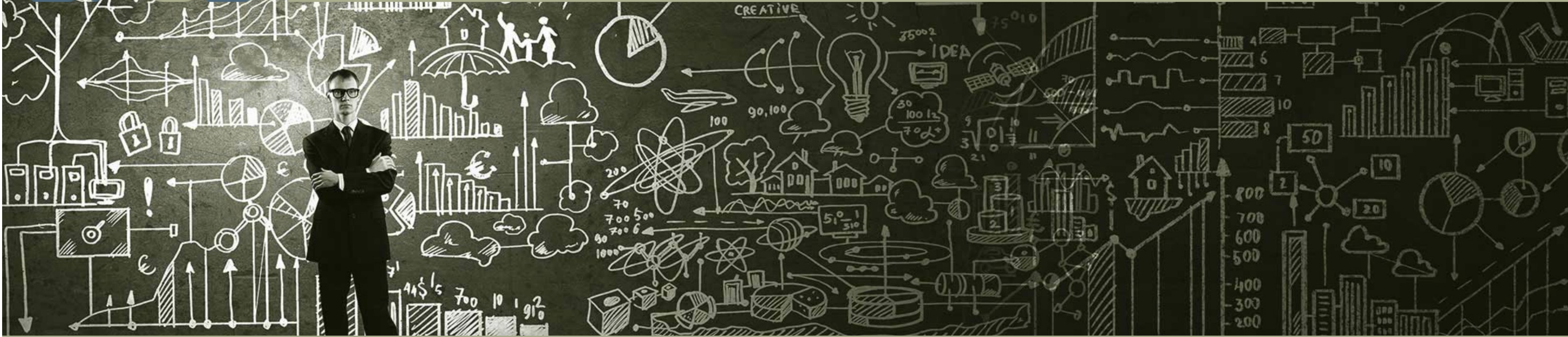
torch and tabnet packages!

May I uninstall python ?

Christophe Regouby
Feb, 2nd 2022

SFdS

Menu



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Python pour les utilisateurs de R

Présentation

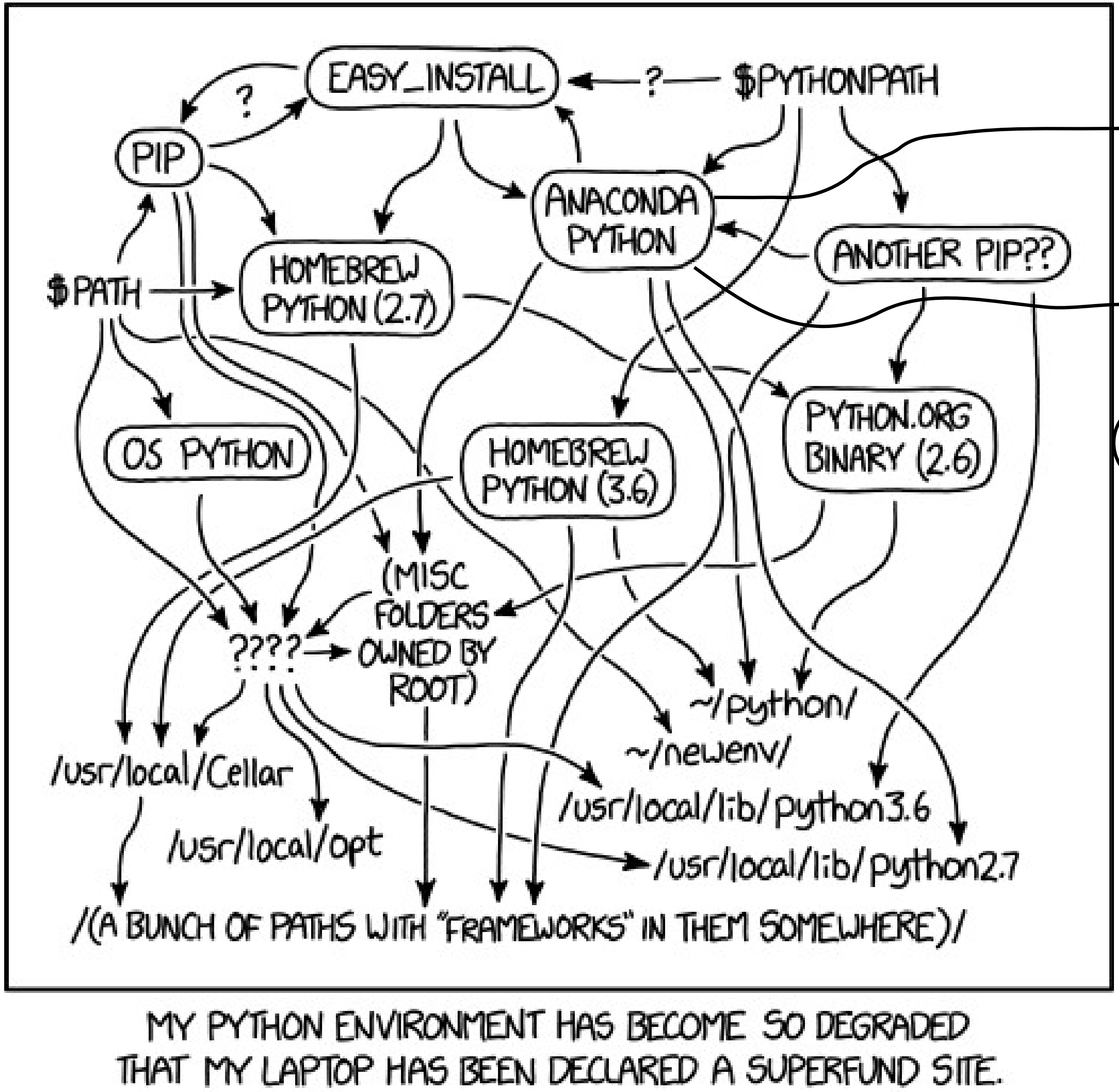
~~Le langage R est un outil logiciel utilisé de longue date par~~ la communauté statisticienne, aussi bien en enseignement, en recherche que dans l'industrie. La communauté informaticienne et du machine learning utilise de son côté le langage Python. La formation s'adresse à un utilisateur R qui peut être amené à rencontrer l'environnement Python, ou qui souhaite simplement s'informer sur ce langage. L'objectif est d'aider ses premiers pas, lui permettant de faire facilement des ponts entre les deux langages.

