Denoising Autoencoder to Fill Missing Values

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Introduction

- Denoising Autoencoder can be used to reconstruct damaged data.
- But…
  - Does it work with all kind of data?
  - Is it superior to other techniques?

- Performance comparison for 3 problems:
  - Only continuous variables;
  - Only categorical variables; and
  - Continuous and categorical variables.

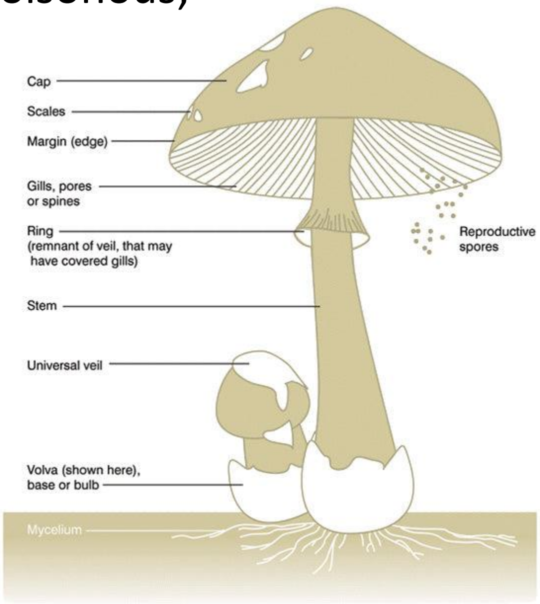
- How to implement autoencoder for each of these situations.

- Github: https://github.com/MaxWienandts/Denoising_Autoencoder_to_Missing_Data_Imputation/tree/main

The Data

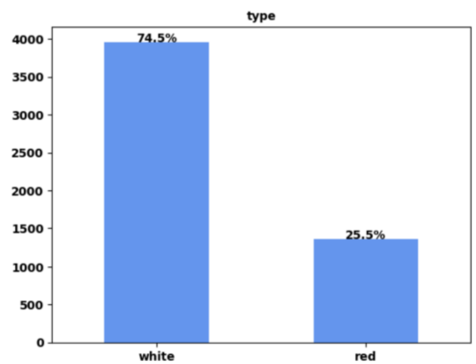
- Wine Quality (https://archive.ics.uci.edu/dataset/186/wine+quality)
  - Problem: Prediction of wine type (red or white);
  - Observations: 6,497;
  - Variables: 11 physicochemical continuous variables.

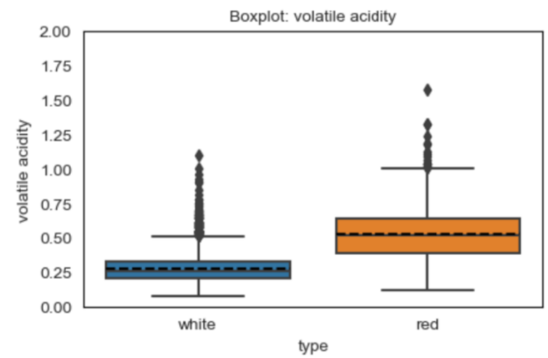
- Mushroom Dataset (https://archive.ics.uci.edu/dataset/848/secondary+mushroom+dataset)
  - Problem: Prediction if a mushroom is edible or poisonous;
  - Observations: 61,069;
  - Variables: 20 physical characteristics:
    - 3 continuous;
    - 17 categorical.
  - Two models:
    - Using only categorical variables;
    - Using all variables.



