambda[i]*rad(knots.sig[i,j],knots.sig[i,k])
  }
}
}

#Join in one list
S_lambda =list("S_lambda.mu"=S_lambda.mu, "S_lambda.sig"=S_lambda.sig)


#lin+GAM+NN models defined for both location and scale parameters
X.mu=list("X.nn.mu"=X.nn.mu, "X.lin.mu"=X.lin.mu,
```

```
               "X.add.basis.mu"=X.add.basis.mu) #Predictors for mu
X.sig=list("X.nn.sig"=X.nn.sig, "X.lin.sig"=X.lin.sig,
               "X.add.basis.sig"=X.add.basis.sig) #Predictors for sigma


#Fit the log-normal model. Note that training is not run to completion.
NN.fit<-lognormal.NN.train(Y.train, Y.valid,X.mu,X.sig, type="MLP",link.loc="identity",
                           n.ep=50, batch.size=50,
                           widths=c(6,3),seed=1,S_lambda=S_lambda)
out<-lognormal.NN.predict(X.mu=X.mu,X.sig=X.sig,NN.fit$model)

print("mu linear coefficients: "); print(round(out$lin.coeff_loc,3))
print("sig linear coefficients: "); print(round(out$lin.coeff_sig,3))

# Note that this is a simple example that can be run in a personal computer.

## To save model, run
# NN.fit$model %>% save_model_tf("model_lognormal")
## To load model, run
#model  <- load_model_tf("model_lognormal",
#                        custom_objects=list(
#                          "lognormal_loss_S_lambda___S_lambda_"=
#                            lognormal_loss(S_lambda=S_lambda))
#)



# Plot splines for the additive predictors

#Location predictors
n.add.preds_loc=dim(X.add.mu)[length(dim(X.add.mu))]
par(mfrow=c(1,n.add.preds_loc))
for(i in 1:n.add.preds_loc){
 plt.x=seq(from=min(knots.mu[i,]),to=max(knots.mu[i,]),length=1000) #Create sequence for x-axis

  tmp=matrix(nrow=length(plt.x),ncol=n.knot.mu)
  for(j in 1:n.knot.mu){
   tmp[,j]=rad(plt.x,knots.mu[i,j]) #Evaluate radial basis function of plt.x and all knots
  }
  plt.y=tmp%*%out$gam.weights_loc[i,]
  plot(plt.x,plt.y,type="l",main=paste0("mu spline: predictor ",i),xlab="x",ylab="f(x)")
  points(knots.mu[i,],rep(mean(plt.y),n.knot.mu),col="red",pch=2)
  #Adds red triangles that denote knot locations

}

#Shape predictors
n.add.preds_sig=dim(X.add.sig)[length(dim(X.add.sig))]
par(mfrow=c(1,n.add.preds_sig))
for(i in 1:n.add.preds_sig){
 plt.x=seq(from=min(knots.sig[i,]),to=max(knots.sig[i,]),length=1000) #Create sequence for x-axis

  tmp=matrix(nrow=length(plt.x),ncol=n.knot.sig)
  for(j in 1:n.knot.sig){
   tmp[,j]=rad(plt.x,knots.sig[i,j]) #Evaluate radial basis function of plt.x and all knots
  }
  plt.y=tmp%*%out$gam.weights_sig[i,]
```

```
 plot(plt.x,plt.y,type="l",main=paste0("sigma spline: predictor ",i),xlab="x",ylab="f(x)")
  points(knots.sig[i,],rep(mean(plt.y),n.knot.sig),col="red",pch=2)
  #Adds red triangles that denote knot locations

}
```

MedWild *Mediterranean Europe Wildfire data*

Description

Data used by Richards et al. (2022) for modelling extreme wildfires in Mediterranean Europe with partially-interpretable neural networks

Usage