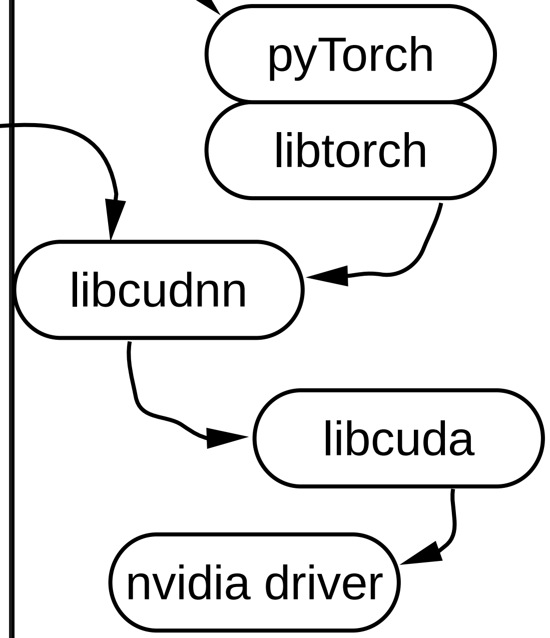
Inutile

Obsolète

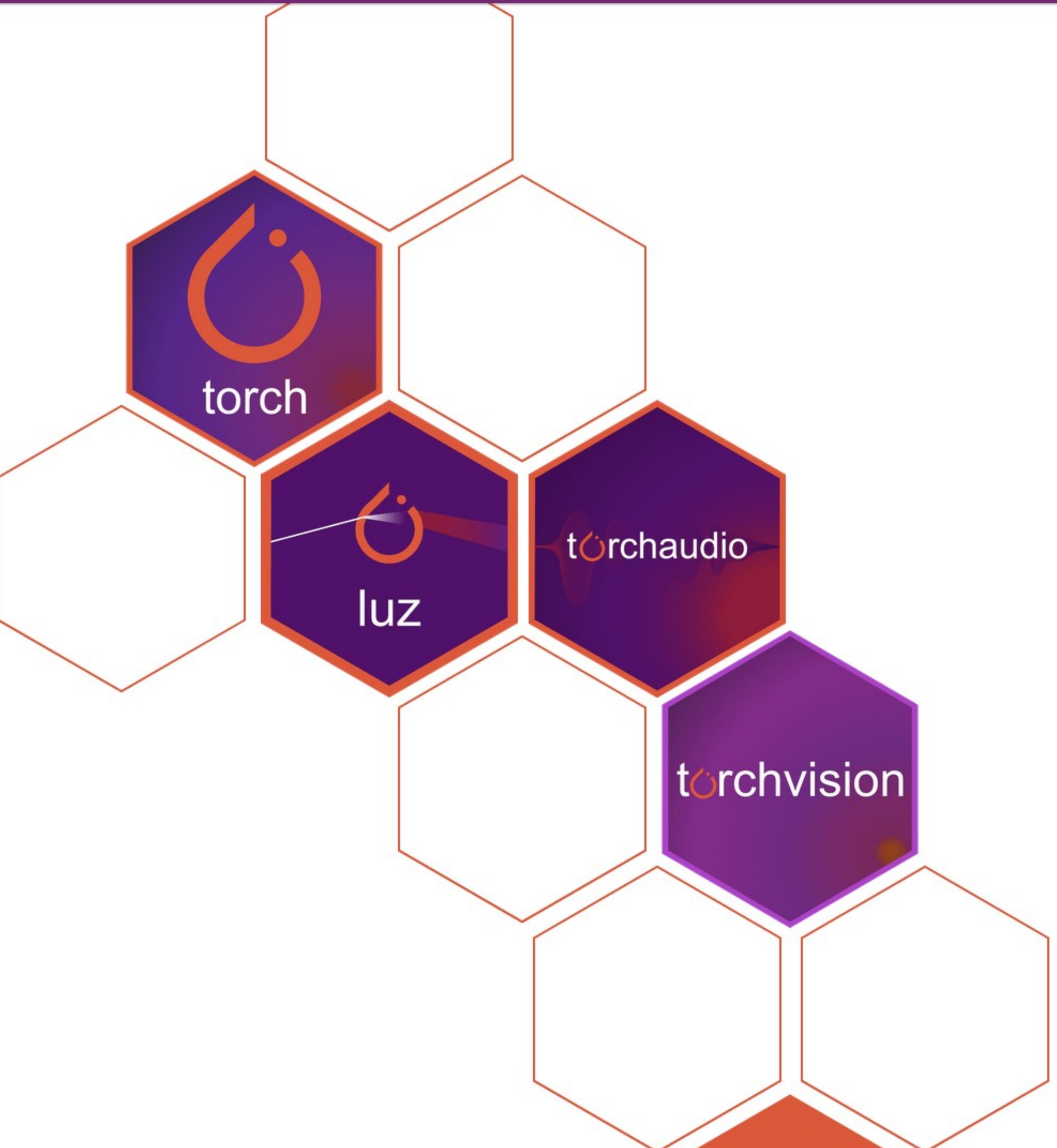
La formation a atteint sa capacité maximale.

Les inscrits recevront quelques jours avant l'atelier un lien de connexion vers la classe virtuelle.



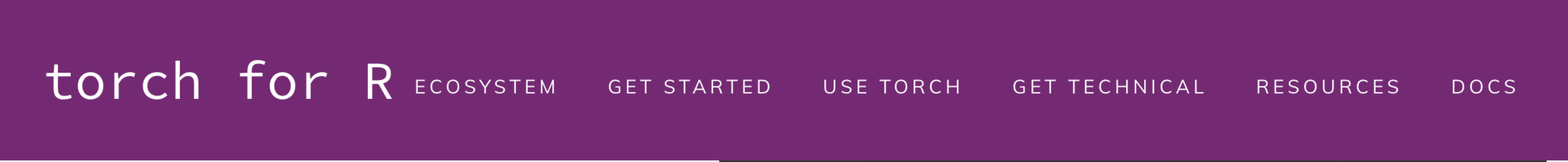


From https://xkcd.com/1987/



TORCH FOR R

An open source machine learning framework based on PyTorch. torch provides fast array computation with strong GPU acceleration and a neural networks library built on a tape-based autograd system. The ‘torch for R’ ecosystem is a collection of extensions for torch.



Is it worth reinventing the well ?

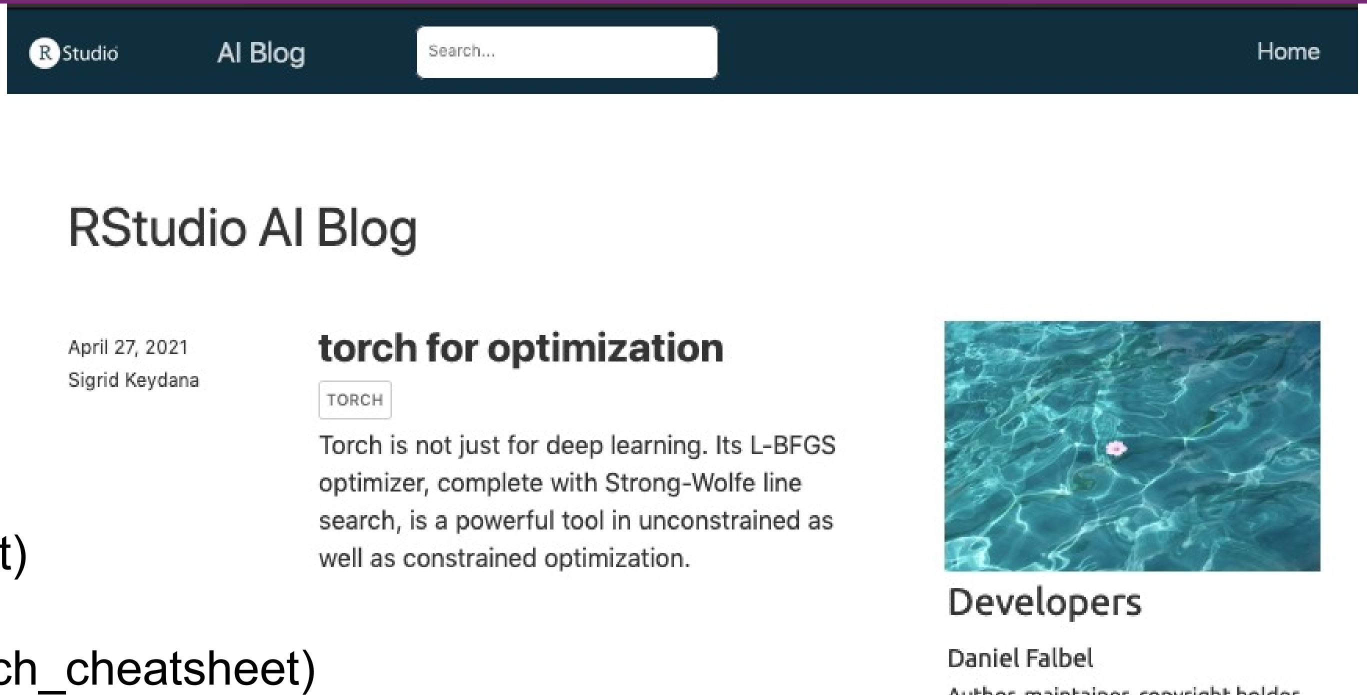
- easy installation on CPU and GPU

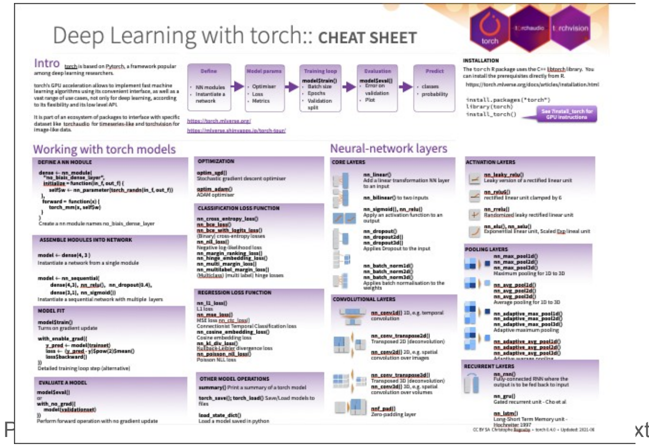
- low footprint installation

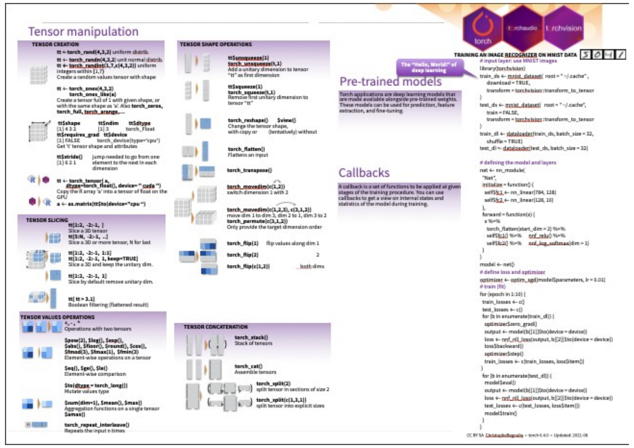
- the inspiring RStudio AI blog

- packages ecosystem (under active development)