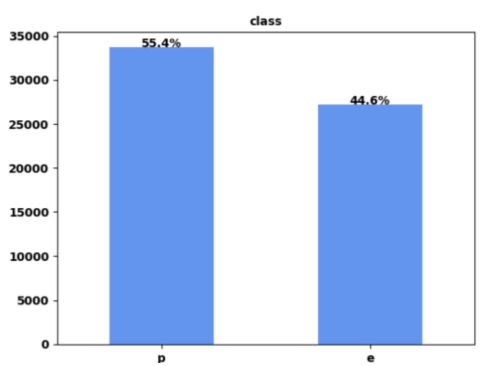
Exploratory Data Analysis

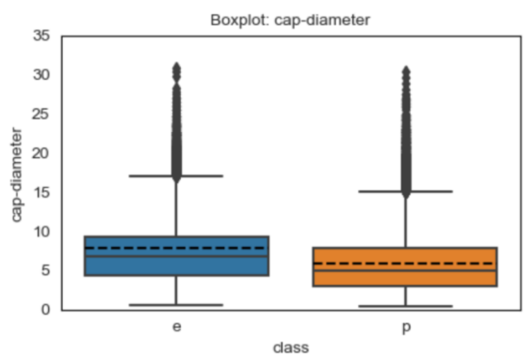
- Wine dataset:
  - Wine\1 EDA Denoising Autoencoder.ipynb;
  - No missing values.

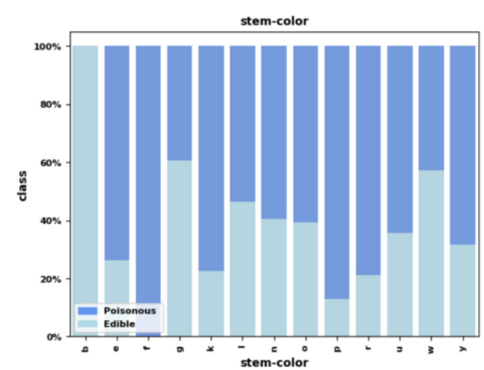




- Mushroom dataset:
  - Mushroom\1 EDA Denoising Autoencoder.ipynb;
  - There are missing values when a mushroom does not have a characteristic, i.e., not all mushroom have a veil.







B = buff
F = none

Autoencoders

- Wine dataset:
  - Wine\2 Denoising Autoencoder.ipynb
  - Coding: 8
  - Activation: SeLU
  - Loss function: Mean Squared Error

```
tf.keras.backend.clear_session()
model_encoder = models.Sequential([
    layers.Dense(8, activation = 'selu', input_shape = [11])
])
model_decoder = models.Sequential([
    layers.Dense(11, activation = 'selu', input_shape = [8])
])
model_autoencoder = models.Sequential([model_encoder, model_decoder])
model_autoencoder.compile(optimizer = keras.optimizers.SGD(learning_rate = 0.05),
                    loss = 'mse', metrics = ['mse'])

model_autoencoder.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential (Sequential)     (None, 8)                 96

 sequential_1 (Sequential)   (None, 11)                99

=================================================================
Total params: 195
Trainable params: 195
Non-trainable params: 0
_________________________________________________________________
```

Autoencoders

- Mushroom dataset (only categorical variables):
  - Mushroom \2 Denoising Autoencoder only Category.ipynb
  - Coding: 90 (there are 92 dummies in total)
  - Activation: ReLU and sigmoid (It is a good idea to map results to 0 and 1)
  - Loss function: Binary Cross Entropy

```
input_shape = X_train_aux.shape[1]

tf.keras.backend.clear_session()
model_encoder = models.Sequential([
    layers.Dense(90, activation = 'relu', input_shape = [input_shape]),
    layers.Dense(90, activation = 'sigmoid', input_shape = [90])
])
model_decoder = models.Sequential([
    layers.Dense(90, activation = 'relu', input_shape = [90]),
    layers.Dense(input_shape, activation = 'sigmoid', input_shape = [90])
])
model_autoencoder = models.Sequential([model_encoder, model_decoder])
model_autoencoder.compile(optimizer = keras.optimizers.SGD(learning_rate = 0.05),
                          loss = 'binary_crossentropy', metrics = ['binary_accuracy'])
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential (Sequential)     (None, 90)                16560

 sequential_1 (Sequential)   (None, 92)                16562

=================================================================
Total params: 33,122
Trainable params: 33,122
Non-trainable params: 0
_________________________________________________________________
```

