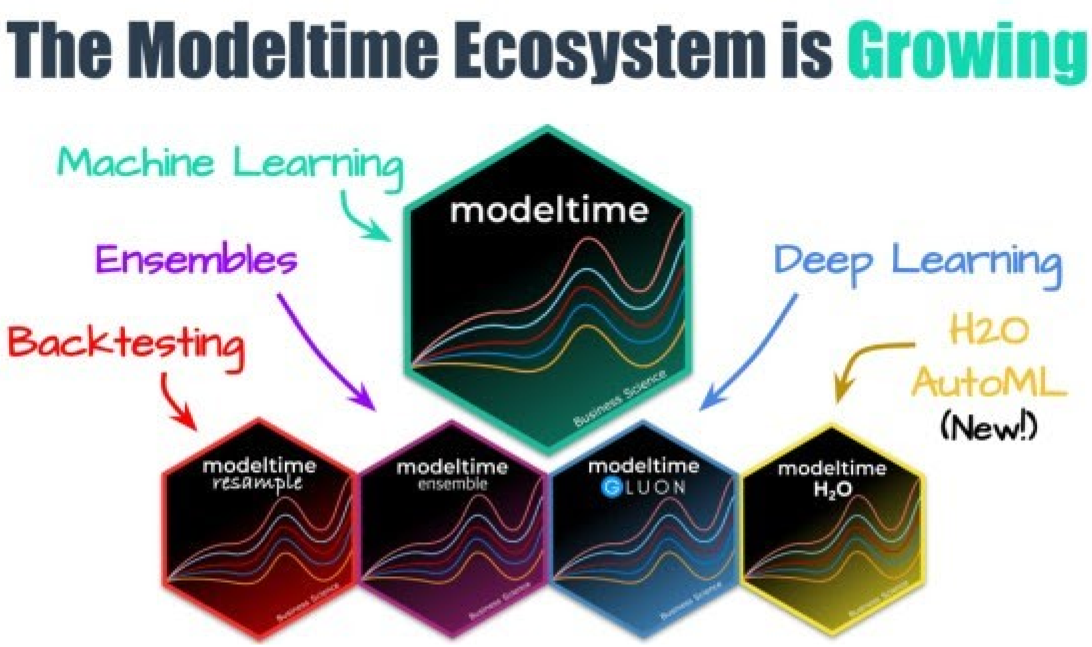
Meet the Modeltime Ecosystem
A **growing** ecosystem for tidymodels forecasting

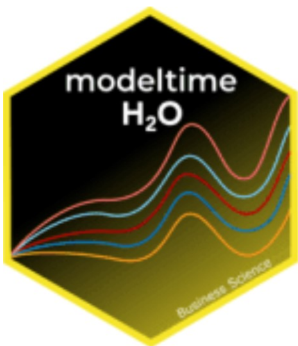


Modeltime H2O is part of a **growing ecosystem** of Modeltime forecasting packages. The main purpose of the Modeltime Ecosystem is to develop scalable forecasting systems.

- Modeltime (Machine Learning, Forecasting Workflow)
- Modeltime H2O (AutoML)
- Modeltime GluonTS (Deep Learning)
- Modeltime Ensemble (Blending Forecasts)
- Modeltime Resample (Backtesting)
- Timetk (Data Transformation, Feature Engineering, Time Series Visualization)

Modeltime H2O
The **H2O AutoML** backend for Modeltime

Modeltime H2O provides an H2O backend to the Modeltime Forecasting Ecosystem. The main algorithm is **H2O AutoML**, an automatic machine learning library that is built for speed and scale.



This forecast was created with **H2O AutoML**. We'll make this forecast in our short tutorial.