- the cheatsheet (https://github.com/cregouby/torch_cheatsheet)





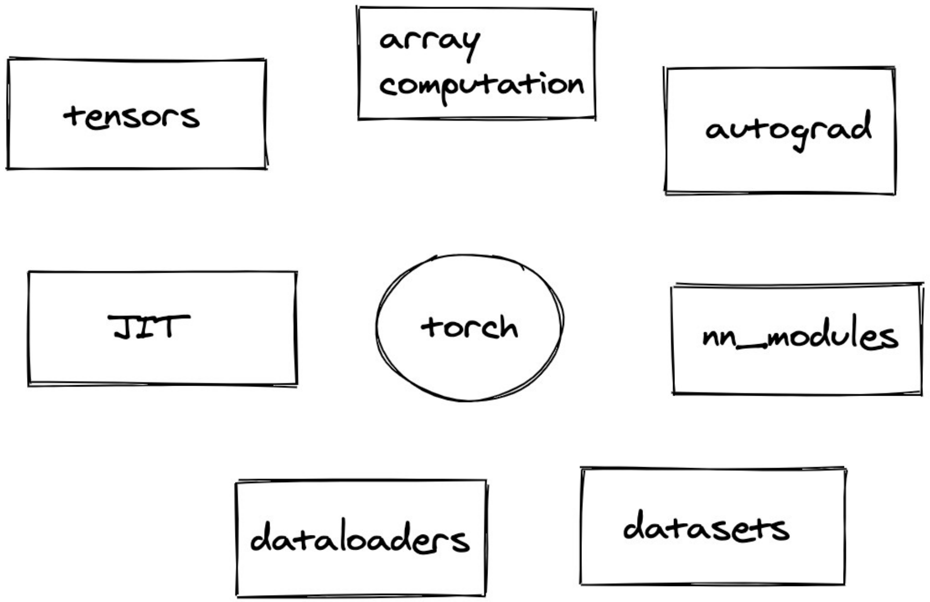


The {torch} qulity and comfort

- full-feature RStudio code highlight and linter / debug / visualise

- all your tensors are 1-indexed (what a confort)

- autograd automatic differentiation



Setup

```
> library(torch)
>
>
trying URL 'https://download.pytorch.org/libtorch/cpu/libtorch-macos-1.9.0.zip'
Content type 'application/zip' length 169481120 bytes (161.6 MB)
==================================================
downloaded 161.6 MB

trying URL 'https://storage.googleapis.com/torch-lantern-builds/refs/heads/cran/v0.6.0/latest/macOS-cp
u.zip'
Content type 'application/zip' length 1741824 bytes (1.7 MB)
==================================================
downloaded 1.7 MB
```

Advanced setup

```
> install_torch( timeout=1200)
```

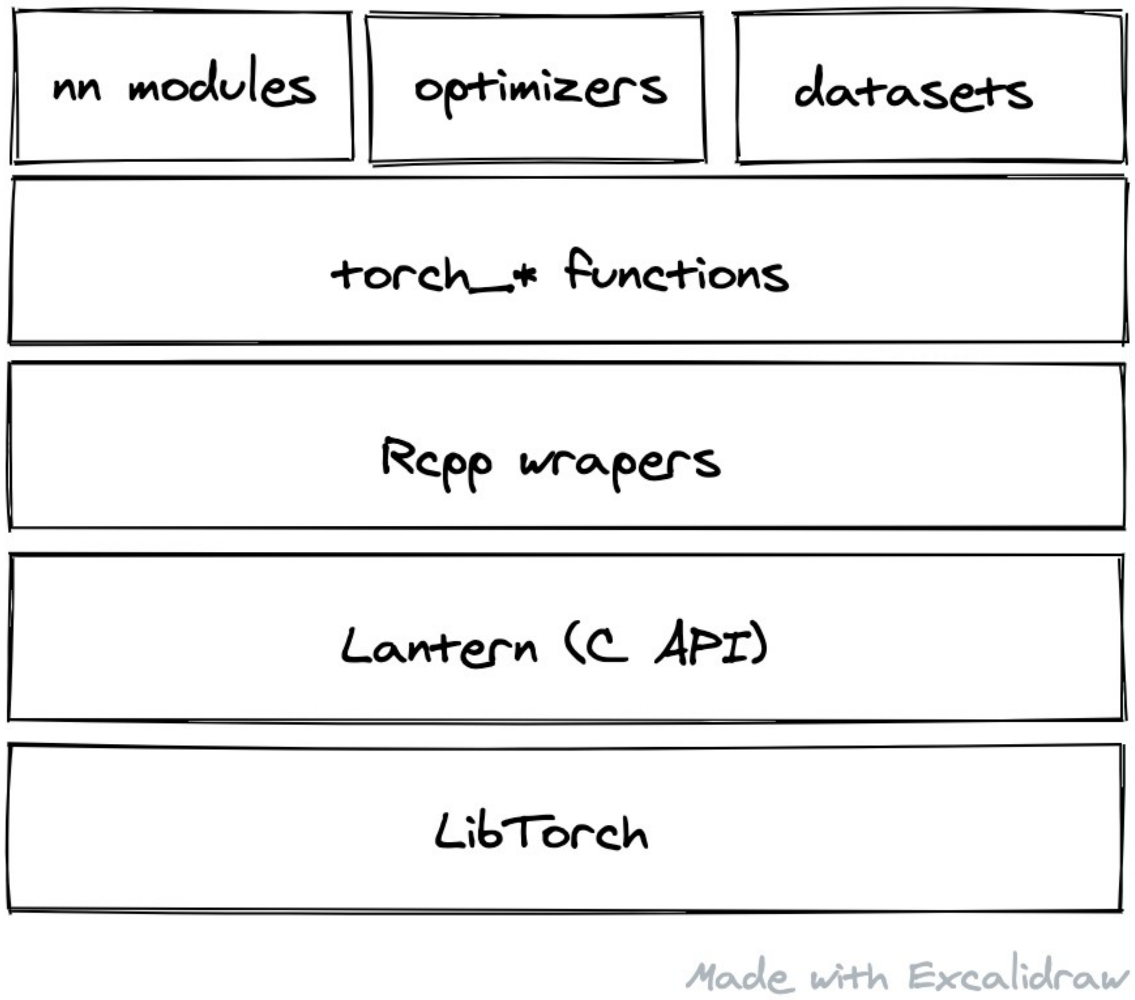
Expert setup

```
> library(torch)
> install_torch( timeout=1
>
> install_torch_from_file()
```

install_torch_from_file(version = "1.9.0", type = install_type(version = version), libtorch, liblantern, ...)