Autoencoders

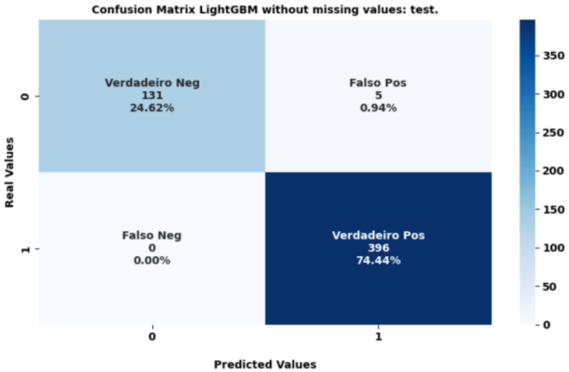
- Mushroom dataset (categorical and continuous variables):
  - Mushroom \2 Denoising Autoencoder Continuous and category.ipynb
  - Coding: 93 (there are 92 dummies plus 3 continuous variables)
  - Activation: ReLU and sigmoid (It is a good idea to map results to 0 and 1)
  - Loss function: Mean Squared Error and Binary Cross Entropy

```python
input_shape = X_train_aux.shape[1]
output_continuous_shape = X_train_continuous_original.shape[1]
output_category_shape = X_train_category_original.shape[1]

tf.keras.backend.clear_session()
inputs = tf.keras.layers.Input(shape=(input_shape,))
encoder_1 = layers.Dense(units = 93, activation = 'relu')(inputs)
encoder_2_continuous =  layers.Lambda(lambda x: x[:, 0: output_continuous_shape])(encoder_1)
encoder_2_category_aux =  layers.Lambda(lambda x: x[:, output_continuous_shape: ])(encoder_1)
encoder_2_category = layers.Dense(units = 90, activation = 'sigmoid')(encoder_2_category_aux)
encoder_3 = layers.Concatenate(axis=1)([encoder_2_continuous, encoder_2_category])

decoder_1 = layers.Dense(units = 93, activation = 'relu')(encoder_3)
decoder_2_continuous =  layers.Lambda(lambda x: x[:, 0: output_continuous_shape], name = 'decoder_2_continuous')(decoder_1)
decoder_2_category_aux =  layers.Lambda(lambda x: x[:, output_continuous_shape: ])(decoder_1)
decoder_2_category = layers.Dense(units = output_category_shape, activation = 'sigmoid', name = 'decoder_2_category')(encoder_2_category_aux)

model_autoencoder = models.Model(inputs = inputs, outputs = [decoder_2_continuous, decoder_2_category])
model_autoencoder.compile(optimizer = keras.optimizers.SGD(learning_rate = 0.05),
                          loss = {'decoder_2_continuous': 'mse',
                                  'decoder_2_category': 'binary_crossentropy'},
                          metrics = {'decoder_2_continuous': 'mse',
                                     'decoder_2_category': 'binary_accuracy'}
                         )

model_1_history = model_autoencoder.fit(X_train_aux, (X_train_continuous_original, X_train_category_original)
                                        , validation_data = [X_val_aux, (X_val_continuous_original, X_val_category_original)]
                                        , verbose = 1
                                        , epochs = 100)
```

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_1 (InputLayer)           [(None, 95)]         0           []

 dense (Dense)                  (None, 93)           8928        ['input_1[0][0]']

 lambda_1 (Lambda)              (None, 90)           0           ['dense[0][0]']

 lambda (Lambda)                (None, 3)            0           ['dense[0][0]']

 dense_1 (Dense)                (None, 90)           8190        ['lambda_1[0][0]']

 concatenate (Concatenate)      (None, 93)           0           ['lambda[0][0]',
                                                                  'dense_1[0][0]']

 dense_2 (Dense)                (None, 93)           8742        ['concatenate[0][0]']

 decoder_2_continuous (Lambda)  (None, 3)            0           ['dense_2[0][0]']

 decoder_2_category (Dense)     (None, 92)           8372        ['lambda_1[0][0]']