Getting Started with Modeltime H2O

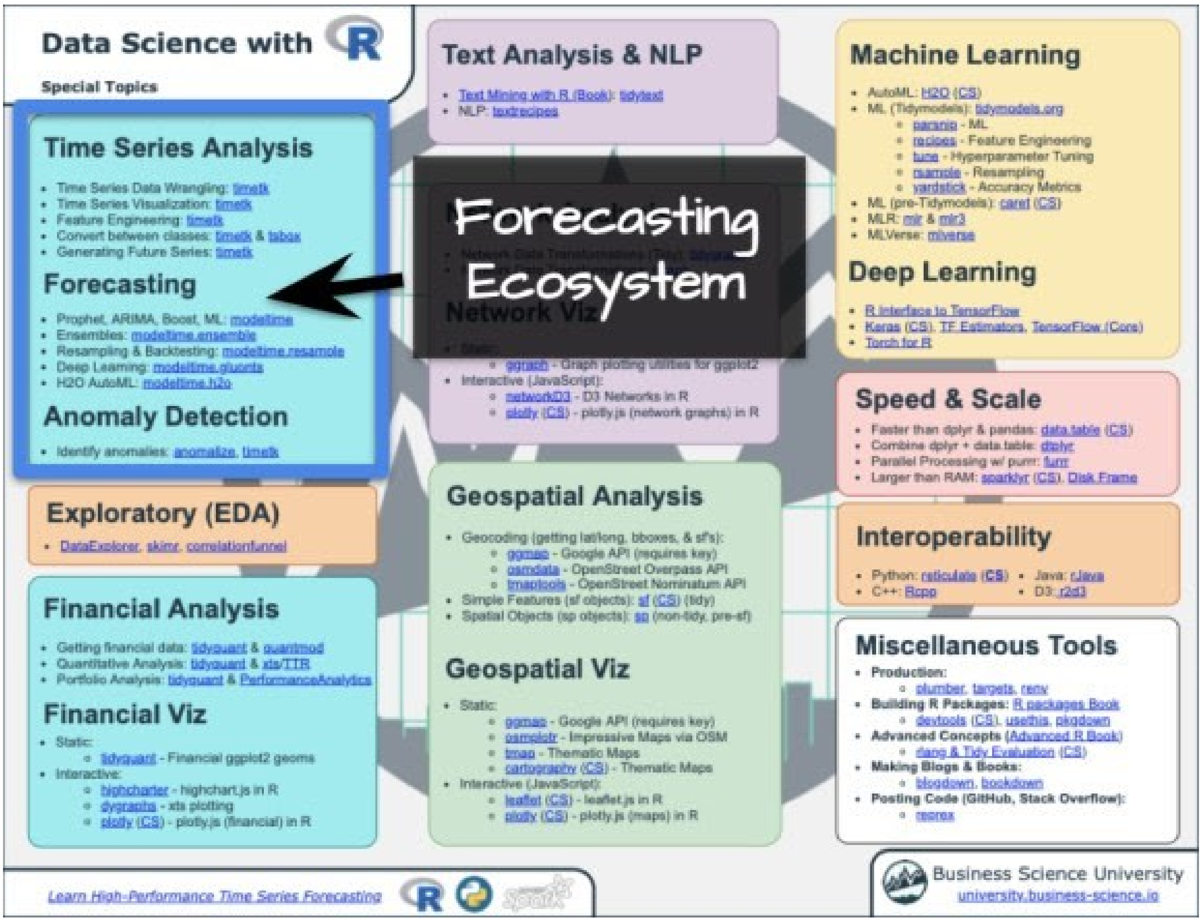
Forecasting with `modeltime.h2o` made easy! This short tutorial shows how you can use:

- **H2O AutoML** for forecasting implemented via `automl_reg()`. This function trains and cross-validates multiple machine learning and deep learning models (XGBoost GBM, GLMs, Random Forest, GBMs…) and then trains two Stacked Ensembled models, one of all the models, and one of only the best models of each kind. Finally, the best model is selected based on a stopping metric. And we take care of all this for you!

- **Save & Load Models** functionality to ensure the persistence of your models.

Get the Cheat Sheet

As you go through this tutorial, it may help to use the Ultimate R Cheat Sheet. Page 3 Covers the Modeltime Forecasting Ecosystem with links to key documentation.