https://torch.mlverse.org/docs/articles/installation.html

Software stack design



Lesson 1 : my first tensor in {torch}

data type

device

layout

tensor

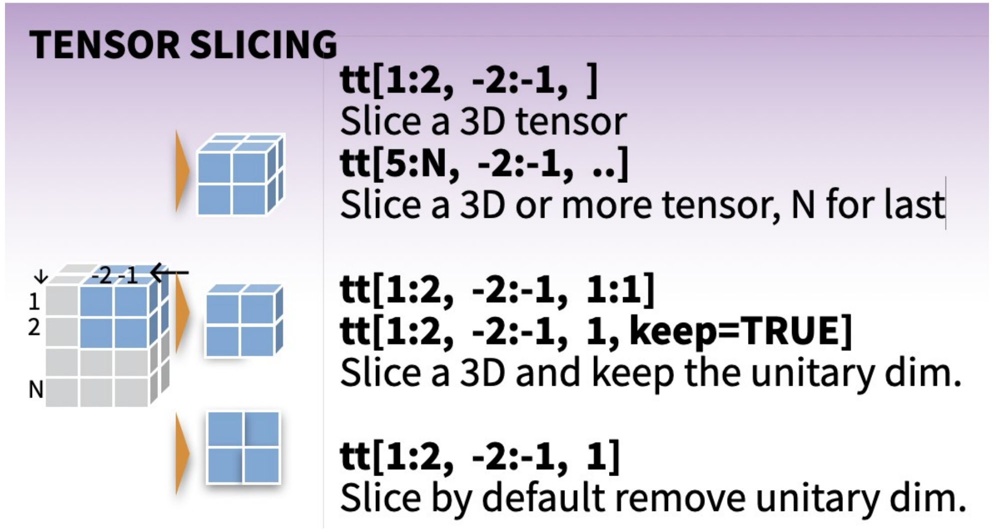
dimensions

methods

requires grad

```
library(torch)
x <- torch_randn(2, 3, 4)
x
#> torch_tensor
#> (1,.,.) =
#>  -2.4627  1.0401 -0.6988 -1.2547
#>   0.1263  0.2173  1.6905 -0.3433
#>   0.0273  0.2175 -0.5804  0.3927
#>
#> (2,.,.) =
#>   1.6249 -0.3749 -0.7716  0.0853
#>   1.1901  0.5338 -0.0599  0.9408
#>   0.0917  0.3540 -0.0884  0.7407
#> [ CPUFloatType{2,3,4} ]
```

```
x[,2:N,]
#> torch_tensor
#> (1,.,.) =
#>  -2.3383  1.7336 -2.6556  2.2428
#>   0.6942 -0.7408 -0.2700 -0.5598
#>
#> (2,.,.) =
#>  -1.3223 -0.1868 -0.4355  0.7440
#>   0.2632  1.0361  0.8857 -1.2174
#> [ CPUFloatType{2,2,4} ]
x[1,2:N,]
#> torch_tensor
#> -2.3383  1.7336 -2.6556  2.2428
#>  0.6942 -0.7408 -0.2700 -0.5598
#> [ CPUFloatType{2,4} ]
x[1:1,2:N,]
#> torch_tensor
#> (1,.,.) =
#>  -2.3383  1.7336 -2.6556  2.2428
#>   0.6942 -0.7408 -0.2700 -0.5598
#> [ CPUFloatType{1,2,4} ]
torch_squeeze(x[1:1,2:N,])
#> torch_tensor
#> -2.3383  1.7336 -2.6556  2.2428
#>  0.6942 -0.7408 -0.2700 -0.5598
#> [ CPUFloatType{2,4} ]
```



Lessons 2 : my first torch module:

mlverse.shinyapps.io/torch-tour

Torch tutorial from UseR-2021

https://raw.githubusercontent.com/mlverse/torch-learnr/master/tutorial-useR-2021/en/torch.Rmd

Il existe en français !

https://raw.githubusercontent.com/mlverse/torch-learnr/master/tutorial-useR-2021/fr/torch.Rmd

{tabnet}

TabNet: Attentive Interpretable Tabular Learning

20 Aug 2019 · Sercan O. Arik, Tomas Pfister · Edit social preview

We propose a novel high-performance and interpretable canonical deep tabular data learning architecture, TabNet. TabNet uses sequential attention to choose which features to reason from at each decision step, enabling interpretability and more efficient learning as the learning capacity is used for the most salient features... read more

PDF Abstract

Code

Edit

google-research/google-research official	★ 19,860	TensorFlow
microsoft/qlib	★ 6,703	
dreamquark-ai/tabnet	★ 1,331	PyTorch
nlpodyssey/spago	★ 969	TensorFlow
titu1994/tf-TabNet	★ 166	TensorFlow
mgrankin/fast_tabnet	★ 107	PyTorch
mlverse/tabnet	★ 59	Torch
ptuls/tabnet-modified	★ 47	TensorFlow

Tasks

Edit

- Decision Making
- Feature Selection
- Poker Hand Classification
- Representation Learning
- Self-Supervised Learning
- Unsupervised Representation Learning

v0.3.0 is on CRAN, github version recommended

{tabnet}

Unsupervised pre-training

Age	Cap. gain	Education	Occupation	Gender	Relationship
53	200000	?	Exec-managerial	F	Wife
19	0	?	Farming-fishing	M	?
?	5000	Doctorate	Prof-specialty	M	Husband
25	?	?	Handlers-cleaners	F	Wife
59	300000	Bachelors	?	?	Husband
33	0	Bachelors	?	F	?
?	0	High-school	Armed-Forces	?	Husband

TabNet encoder

TabNet decoder

Age	Cap. gain	Education	Occupation	Gender	Relationship
		Masters			
		High-school			Unmarried
43					
	0	High-school		F	
			Exec-managerial	M	
			Adm-clerical		Wife
39				M	

Supervised fine-tuning

Age	Cap. gain	Education	Occupation	Gender	Relationship
60	200000	Bachelors	Exec-managerial	M	Husband
23	0	High-school	Farming-fishing	M	Unmarried
45	5000	Doctorate	Prof-specialty	M	Husband
23	0	High-school	Handlers-cleaners	F	Wife
56	300000	Bachelors	Exec-managerial	M	Husband
38	10000	Bachelors	Prof-specialty	F	Wife
23	0	High-school	Armed-Forces	M	Husband

TabNet encoder

Decision making

Income > $50k
True
False
True
False
True
True
False

{tabnet} Ames (Oiho) city real estate dataset

```
suppressPackageStartupMessages(library(dplyr))
data("ames", package = "modeldata")
summary(ames %>% select(Sale_Price, Overall_Cond))
#>    Sale_Price           Overall_Cond
#>  Min.   : 12789   Average      :1654
#>  1st Qu.:129500   Above_Average: 533
#>  Median :160000   Good         : 390
#>  Mean   :180796   Very_Good    : 144
#>  3rd Qu.:213500   Below_Average: 101
#>  Max.   :755000   Fair         :  50
#>                   (Other)      :  58
str(ames)
#> tibble [2,930 × 74] (S3: tbl_df/tbl/data.frame)
#>  $ MS_SubClass        : Factor w/ 16 levels "One_Story_1946_and_
#>  $ MS_Zoning          : Factor w/ 7 levels "Floating_Village_Res
#>  $ Lot_Frontage       : num [1:2930] 141 80 81 93 74 78 41 43 39
#>  $ Lot_Area           : int [1:2930] 31770 11622 14267 11160 138
#>  $ Street             : Factor w/ 2 levels "Grvl","Pave": 2 2 2
#>  $ Alley              : Factor w/ 3 levels "Gravel","No_Alley_Ac
#>  $ Lot_Shape          : Factor w/ 4 levels "Regular","Slightly_I
#>  $ Land_Contour       : Factor w/ 4 levels "Bnk","HLS","Low",..:
#>  $ Utilities          : Factor w/ 3 levels "AllPub","NoSeWa",..:
#>  $ Lot_Config         : Factor w/ 5 levels "Corner","CulDSac",..
#>  $ Land_Slope         : Factor w/ 3 levels "Gtl","Mod","Sev": 1
#>  $ Neighborhood       : Factor w/ 29 levels "North_Ames","Colleg
#>  $ Condition_1        : Factor w/ 9 levels "Artery","Feedr",..:
#>  $ Condition_2        : Factor w/ 8 levels "Artery","Feedr",..:
#>  $ Bldg_Type          : Factor w/ 5 levels "OneFam","TwoFmCon",.
#>  $ House_Style        : Factor w/ 8 levels "One_and_Half_Fin",..
#>  $ Overall_Cond       : Factor w/ 10 levels "Very_Poor","Poor",.
#>  $ Year_Built         : int [1:2930] 1960 1961 1958 1968 1997 19
#>  $ Year_Remod_Add     : int [1:2930] 1960 1961 1958 1968 1998 19
```

{tabnet} is integrated in your usual data-modeling flow

{recipe} supervised training, regression

```
library(tabnet)
suppressPackageStartupMessages(library(recipes))
data("ames", package = "modeldata")
rec <- recipe(Sale_Price ~ ., data = ames) %>%
  step_normalize(all_numeric(), -all_outcomes())

fit_regression <- tabnet_fit(rec, ames, epochs = 30, valid_split = 0.25,
                             verbose = TRUE)
#> [Epoch 001] Loss: 39245544106.666664 Valid loss: 39583477760.000000
#> [Epoch 002] Loss: 38844006400.000000 Valid loss: 39582598485.333336
#> [Epoch 003] Loss: 38972246698.666664 Valid loss: 39580202325.333336
#> [Epoch 004] Loss: 39097417728.000000 Valid loss: 39574796970.666664
#> [Epoch 005] Loss: 39010614840.888885 Valid loss: 39561375744.000000
#> [Epoch 006] Loss: 38956964977.777779 Valid loss: 39544356864.000000
#> [Epoch 007] Loss: 38897157916.444443 Valid loss: 39531372544.000000
#> [Epoch 008] Loss: 39015064007.111115 Valid loss: 39497311573.333336
#> [Epoch 009] Loss: 38675581838.222221 Valid loss: 39459367594.666664
#> [Epoch 010] Loss: 38786213205.333336 Valid loss: 39441838080.000000
#> [Epoch 011] Loss: 38905815950.222221 Valid loss: 39394590720.000000
#> [Epoch 012] Loss: 38912344519.111115 Valid loss: 39346851840.000000
#> [Epoch 013] Loss: 38994933077.333336 Valid loss: 39333430613.333336
#> [Epoch 014] Loss: 38669082396.444443 Valid loss: 39284916224.000000
#> [Epoch 015] Loss: 38847803392.000000 Valid loss: 39200889514.666664
#> [Epoch 016] Loss: 38777508750.222221 Valid loss: 39085748224.000000
```

```
#> [Epoch 029] Loss: 37753581112.888885 Valid loss: 38111879168
#> [Epoch 030] Loss: 37558078577.777779 Valid loss: 36924513621
predict(fit_regression, ames)
#> # A tibble: 2,930 × 1
#>      .pred
#>      <dbl>
#>  1 10130.
#>  2  1182.
#>  3  7408.
#>  4 12563.
#>  5  7759.
#>  6  8090.
#>  7  7457.
#>  8  7580.
#>  9 12154.
#> 10  8051.
#> # … with 2,920 more rows
```