==================================================================================================
Total params: 34,232
Trainable params: 34,232
Non-trainable params: 0
__________________________________________________________________________________________________
```

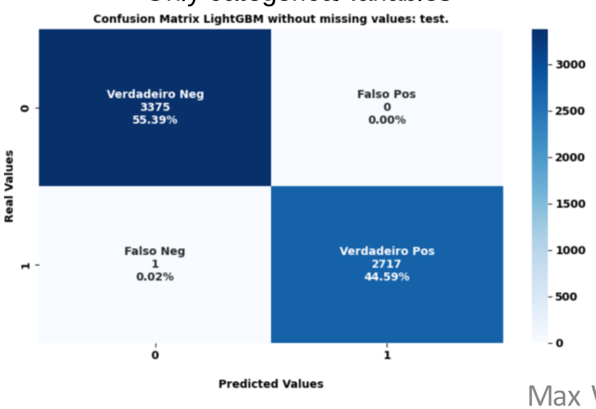
LightGBM without missing

- Wine:
  - Wine\2 Denoising Autoencoder.ipynb
  - Test set represent 10% of the data unseen by the model
  - Accuracy: 99%

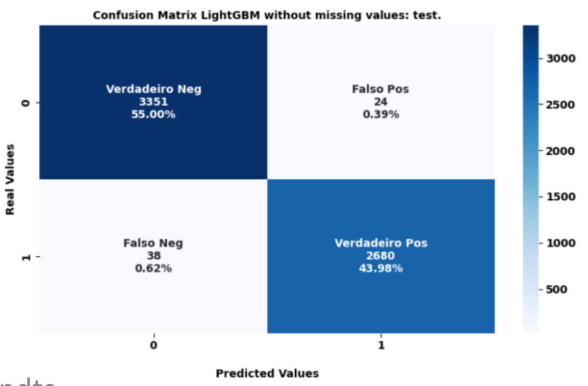


- Mushroom (only categorical variables):