Forecasting Ecosystem Links (Ultimate R Cheat Sheet)

Libraries

The `modeltime.h2o` package is not on CRAN yet (though it should be sometime in the next 2 weeks). Until then, you can install it with this:

```
# Install Modeltime H2O Development Version
devtools::install_github("business-science/modeltime.h2o")
```

Load the following libraries:

```
library(tidymodels)
library(modeltime.h2o)
library(tidyverse)
library(timetk)
```

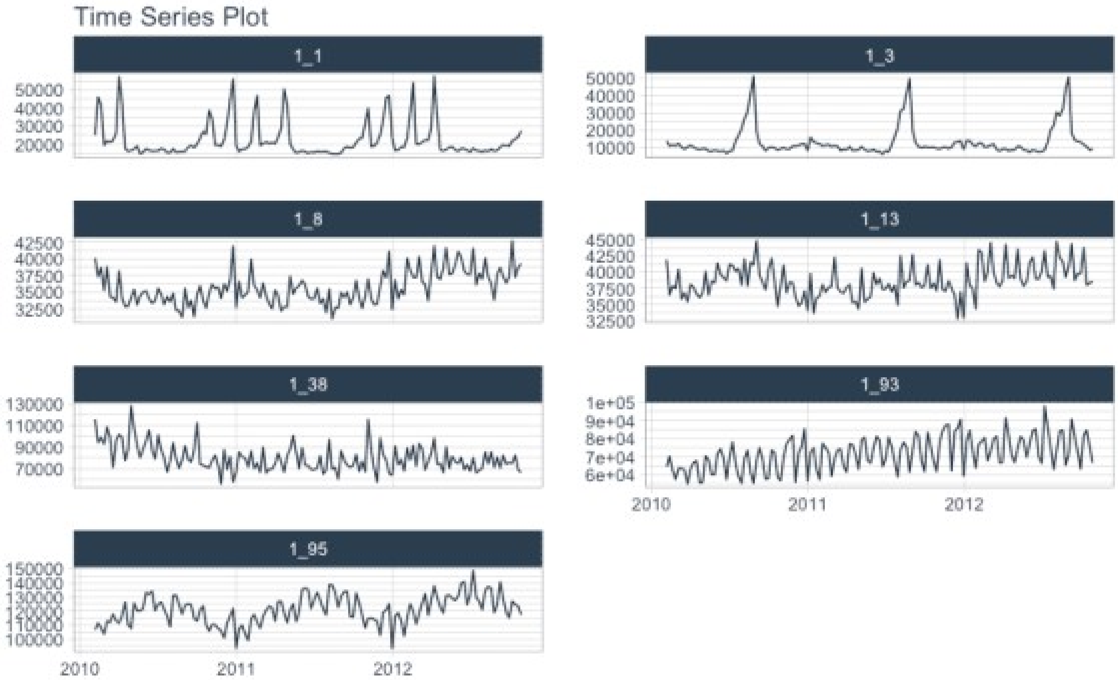
Collect data and split into training and test sets

Next, we load the walmart_sales_weekly data containing 7 time series and visualize them using the `timetk::plot_time_series()` function.

```
data_tbl <- walmart_sales_weekly %>%
    select(id, Date, Weekly_Sales)

data_tbl %>%
  group_by(id) %>%
  plot_time_series(
      .date_var    = Date,
```

```
        .value       = Weekly_Sales,
        .facet_ncol  = 2,
        .smooth      = F,
        .interactive = F
    )
```



Then, we separate the data with the `initial_time_split()` function and generate a training dataset and a test one.

```
splits <- time_series_split(data_tbl, assess = "3 month",
cumulative = TRUE)

recipe_spec <- recipe(Weekly_Sales ~ ., data =
training(splits)) %>%
    step_timeseries_signature(Date)

train_tbl <- training(splits) %>% bake(prep(recipe_spec), .)
test_tbl  <- testing(splits) %>% bake(prep(recipe_spec), .)
```

Model specification, training and prediction

In order to correctly use `modeltime.h2o`, it is necessary to connect to an H2O cluster through the `h2o.init()` function. You can find more information on how to set up the cluster by typing `?h2o.init` or by visiting the official site.

```
h2o.init(
    nthreads = -1,
    ip       = 'localhost',
    port     = 54321
)

##  Connection successful!
##
```

```
## R is connected to the H2O cluster:
##     H2O cluster uptime:         2 days 8 hours
##     H2O cluster timezone:       America/New_York
##     H2O data parsing timezone:  UTC
##     H2O cluster version:        3.32.0.1
##     H2O cluster version age:    5 months and 6 days !!!
##     H2O cluster name:
H2O_started_from_R_mdancho_rfu672
##     H2O cluster total nodes:    1
##     H2O cluster total memory:   7.70 GB
##     H2O cluster total cores:    12
##     H2O cluster allowed cores:  12
##     H2O cluster healthy:        TRUE
##     H2O Connection ip:          localhost
##     H2O Connection port:        54321
##     H2O Connection proxy:       NA
##     H2O Internal Security:      FALSE
##     H2O API Extensions:         Amazon S3, XGBoost, Algos,
AutoML, Core V3, TargetEncoder, Core V4
##     R Version:                  R version 4.0.2
(2020-06-22)
```