```
data(MedWild)
```

Format

A list with 6 elements:

BA An array with dimension (120, 200, 80), corresponding to the burnt area response data.

lambda An array with dimension (120, 200, 80), corresponding to the area of the spatial gridcell. Note that this is a dynamic variable.

X A list with 4 elements:

- **X.met** An array with dimension (120, 200, 80, 13) corresponding to the meterological predictors described below.
- **X.lc** An array with dimension (120, 200, 80, 21) corresponding to the land cover predictors described below.
- **lc.flags** A vector of length 21 giving the names of the land cover types.
- **X.oro** An array with dimension (120, 200, 80, 2) corresponding to the oropgraphical predictors described below.

times A vector of length 120 giving the observation indices. Format is "year-month". Corresponds to first dimension of BA.

lon A matrix of dimension (200, 80) giving the longitude ordinate for the second and third dimensions of BA.

lat A matrix of dimension (200, 80) giving the latitude ordinate for the second and third dimensions of BA.

Details

The response data BA are observations of monthly aggregated burnt area (km^2) for over 10000 spatial grid-cells located across countries surrounding the Mediterranean Basin and southern Europe. The observation period covers 2001 to 2020, using only months between June and November, inclusive, leaving 120 observed spatial fields. Grid-cells are arranged on a regular latitude/longitude grid with spatial resolution 0.25deg by 0.25deg. Observations are derived from version 5.1 of the FireCCI dataset (Lizundia-Loiola et al., 2020), which is generated by the Moderate Resolution Imaging Spectroradiometer (MODIS) 250m reflectance data and guided by 1km active fires (Otón

et al., 2021). Alongside values of BA, we provide a measure of burnable-area for a space-time grid-cell, given in `lambda`; this is equivalent to $\lambda(s,t)$ in Richards et al., 2022, and can be specified as an offset term in both GPD.NN and quant.NN.

Both the response data and the subsequently described predictors have been re-gridded to a regular spatio-temporal grid with missing values set to `-1e10`. For `BA` and entries to `X`, the first three dimensions correspond to time $\times$ latitude $\times$ longitude with their respective ordinate values given in `times`, `lat` and `lon`.

We consider three types of predictor variables, given in `X`: these are meteorological (`X.met`), land cover proportions (`X.lc`) and orograhical (`X.oro`).

Thirteen meteorological variables are considered and given as monthly means in `X.met`. Eleven variables are provided by the ERA5-reanalysis on single levels (Hersbach et al., 2019), available through the COPERNICUS Climate Data Service. Monthly total precipitation (m) is used to derive a three-month standardized precipitation index (SPI, unitless) and hourly temperature and dewpoint temperature at a 2m altitude (K) are used to derive monthly vapour-pressure deficit (VPD, measured in Pa). The variables are ordered as followed: VPD (Pa), temperature at a 2m altitude (K), SPI (unitless), both eastern and northern components of wind velocity at a 10m altitude (m/s), potential evaporation (m), surface pressure (Pa), evaporation (m of water equiv.), surface net thermal, and solar, radiation (J/m^2), snow evaporation (m of water equiv.), snowmelt (m of water equiv.) and snowfall (m of water equiv.)

The land cover variables that are given in `X.lc` describe the proportion of a grid-cell which is covered by one of 21 different types, e.g., urban, grassland, water. Land cover predictors are derived using a gridded land cover map, of spatial resolution 300m and temporal resolution one year, produced by COPERNICUS and available through their Climate Data Service. For each 0.25deg $\times$ 0.25deg spatial grid-cell, the proportion of a cell consisting of a specific land cover type is derived from the high-resolution product. The variables are named in `lc.flags`.

The two orographical predictors given in `X.oro` are the mean and standard deviation of the altitude (m) for each grid-cell; estimates are derived using the R package “elevatr", which accesses Amazon Web Services Terrain Tiles (`https://registry.opendata.aws/terrain-tiles/`).

References

Bontemps, S., Boettcher, M., Brockmann, C., Kirches, G., Lamarche, C., Radoux, J., Santoro, M., Vanbogaert, E., Wegmüller, U., Herold, M., Achard, F., Ramoino, F., Arino,O., and Defourny, P. (2015). *Multi-year global land cover mapping at 300 M and characterization for climate modelling: Achievements of the land cover component of the ESA climate change initiative.* The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 40(7):323.(doi)

Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicola s,J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., and Tépaut, J.-N. (2019). *ERA5 monthly averaged data on single levels from 1959 to present.* Copernicus Climate Change Service (C3S) Climate Data Store (CDS), 10:252–266. (doi)

Lizundia-Loiola, J., Otón, G., Ramo, R., and Chuvieco, E. (2020). *A spatio-temporal active-fire clustering approach for global burned area mapping at 250 m from MODIS data.* Remote Sensing of Environment, 236:111493. (doi)

Otón, G., Pereira, J. M. C., Silva, J. M. N., and Chuvieco, E. (2021). *Analysis of trends in the FireCCI global long term burned area product (1982–2018).* Fire, 4(4). (doi)

Richards, J., Huser, R., Bevacqua, E., Zscheischler, J, (2022), *Insights into the drivers and spatio-temporal trends of extreme Mediterranean wildfires with statistical deep-learning.* (arXiv:2212.01796)

Examples