  - Mushroom \2 Denoising Autoencoder only Category.ipynb
  - Mushroom \2 Denoising Autoencoder Continuous and category.ipynb
  - Test set represent 10% of the data unseen by the model
  - Accuracy: 99%

Only categorical variables



Categorical and Continuous variables

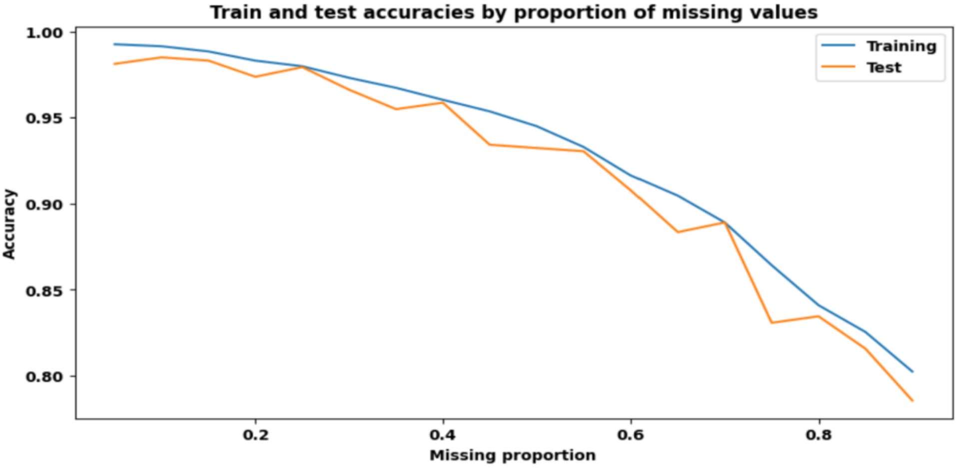


Missing Values Simulation

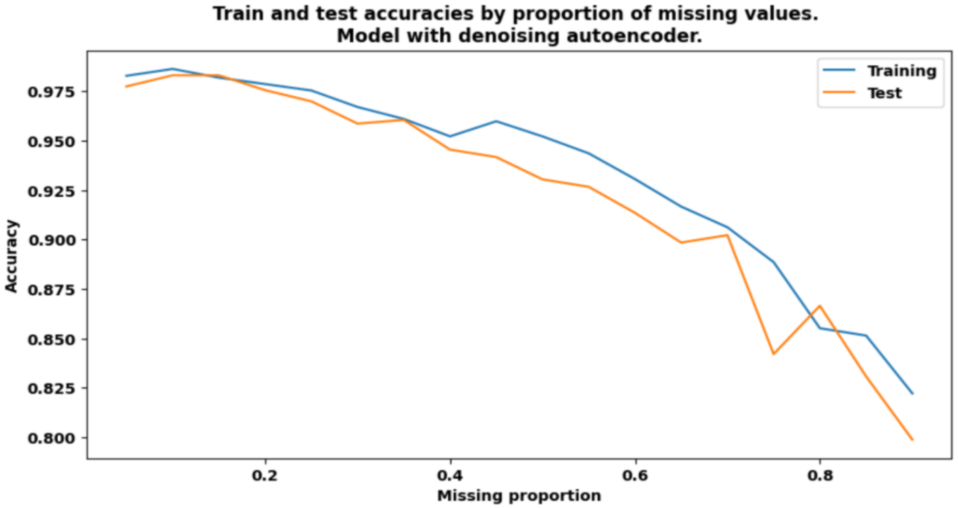
- 18 datasets for each problem were created
- Each dataset with a different proportion of randomly fabricated missing values. Proportions used: .05, .10, .15, .20, .25, .30, .35, .40, .45, .50, .55, .60, .65, .70, .75, .80, .85, .90