Created on 2021-10-15 by the reprex package (v2.0.1)

{tabnet} is integrated in your usual data-modeling flow

{recipe} supervised training, classification

```r
library(tabnet)
suppressPackageStartupMessages(library(recipes))
data("ames", package = "modeldata")
rec <- recipe(Overall_Cond ~ ., data = ames) %>%
  step_normalize(all_numeric(), -all_outcomes())

fit_classification <- tabnet_fit(rec, ames, epochs = 30, valid_split = 0.25,
                                 verbose = TRUE)
#> [Epoch 001] Loss: 2.241868 Valid loss: 1.534453
#> [Epoch 002] Loss: 1.462668 Valid loss: 1.445169
#> [Epoch 003] Loss: 1.284300 Valid loss: 1.374422
#> [Epoch 004] Loss: 1.226473 Valid loss: 1.360221
#> [Epoch 005] Loss: 1.181023 Valid loss: 1.345467
#> [Epoch 006] Loss: 1.150171 Valid loss: 1.287703
#> [Epoch 007] Loss: 1.118057 Valid loss: 1.256181
#> [Epoch 008] Loss: 1.105949 Valid loss: 1.223070
#> [Epoch 009] Loss: 1.092315 Valid loss: 1.228600
#> [Epoch 010] Loss: 1.095613 Valid loss: 1.215642
#> [Epoch 011] Loss: 1.064028 Valid loss: 1.205997
#> [Epoch 012] Loss: 1.049421 Valid loss: 1.196188
#> [Epoch 013] Loss: 1.053335 Valid loss: 1.175956
#> [Epoch 014] Loss: 1.030083 Valid loss: 1.161648
#> [Epoch 015] Loss: 1.026980 Valid loss: 1.160530
#> [Epoch 016] Loss: 1.011996 Valid loss: 1.146073
```

```r
#> [Epoch 029] Loss: 0.938634 Valid loss: 1.106678
#> [Epoch 030] Loss: 0.947539 Valid loss: 1.092313
predict(fit_classification, ames)
#> # A tibble: 2,930 × 1
#>    .pred_class
#>    <fct>
#>  1 Average
#>  2 Average
#>  3 Average
#>  4 Average
#>  5 Average
#>  6 Average
#>  7 Average
#>  8 Average
#>  9 Average
#> 10 Average
#> # … with 2,920 more rows
```

Created on 2021-10-18 by the reprex package (v2.0.1)

{tabnet} is integrated in your usual data-modeling flow

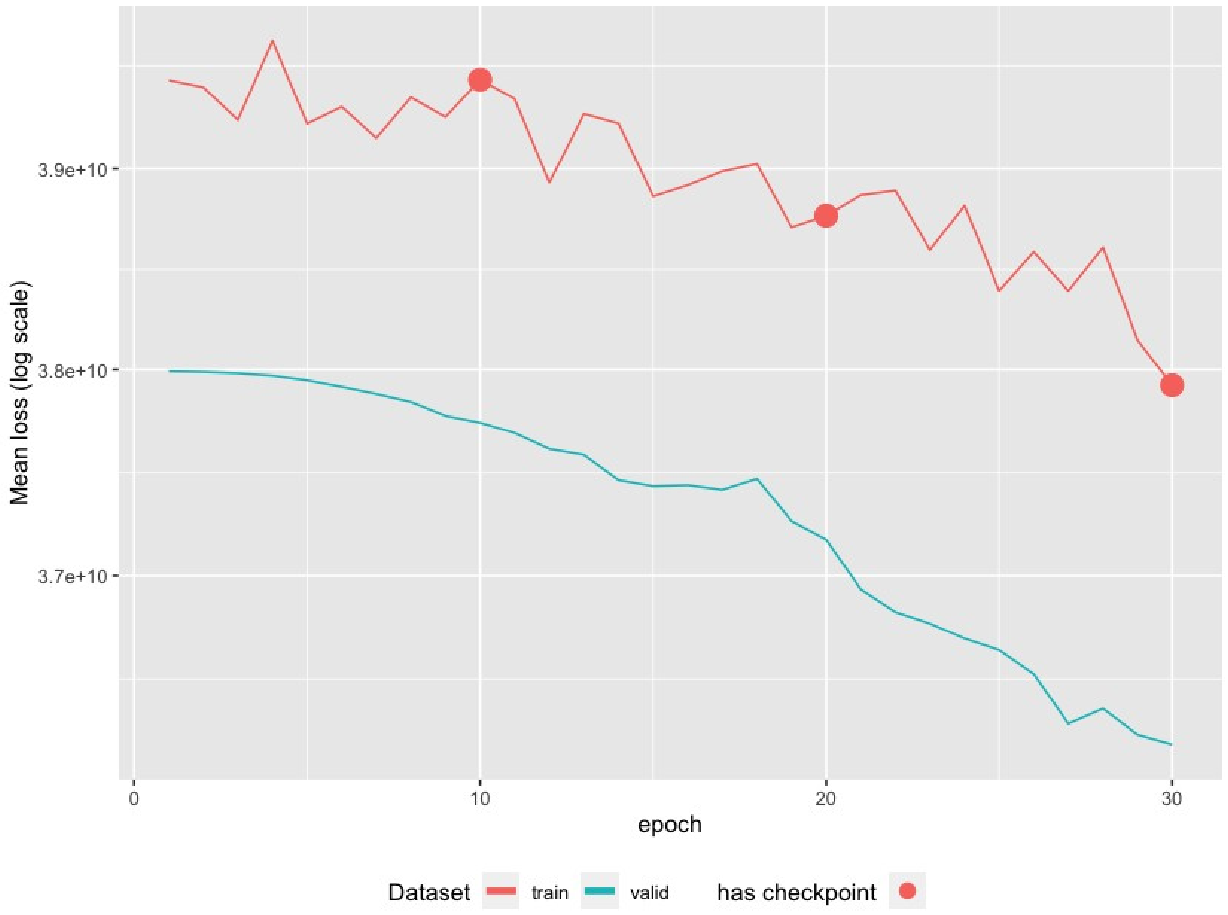
{workflow} training

```r
library(tabnet)
library(parsnip)
data("ames", package = "modeldata")

model <- tabnet(penalty = tune(), epochs = tune()) %>%
  set_mode("regression") %>%
  set_engine("torch")

wf <- workflows::workflow() %>%
  workflows::add_model(model) %>%
  workflows::add_formula(Sale_Price ~ .)

wf <- tune::finalize_workflow(wf, tibble::tibble(penalty = 0.01, epochs = 1))
#> Registered S3 method overwritten by 'tune':
#>   method                   from
#>   required_pkgs.model_spec parsnip

fit <- wf %>% fit(data = ames)
```