```
data(MedWild)
```

quant.NN *Non-parametric single quantile regression PINN*

Description

Build and train a partially-interpretable neural network for non-parametric single quantile regression

Usage

```
quant.NN.train(Y.train, Y.valid = NULL, X, type = "MLP",
  link = "identity", tau = NULL, offset = NULL, n.ep = 100,
  batch.size = 100, init.q = NULL, widths = c(6, 3), filter.dim = c(3,
  3), seed = NULL, init.wb_path = NULL, S_lambda = NULL)

quant.NN.predict(X, model, offset = NULL)
```

Arguments

`Y.train, Y.valid`

a 2 or 3 dimensional array of training or validation real response values. Missing values can be handled by setting corresponding entries to `Y.train` or `Y.valid` to `-1e10`. The first dimension should be the observation indices, e.g., time.

If `type=="CNN"`, then `Y.train` and `Y.valid` must have three dimensions with the latter two corresponding to an M by N regular grid of spatial locations. If `Y.valid==NULL`, no validation loss will be computed and the returned model will be that which minimises the training loss over `n.ep` epochs.

`X`

list of arrays corresponding to complementary subsets of the $d \geq 1$ predictors which are used for modelling. Must contain at least one of the following three named entries:

`X.lin` A 3 or 4 dimensional array of "linear" predictor values. One more dimension than `Y.train`. If `NULL`, a model without the linear component is built and trained. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $l \geq 0$ 'linear' predictor values.

`X.add.basis` A 4 or 5 dimensional array of basis function evaluations for the "additive" predictor values. The first 2/3 dimensions should be equal to that of `Y.train`; the penultimate dimensions corresponds to the chosen $a \geq 0$ 'linear' predictor values and the last dimension is equal to the number of knots used for estimating the splines. See example. If `NULL`, a model without the additive component is built and trained.

`X.nn` A 3 or 4 dimensional array of "non-additive" predictor values. If `NULL`, a model without the NN component is built and trained; if this is the case, then `type` has no effect. The first 2/3 dimensions should be equal to that of `Y.train`; the last dimension corresponds to the chosen $d - l - a \geq 0$ 'non-additive' predictor values.

Note that `X` is the predictors for both `Y.train` and `Y.valid`.

`type`

string defining the type of network to be built. If `type=="MLP"`, the network will have all densely connected layers; if `type=="CNN"`, the network will have all convolutional layers. Defaults to an MLP.

link	string defining the link function used, see h below. If link=="exp", then $h = \exp(x)$; if link=="identity", then $h(x) = x$.
tau	quantile level. Must satisfy 0 < tau < 1.
offset	an array of strictly positive scalars the same dimension as Y.train, containing the offset values used for modelling the quantile. If offset=NULL, then no offset is used (equivalently, offset is populated with ones). Defaults to NULL.
n.ep	number of epochs used for training. Defaults to 1000.
batch.size	batch size for stochastic gradient descent. If larger than dim(Y.train)[1], i.e., the number of observations, then regular gradient descent used.
init.q	sets the initial tau-quantile estimate across all dimensions of Y.train. Defaults to empirical estimate. Overriden by init.wb_path if !is.null(init.wb_path). Note that if !is.null(offset), then the initial quantile array will be init.q*offset.
widths	vector of widths/filters for hidden dense/convolution layers. Number of layers is equal to length(widths). Defaults to (6,3).
filter.dim	if type=="CNN", this 2-vector gives the dimensions of the convolution filter kernel; must have odd integer inputs. Note that filter.dim=c(1,1) is equivalent to type=="MLP". The same filter is applied for each hidden layer.
seed	seed for random initial weights and biases.
init.wb_path	filepath to a keras model which is then used as initial weights and biases for training the new model. The original model must have the exact same architecture and trained with the same input data as the new model. If NULL, then initial weights and biases are random (with seed seed) but the final layer has zero initial weights to ensure that the initial quantile estimate is init.q across all dimensions.
model	fitted keras model. Output from quant.NN.train.
S_lamda	smoothing penalty matrix for the splines modelling the effect of X.add.basis on the inverse-link of the tau-quantile; only used if !is.null(X.add.basis). If is.null(S_lambda), then no smoothing penalty is used.

Details

Consider a real-valued random variable Y and let $\mathbf{X}$ denote a d-dimensional predictor set with observations $\mathbf{x}$. For integers $l \geq 0, a \geq 0$ and $0 \leq l + a \leq d$, let $\mathbf{X}_L, \mathbf{X}_A$ and $\mathbf{X}_N$ be distinct sub-vectors of $\mathbf{X}$, with observations of each component denoted $\mathbf{x}_L, \mathbf{x}_A$ and $\mathbf{x}_N$, respectively; the lengths of the sub-vectors are l, a and $d-l-a$, respectively. We model $\Pr\{Y \leq y_\tau(\mathbf{x})|\mathbf{X} = \mathbf{x}\} = \tau$ with

$$y_\tau(\mathbf{x}) = C(\mathbf{x})h\{\eta_0 + m_L(\mathbf{x}_L) + m_A(\mathbf{x}_A) + m_N(\mathbf{x}_N)\}$$

where h is some link-function, η_0 is a constant intercept and $C(\mathbf{x})$ is a fixed offset term (see Richards et al., 2022). The unknown functions m_L and m_A are estimated using a linear function and spline, respectively, and are both returned as outputs by quant.NN.predict; m_N is estimated using a neural network. The offset term is, by default, $C(\mathbf{x}) = 1$ for all $\mathbf{x}$; if !is.null(offset), then offset determines $C(\mathbf{x})$.

The model is fitted by minimising the penalised tilted loss over n.ep training epochs; the loss is given by

$$l(y_\tau; y) = \max\{\tau(y - y_\tau), (\tau - 1)(y - y_\tau)\}$$

plus some smoothing penalty for the additive functions (determined by S_lambda; see Richards and Huser, 2022) and is averaged over all entries to Y.train (or Y.valid). Although the model is trained by minimising the loss evaluated for Y.train, the final returned model may minimise some

other loss. The current state of the model is saved after each epoch, using `keras::callback_model_checkpoint`, if the value of some criterion subcedes that of the model from the previous checkpoint; this criterion is the loss evaluated for validation set `Y.valid` if `!is.null(Y.valid)` and for `Y.train`, otherwise.

Value

`quant.NN.train` returns the fitted `model`. `quant.NN.predict` is a wrapper for `keras::predict` that returns the predicted `tau`-quantile estimates, and, if applicable, the linear regression coefficients and spline bases weights.

References

Richards, J. and Huser, R. (2022), *Regression modelling of spatiotemporal extreme U.S. wildfires via partially-interpretable neural networks*. (arXiv:2208.07581).

Richards, J., Huser, R., Bevacqua, E., Zscheischler, J, (2022), *Insights into the drivers and spatio-temporal trends of extreme Mediterranean wildfires with statistical deep-learning.* (arXiv:2212.01796)

Examples