- For both mushroom studies, the missing values were only created in the categorical variables. First, the variables were one-hot encoded. After, each value was randomly set to zero.

Results: Wine Dataset

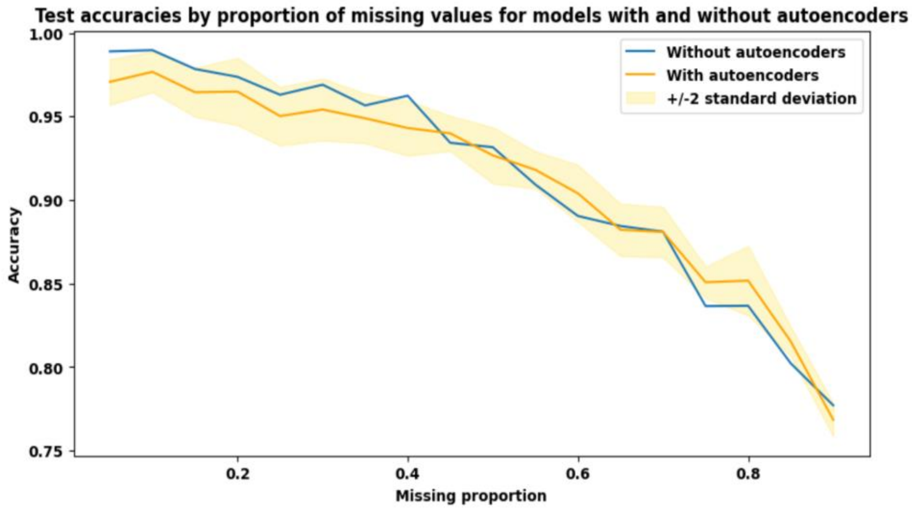
LightGBM without denoising autoencoder:
Missing values were filled with the median.



LightGBM with denoising autoencoder:

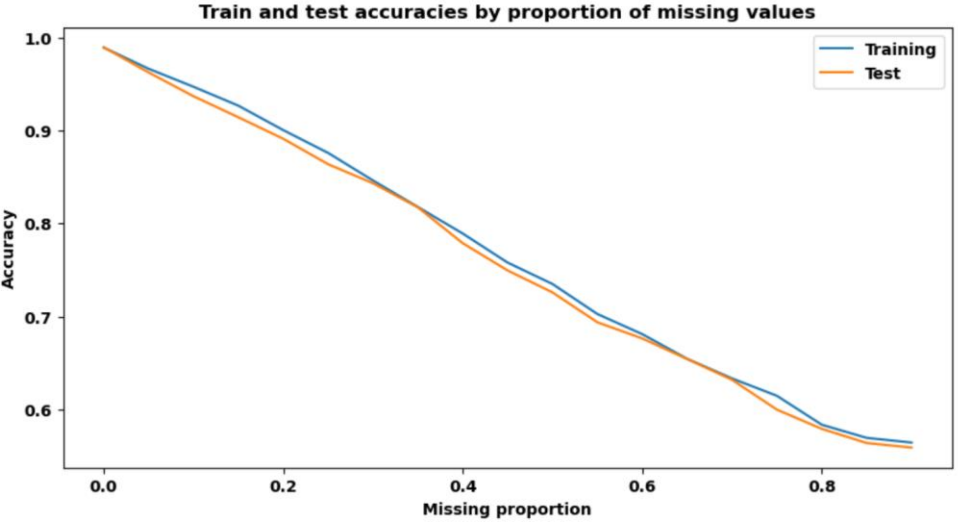


Comparison with and without autoencoder using bootstrap.