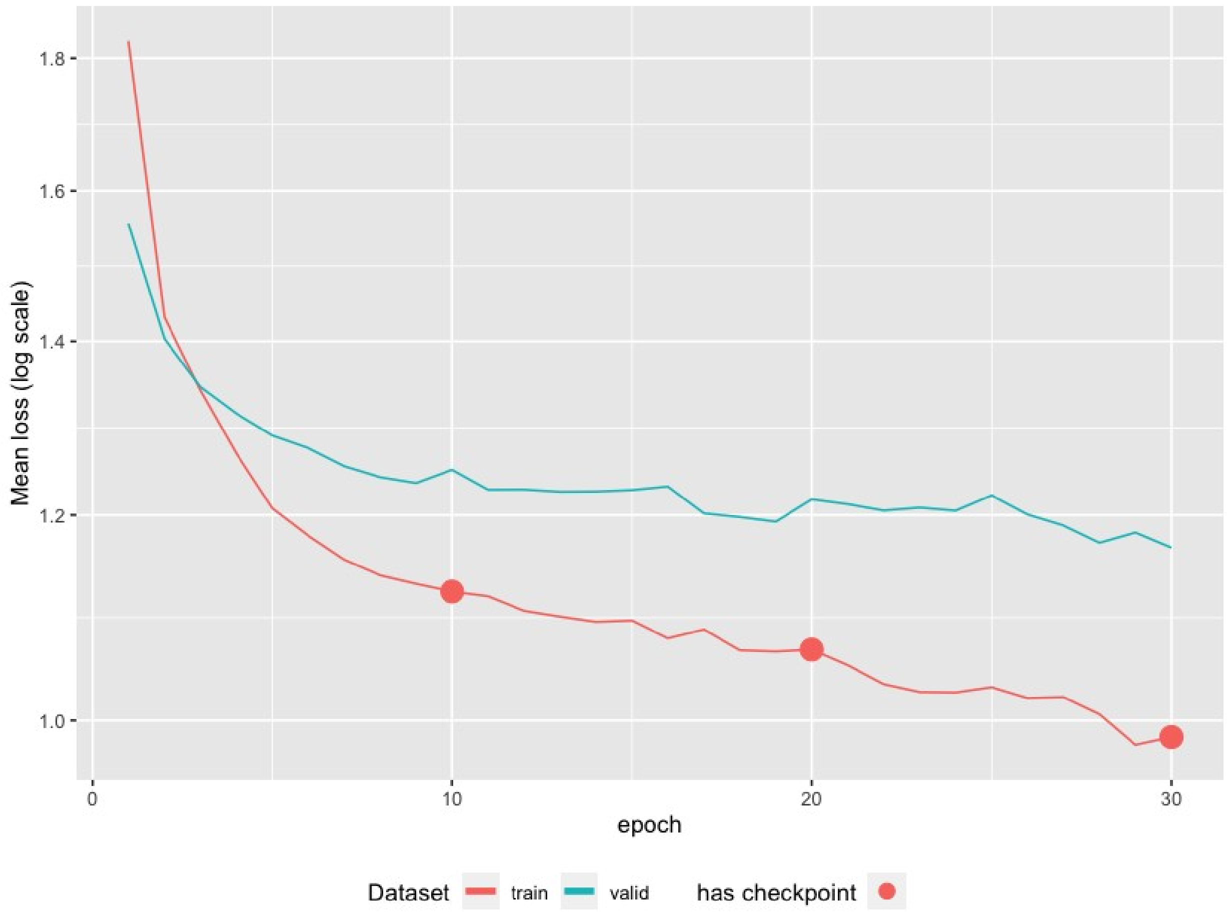
{tabnet} model-training diagnostic plot

`ggplot2::autoplot()` diagnostic plot the model training

```
ggplot2::autoplot(fit_regression)
```




```
ggplot2::autoplot(fit_classification)
```



{tabnet} sauve and restore model to disk

saveRDS(tabnet_model)

```
> tmp <- tempfile("model", fileext = ".rds")
> saveRDS(fit_regression, tmp)
> file.info(tmp)
                                                                          size isdir mode
/var/folders/dp/8_b9182d7sjg176vhnsjwvfw0000gn/T//RtmpDktXgP/model3093382471a0.rds 9657466 FALSE  666
```

readRDS(file.Rds)

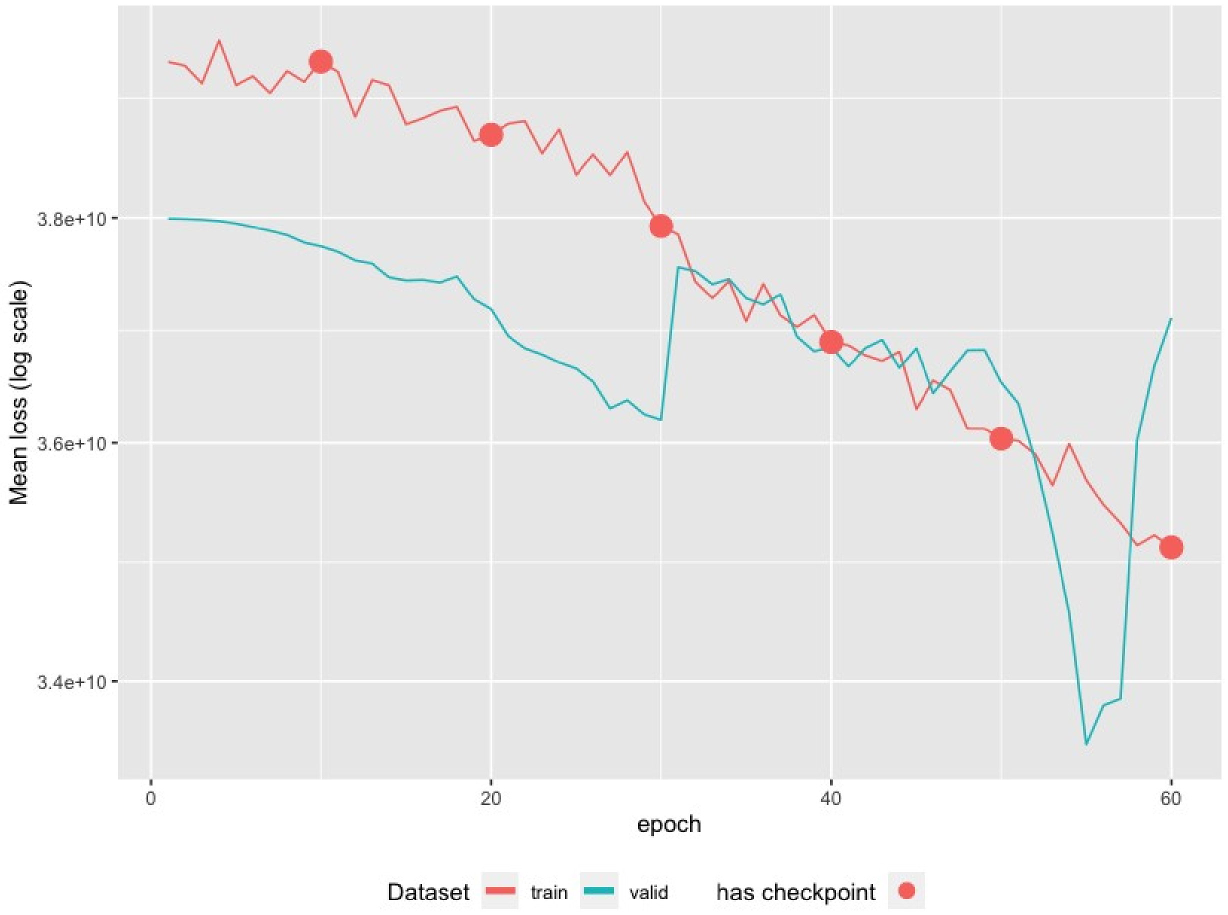
```
> fit_regression2 <- readRDS(tmp)
> predict(fit_regression2, ames)
# A tibble: 2,930 × 1
   .pred
   <dbl>
 1 4814.
 2 3472.
 3 4281.
```

{tabnet} continue a model training

tabnet_fit(…, tabnet_model = <previous model> , from_epoch = 17)

- from in-memory model

```
fit_regression_3 <- tabnet_fit(rec, ames, epochs = 30, valid_split = 0.25,
                               tabnet_model = fit_regress
                               verbose = TRUE)
ggplot2::autoplot(fit_regression_3)
```



- from disk-saved model

Idem, but `from_epoch` must be a chackpoint

- with new training parameters (`lr`, `batch size`, ...)

- but with no change of the model design parameters !