Now comes the fun part! We define our model specification with the `automl_reg()` function and pass the arguments through the engine:

```
model_spec <- automl_reg(mode = 'regression') %>%
    set_engine(
         engine                     = 'h2o',
         max_runtime_secs           = 5,
         max_runtime_secs_per_model = 3,
         max_models                 = 3,
         nfolds                     = 5,
         exclude_algos              = c("DeepLearning"),
         verbosity                  = NULL,
         seed                       = 786
    )

model_spec

## H2O AutoML Model Specification (regression)
##
## Engine-Specific Arguments:
##   max_runtime_secs = 5
##   max_runtime_secs_per_model = 3
##   max_models = 3
##   nfolds = 5
##   exclude_algos = c("DeepLearning")
##   verbosity = NULL
##   seed = 786
##
## Computational engine: h2o
```

Next, let's train the model!

```
model_fitted <- model_spec %>%
    fit(Weekly_Sales ~ ., data = train_tbl)
```

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##                                              model_id
mean_residual_deviance
## 1 StackedEnsemble_AllModels_AutoML_20210314_202927
35931457
## 2                XGBoost_3_AutoML_20210314_202927
37716780
## 3                XGBoost_2_AutoML_20210314_202927
39595467
## 4                XGBoost_1_AutoML_20210314_202927
40327699
##       rmse      mse      mae     rmsle
## 1 5994.285 35931457 3624.093 0.1408371
## 2 6141.399 37716780 3778.491 0.1468337
## 3 6292.493 39595467 3932.025 0.1553225
## 4 6350.409 40327699 4089.680 0.1659641
##
## [4 rows x 6 columns]
```

We can check out the trained H2O AutoML model.

```
model_fitted

## parsnip model object
##
## Fit time:  8.1s
##
## H2O AutoML - Stackedensemble
## --------
## Model: Model Details:
## ==============
##
## H2ORegressionModel: stackedensemble
## Model ID:  StackedEnsemble_AllModels_
AutoML_20210314_202927
## Number of Base Models: 3
##
## Base Models (count by algorithm type):
##
## xgboost
##       3
##
## Metalearner:
##
## Metalearner algorithm: glm
## Metalearner cross-validation fold assignment:
##   Fold assignment scheme: AUTO
##   Number of folds: 5
##   Fold column: NULL
## Metalearner hyperparameters:
##
##
## H2ORegressionMetrics: stackedensemble
## ** Reported on training data. **
##
## MSE:  14187153
## RMSE:  3766.584
## MAE:  2342.327
## RMSLE:  0.08087684
## Mean Residual Deviance :  14187153
##
##
##
## H2ORegressionMetrics: stackedensemble
## ** Reported on cross-validation data. **
## ** 5-fold cross-validation on training data (Metrics
computed for combined holdout predictions) **
##
## MSE:  35931457
## RMSE:  5994.285
## MAE:  3624.093
## RMSLE:  0.1408371
## Mean Residual Deviance :  35931457
```

Finally, we predict on the test dataset:

```
predict(model_fitted, test_tbl)
```

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```

```
## # A tibble: 84 x 1
##      .pred
##
##  1  18233.
##  2  31529.
##  3  37662.
##  4  40605.
##  5  74633.
##  6  81293.
##  7 134751.
##  8  17794.
##  9  36732.
## 10  37074.
## # … with 74 more rows
```

Modeltime Workflow

Once we have our fitted model, we can follow the Modeltime Workflow:

- Add fitted models to a **Model Table**.
- **Calibrate** the models to a testing set.
- Perform Testing Set **Forecast Assessment** & Accuracy Evaluation.
- **Refit** the models to Full Dataset & Forecast Forward

Add fitted models to a Model Table

First, we create the model table:

```
modeltime_tbl <- modeltime_table(
    model_fitted
)
```

```
modeltime_tbl
```

```
## # Modeltime Table
## # A tibble: 1 x 3
##   .model_id .model   .model_desc
##
## 1         1  H2O AUTOML - STACKEDENSEMBLE
```

Calibrate & Testing Set Forecast & Accuracy Evaluation

Next, we calibrate to the testing set and visualize the forecasts:

```
modeltime_tbl %>%
  modeltime_calibrate(test_tbl) %>%
    modeltime_forecast(
        new_data    = test_tbl,
        actual_data = data_tbl,
        keep_data   = TRUE
    ) %>%
    group_by(id) %>%
    plot_modeltime_forecast(
        .facet_ncol = 2,
        .interactive = FALSE
    )
```

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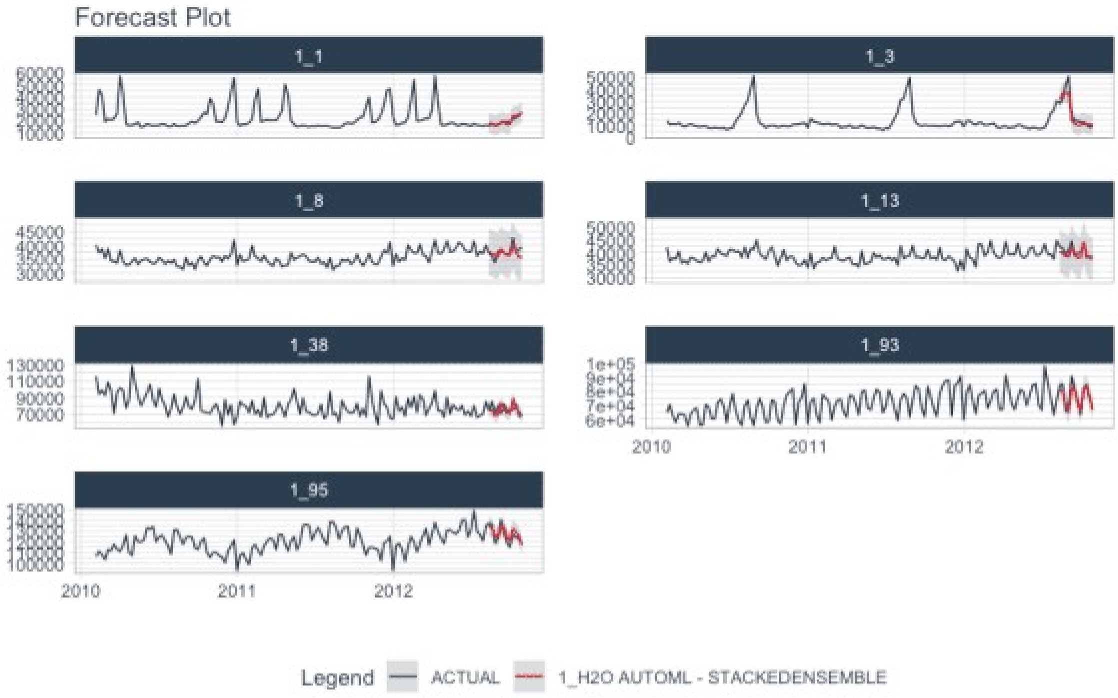
```



Refit to Full Dataset & Forecast Forward

Before using **refit** on our dataset, let's prepare our data. We create `data_prepared_tbl` which represents the complete dataset (the union of train and test) with the variables created with the recipe named recipe_spec. Subsequently, we create the dataset `future_prepared_tbl` that represents the dataset with the future data to one year and the required variables.

```
data_prepared_tbl <- bind_rows(train_tbl, test_tbl)

future_tbl <- data_prepared_tbl %>%
    group_by(id) %>%
    future_frame(.length_out = "1 year") %>%
    ungroup()

future_prepared_tbl <- bake(prep(recipe_spec), future_tbl)
```