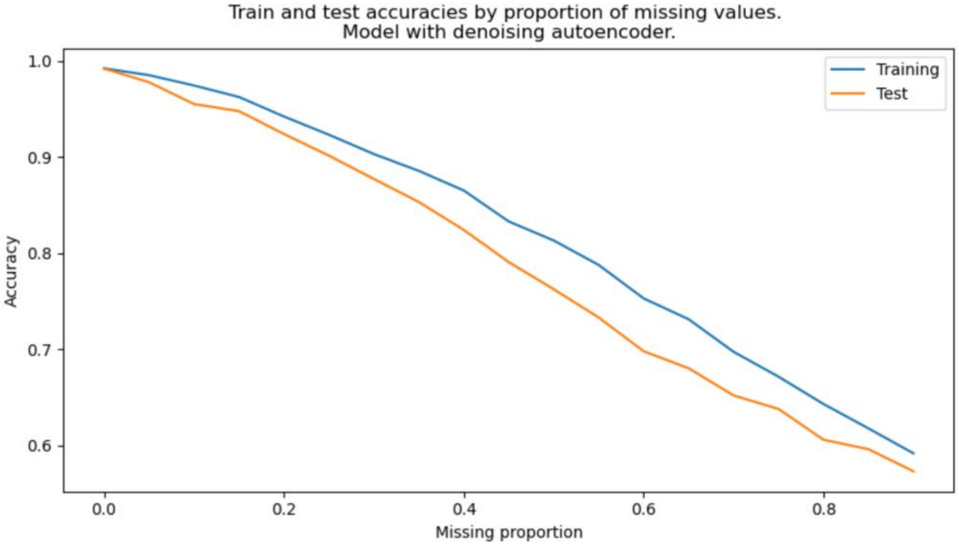


Results: Mushroom Only Categoric

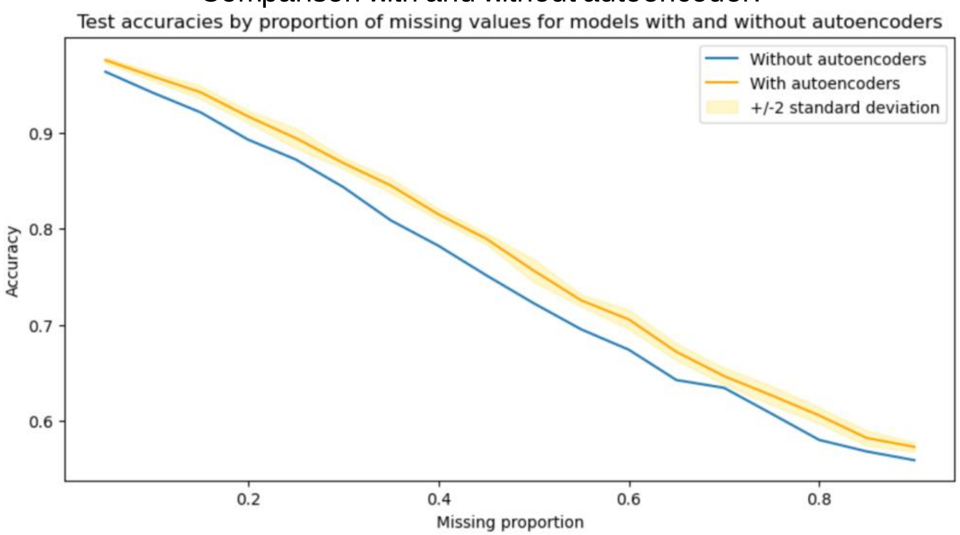
LightGBM without denoising autoencoder:
Missing values were filled with the median.



LightGBM with denoising autoencoder:

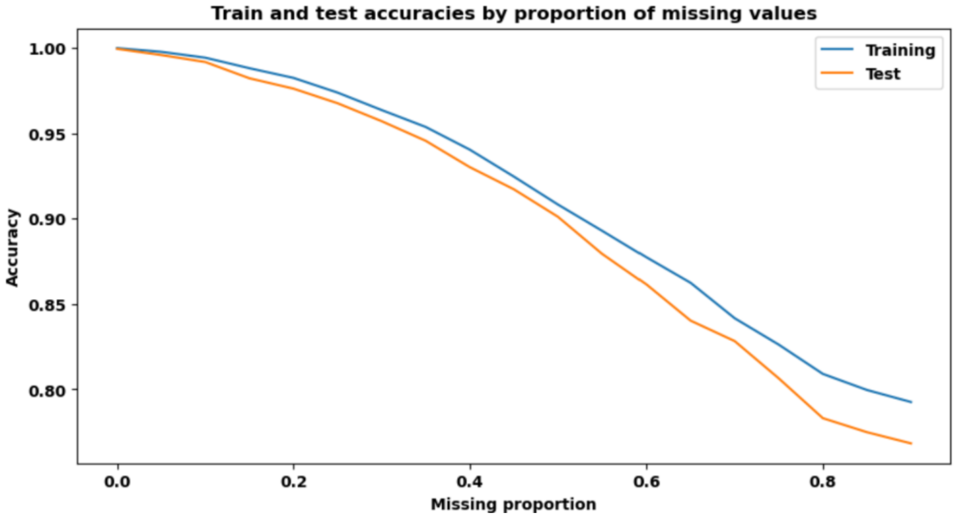


Comparison with and without autoencoder.

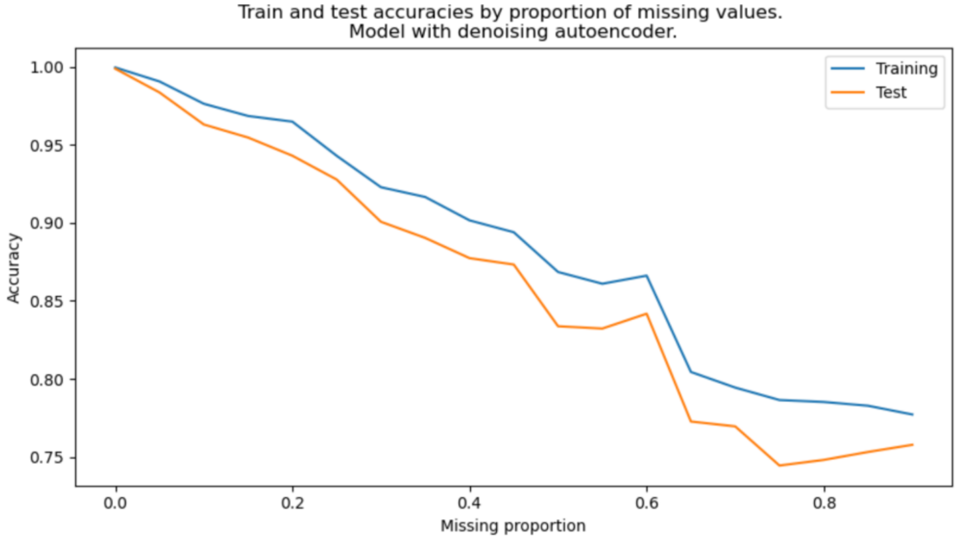


Results: Mushroom all variables

LightGBM without denoising autoencoder:
Missing values were filled with the median.



LightGBM with denoising autoencoder:



Comparison with and without autoencoder.