{tabnet} masked pretraining

tabnet_pretrain() unsupervised training

- load required libraries

```
library(tabnet)
library(tidymodels)
```

- make a fake unsupervised training set

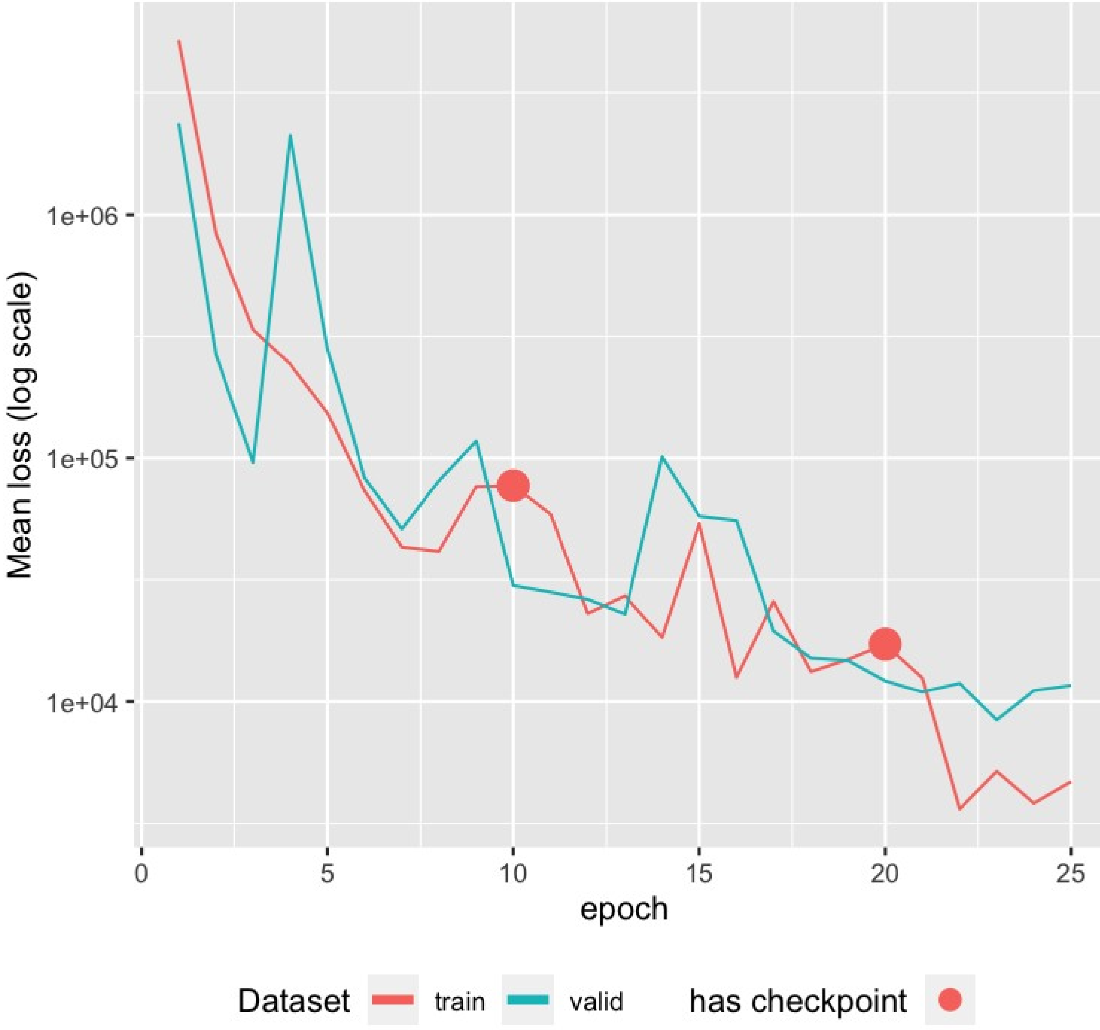
```
data("lending_club", package = "modeldata")
split ← initial_split(lending_club, strata = Class, prop = 9/10)
unsupervised ← training(split) %>% mutate(Class=NA)
supervised  ← testing(split)
```

- recipe, preparation and baking of data

```
prep_unsup ← recipe(Class ~ ., unsupervised) %>%
  step_normalize(all_numeric()) %>%
  prep
unsupervised_baked_df ← prep_unsup %>%
  bake(new_data=NULL)
```

- and unsupervised training

```
pretrained_mod ← tabnet_pretrain(x= unsupervised_baked_df %>% select(-Class),
                                 y=NULL, epochs = 25, valid_split = 0.2,
                                 verbose = TRUE)

ggplot2::autoplot(pretrained_mod)
```



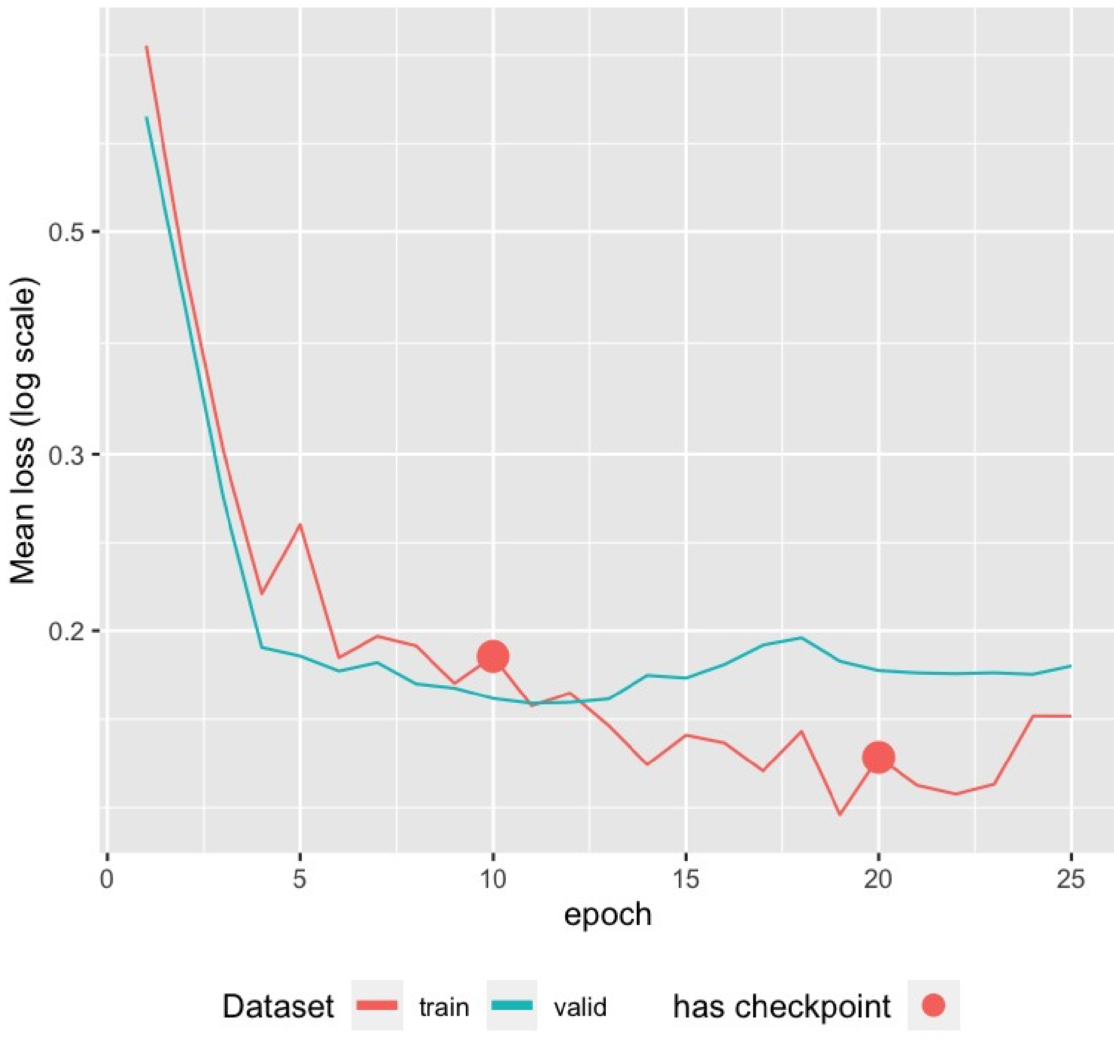
{tabnet} continue model training with supervised dataset

tabnet_fit(…, tabnet_model = <unsupervised model>)

- compared to the unsupervised training, we change the cost function

```
split_s ← initial_split(supervised, strata = Class)
train ← training(split_s)
supervised_train_df ← prep_unsup %>%
  bake(new_data= train)
```

```
model_fit ← tabnet_fit(x=supervised_train_df %>% select(-Class),
                        y= supervised_train_df$Class,
                        tabnet_model = pretrained_mod,
                        valid_split = 0.2, epochs = 25, verbose=TRUE)

ggplot2::autoplot(model_fit)
```