```
# Build and train a simple MLP for toy data

set.seed(1)

# Create  predictors
preds<-rnorm(prod(c(500,12,12,10)))

#Re-shape to a 4d array. First dimension corresponds to observations,
#last to the different components of the predictor set.
#Other dimensions correspond to indices of predictors, e.g., a grid of locations. Can be just a 1D grid.
dim(preds)=c(500,12,12,10)
#' #We have 500 observations of ten predictors on a 12 by 12 grid.


X.nn=preds[,,,1:5] #Five nn predictors
X.lin=preds[,,,6:8] #Three linear predictors
X.add=preds[,,,9:10] #Two additive predictors

# Create toy response data

#Linear contribution
m_L = 0.3*X.lin[,,,1]+0.6*X.lin[,,,2]-0.2*X.lin[,,,3]

# Additive contribution
m_A = 0.2*X.add[,,,1]^2+0.05*X.add[,,,1]-0.1*X.add[,,,2]^2+
0.1*X.add[,,,2]^3

#Non-additive contribution - to be estimated by NN
m_N = exp(-3+X.nn[,,,2]+X.nn[,,,3])+
sin(X.nn[,,,1]-X.nn[,,,2])*(X.nn[,,,4]+X.nn[,,,5])

theta=1+m_L+m_A+m_N #Identity link
#We simulate normal data and estimate the median, i.e., the 50% quantile or mean,
#as the form for this is known
Y=apply(theta,1:3,function(x) rnorm(1,mean=x,sd=2))
```