Finally, we use `modeltime_refit()` to re-train our model on the entire dataset. This is a best-practice for improving forecast results.

```
refit_tbl <- modeltime_tbl %>%
    modeltime_refit(data_prepared_tbl)

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##                                          model_id
mean_residual_deviance
## 1 StackedEnsemble_AllModels_AutoML_20210314_202938
34093669
## 2                XGBoost_3_AutoML_20210314_202938
37000407
## 3                XGBoost_2_AutoML_20210314_202938
37884414
## 4                XGBoost_1_AutoML_20210314_202938
39079782
##       rmse      mse      mae     rmsle
## 1 5838.978 34093669 3565.292 0.1407856
## 2 6082.796 37000407 3695.199 0.1446849
## 3 6155.032 37884414 3928.093 0.1623624
## 4 6251.382 39079782 4207.449 0.1819081
##
## [4 rows x 6 columns]
```

Let's visualize the final forecast

We can quickly visualize the final forecast with `modeltime_forecast()` and it's plotting utility function, `plot_modeltime_forecast()`.

```
refit_tbl %>%
    modeltime_forecast(
        new_data    = future_prepared_tbl,
        actual_data = data_prepared_tbl,
        keep_data   = TRUE
    ) %>%
    group_by(id) %>%
    plot_modeltime_forecast(
        .facet_ncol  = 2,
```

```
        .interactive = FALSE
    )

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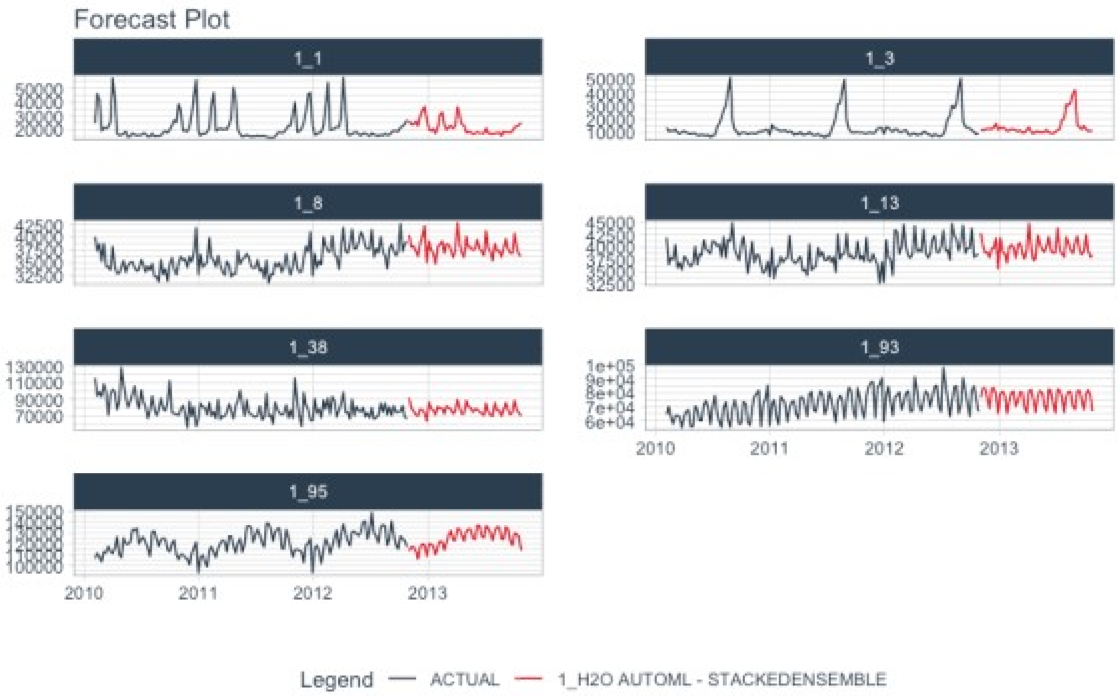
```



We can likely do better than this if we train longer but really good for a quick example!

Saving and Loading Models

H2O models will need to "serialized" (a fancy word for saved to a directory that contains the recipe for recreating the models). To save the models, use `save_h2o_model()`.

- Provide a directory where you want to save the model.
- This saves the model file in the directory.

```
model_fitted %>%
  save_h2o_model(path = "../model_fitted", overwrite = TRUE)
```

You can reload the model into R using `load_h2o_model()`.

```
model_h2o <- load_h2o_model(path = "../model_fitted/")
```