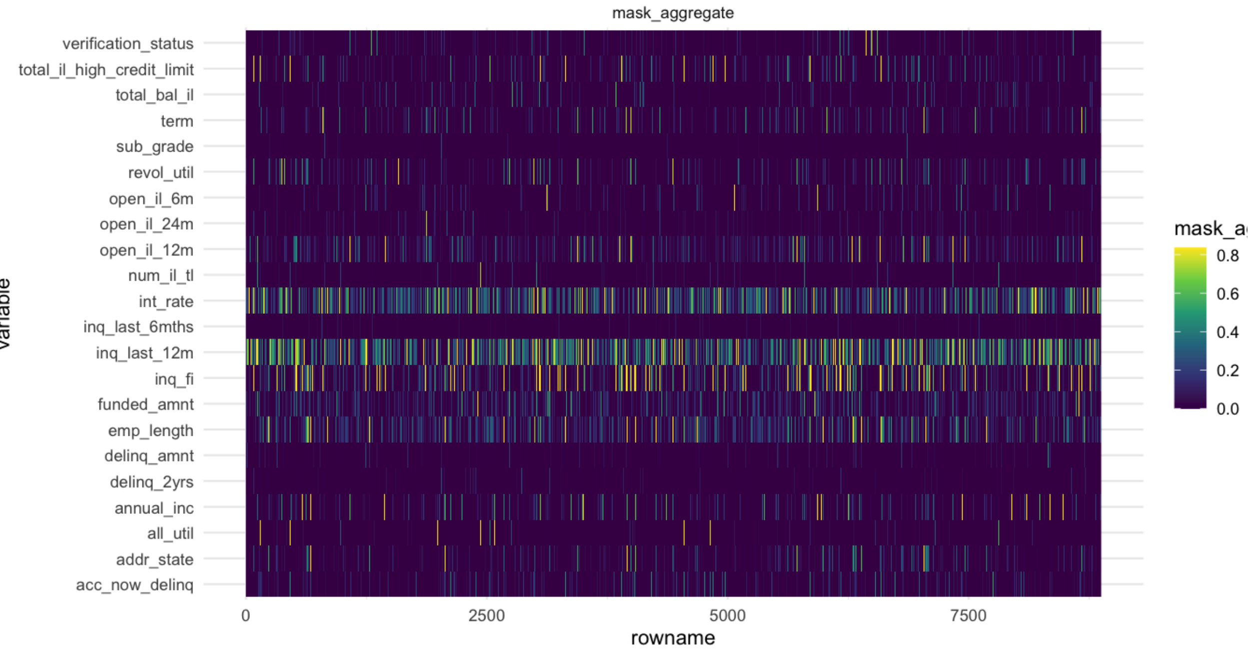


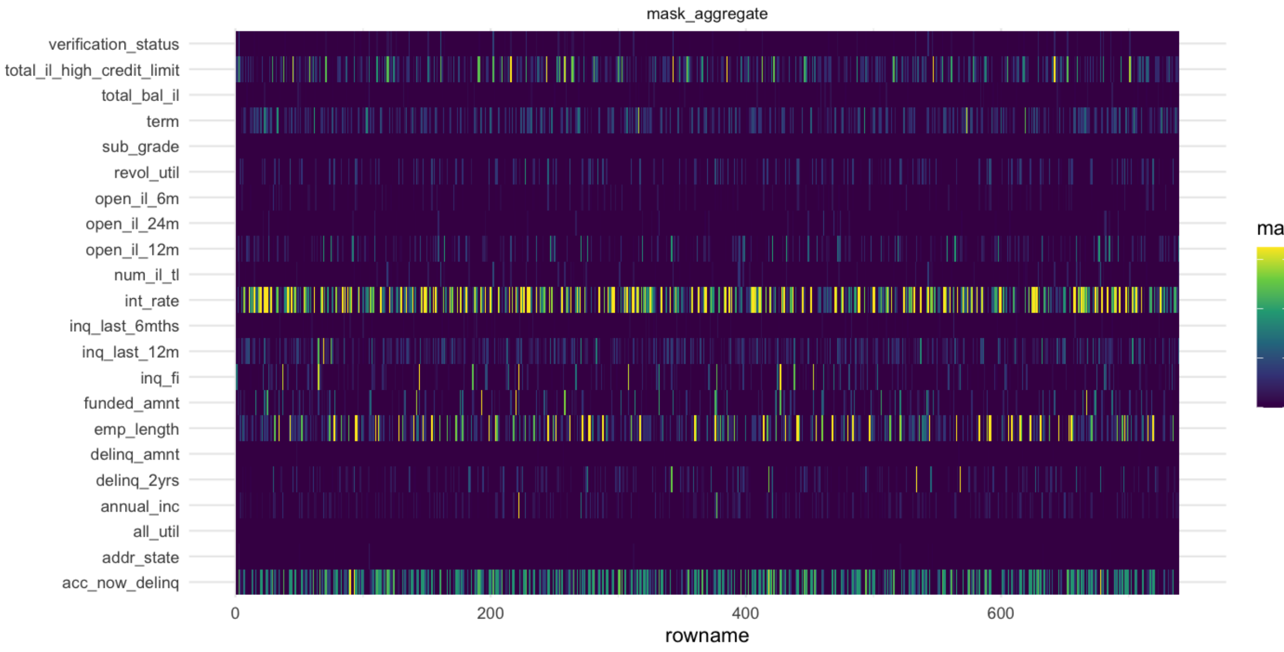
{tabnet} has intrinsec explainability

tabnet_explain() extraction du masque agrégé

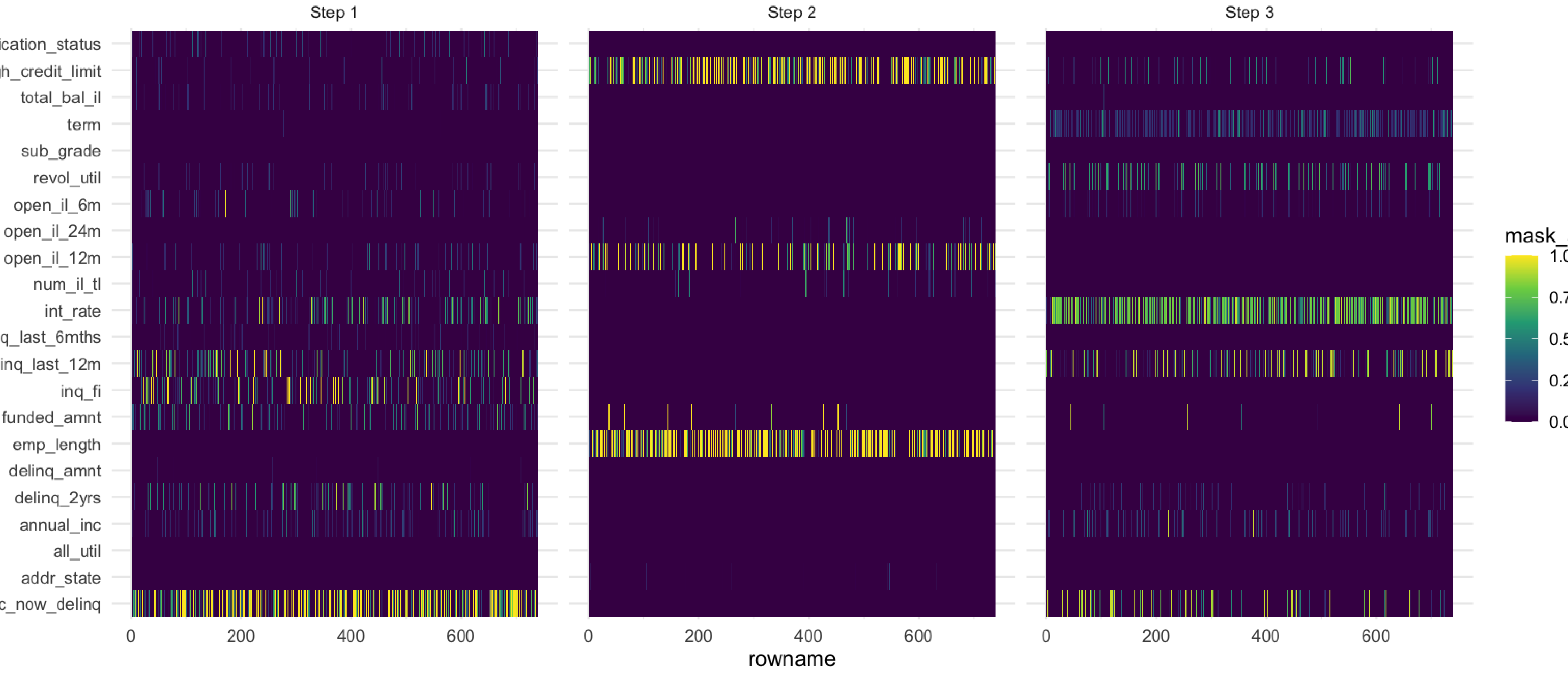
-
```
pretrain_explain <- tabnet_explain(
  pretrained_mod,
  new_data = unsupervised_baked_df
  )
autoplot(pretrain_explain, quantile=0.99)
```

```
model_explain <- tabnet_explain(
  model_fit,
  new_data = supervised_train_df
  )
autoplot(model_explain, quantile=0.99)
```





{tabnet}



Step 1
Step 2
Step 3
ication_status
h_credit_limit
total_bal_il
term
sub_grade
revol_util
open_il_6m
open_il_24m
open_il_12m
num_il_tl
int_rate
q_last_6mths
inq_last_12m
inq_fi
funded_amnt
emp_length
delinq_amnt
delinq_2yrs
annual_inc
all_util
addr_state
c_now_delinq
0
200
400
600
rowname
mask_
1.0
0.7
0.5
0.2
0.0

{tabnet} latest news

- `early-stopping`
- `pretrain` from dataset with missing data
- `fit` from dataset with missing data
- `explain` from dataset with missing data
- cleaner plots