```
#Create training and validation, respectively.
#We mask 20% of the Y values and use this for validation.
#Masked values must be set to -1e10 and are treated as missing whilst training

mask_inds=sample(1:length(Y),size=length(Y)*0.8)

Y.train<-Y.valid<-Y #Create training and validation, respectively.
Y.train[-mask_inds]=-1e10
Y.valid[mask_inds]=-1e10



#To build a model with an additive component, we require an array of evaluations of
#the basis functions for each pre-specified knot and entry to X.add

rad=function(x,c){ #Define a basis function. Here we use the radial bases
  out=abs(x-c)^2*log(abs(x-c))
  out[(x-c)==0]=0
  return(out)
}

n.knot = 5 # set number of knots. Must be the same for each additive predictor
knots=matrix(nrow=dim(X.add)[4],ncol=n.knot)

#We set knots to be equally-spaced marginal quantiles
for( i in 1:dim(X.add)[4]){
 knots[i,]=quantile(X.add[,,,i],probs=seq(0,1,length=n.knot))
 }

X.add.basis<-array(dim=c(dim(X.add),n.knot))
for( i in 1:dim(X.add)[4]) {
for(k in 1:n.knot) {
X.add.basis[,,,i,k]= rad(x=X.add[,,,i],c=knots[i,k])
#Evaluate rad at all entries to X.add and for all knots
}}


#Penalty matrix for additive functions

# Set smoothness parameters for first and second additive functions
 lambda = c(0.2,0.1)

S_lambda=matrix(0,nrow=n.knot*dim(X.add)[4],ncol=n.knot*dim(X.add)[4])
for(i in 1:dim(X.add)[4]){
 for(j in 1:n.knot){
  for(k in 1:n.knot){
     S_lambda[(j+(i-1)*n.knot),(k+(i-1)*n.knot)]=lambda[i]*rad(knots[i,j],knots[i,k])
  }
}
}

#Build lin+GAM+NN model.
X=list("X.nn"=X.nn, "X.lin"=X.lin,
"X.add.basis"=X.add.basis)

#Build and train a two-layered "lin+GAM+NN" MLP. Note that training is not run to completion.
```

```
NN.fit<-quant.NN.train(Y.train, Y.valid,X,  type="MLP",link="identity",tau=0.5,n.ep=600,
                       batch.size=100, widths=c(6,3),S_lambda=S_lambda)

out<-quant.NN.predict(X,model=NN.fit$model)
hist(out$pred.q) #Plot histogram of predicted quantiles
print(out$lin.coeff)

n.add.preds=dim(X.add)[length(dim(X.add))]
par(mfrow=c(1,n.add.preds))
for(i in 1:n.add.preds){
 plt.x=seq(from=min(knots[i,]),to=max(knots[i,]),length=1000) #Create sequence for x-axis

 tmp=matrix(nrow=length(plt.x),ncol=n.knot)
 for(j in 1:n.knot){
   tmp[,j]=rad(plt.x,knots[i,j]) #Evaluate radial basis function of plt.x and all knots
 }
 plt.y=tmp%*%out$gam.weights[i,]
 plot(plt.x,plt.y,type="l",main=paste0("Quantile spline: predictor ",i),xlab="x",ylab="f(x)")
 points(knots[i,],rep(mean(plt.y),n.knot),col="red",pch=2)
 #Adds red triangles that denote knot locations
}

tau <- 0.5
#To save model, run
# NN.fit$model %>% save_model_tf(paste0("model_",tau,"-quantile"))
#To load model, run
#model  <- load_model_tf(paste0("model_",tau,"-quantile"),
#custom_objects=list("tilted_loss_tau___tau__S_lambda_"=tilted.loss(tau,S_lambda)))
```

`USWild` *US Wildfires data*

Description

Data used by Richards and Huser (2022) for modelling extreme wildfires in the contiguous U.S. with partially-interpretable neural networks

Usage

```
data(USWild)
```

Format

A list with 7 elements:

BA An array with dimension (161, 129, 61), corresponding to the burnt area response data.

X A list with 4 elements:

- **X.t2m** An array with dimension (161, 129, 61, 1) of 2m air temperature values, as described below.
- **X.SPI** An array with dimension (161, 129, 61, 1) of standardised precipitation index (SPI) values, as described below.

X.N An array with dimension (161, 129, 61, 40) of the "non-interpretable" neural network predictors, as described below.

cov.names A vector of length 40 giving shorthand names for the covariates that correspond to the last dimension of `X.N`. See below.

times A vector of length 161 giving the monthly observation indices. Format is "year-month". Corresponds to first dimension of `BA`.

lon A vector of length 129 giving the longitude ordinate for the second dimension of `BA`.

lat A vector of length 61 giving the latitude ordinate for the third dimension of `BA`.

state.ids A (129,61) matrix providing the state ID number for each spatial grid-cell. A value of 0 corresponds to grid-cells outside of the CONUS, e.g., over sea.

state.flags A vector of length 45 providing the name associated with each state ID.

Details

The response data `BA` are observations of monthly aggregated burnt area (acres) of 3503 spatial grid-cells located across the contiguous United States, with the states of Alaska and Hawaii excluded. The observation period covers 1993 to 2015, using only months between March and September, inclusive, leaving 161 observed spatial fields. Grid-cells are arranged on a regular 129 by 61 latitude/longitude grid with spatial resolution 0.5deg by 0.5deg. Observations are provided by the Fire Program Analysis fire-occurrence database (Short, 2017) which collates U.S. wildfire records from the reporting systems of federal, state and local organisations.

Both the response data and the subsequently described predictors have been re-gridded to a regular spatio-temporal grid with missing values set to `-1e10`. For `BA` and entries to `X`, the first three dimensions correspond to time $\times$ latitude $\times$ longitude with their respective ordinate values given in `times`, `lat`, and `lon`.

We consider three types of predictor variables, given in `X`: these are the two "interpretable" predictors, 2m air temperature (K; `X.t2m`) and the standardised precipitation index (SPI; unitless; `X.SPI`), that Richards and Huser (2024) model using linear and additive functions, and the 40 non-interpretable predictors (`X.N`) that feed the neural network component of the models.

For `X.N`, the names of each variable are contained with `X$cov.names`. These include 11 meteorological variables, which are given as monthly means. These variables are provided by the ERA5-reanalysis on single levels, available through the COPERNICUS Climate Data Service (doi:10.24381/cds.f17050d7), which is given on a 0.1deg $\times$ 0.1deg grid; the values have then been aggregated to a 0.5deg $\times$ 0.5deg resolution. The variables are: eastern (u10; m/s) and northern (v10; m/s) components of wind velocity at 10m above ground level, potential evaporation (pev; m), evaporation (e; m of water equivalent), surface pressure (sp; Pa), surface net solar (ssr; J/m^2) and thermal radiation (str; J/m^2), snowfall (sf; m of water equivalent), snow-melt (smlt; m of water equivalent), snow evaporation (es; m of water equivalent), and surface run-off (sro; m). The reanalysis also provides three variables relating to sub-gridscale orography: angle (anor; radians), anisotropy (isor; unitless), slope (slor; unitless), as well as the standard deviation of orography (sdor; unitless).

We also provide land cover variables in `X.N` that describe the proportion of a grid-cell which is covered by one of 25 different types, e.g., urban, grassland, water (see Opitz (2022) for details on a subset of these data). Land cover predictors are derived using a gridded land cover map, of spatial resolution 300m and temporal resolution one year, produced by COPERNICUS and available through their Climate Data Service. For each 0.5deg $\times$ 0.5deg grid-cell, the proportion of a cell consisting of a specific land cover type is derived from the high-resolution product. The land cover variables names are provided explicitly in `cov.names`.

Also provided are `state.flags` and `state.IDs`, which provide the state in which each of the (129 by 61) spatial grid-cells are located. A value of zero corresponds to a spatial grid-cell located outside of the CONUS. Note that some of the smaller states have been merged.

References

Richards, J. and Huser, R. (2024+), *Regression modelling of spatiotemporal extreme U.S. wildfires via partially-interpretable neural networks*. (arXiv:2208.07581).

Short, K. C. (2017), *Spatial wildfire occurrence data for the United States, 1992-2015 FPA_FOD_20170508. 4th Ed. Fort Collins, CO: Forest Service Research Data Archive.*

Opitz, T.. (2022), *Editorial: EVA 2021 Data Competition on spatio-temporal prediction of wildfire activity in the United States.* Extremes, to appear.

Examples

```
data(USWild)
```

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