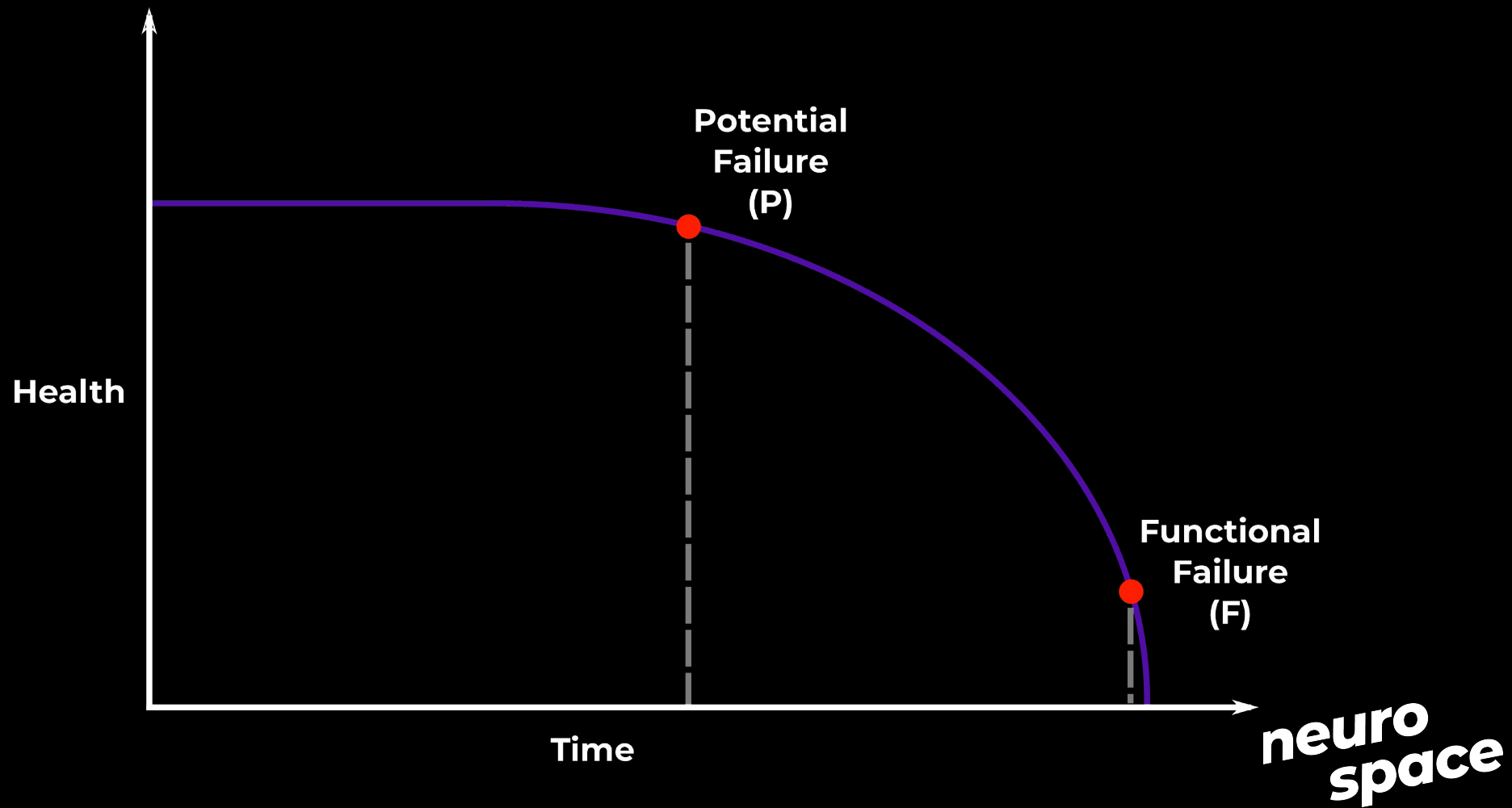
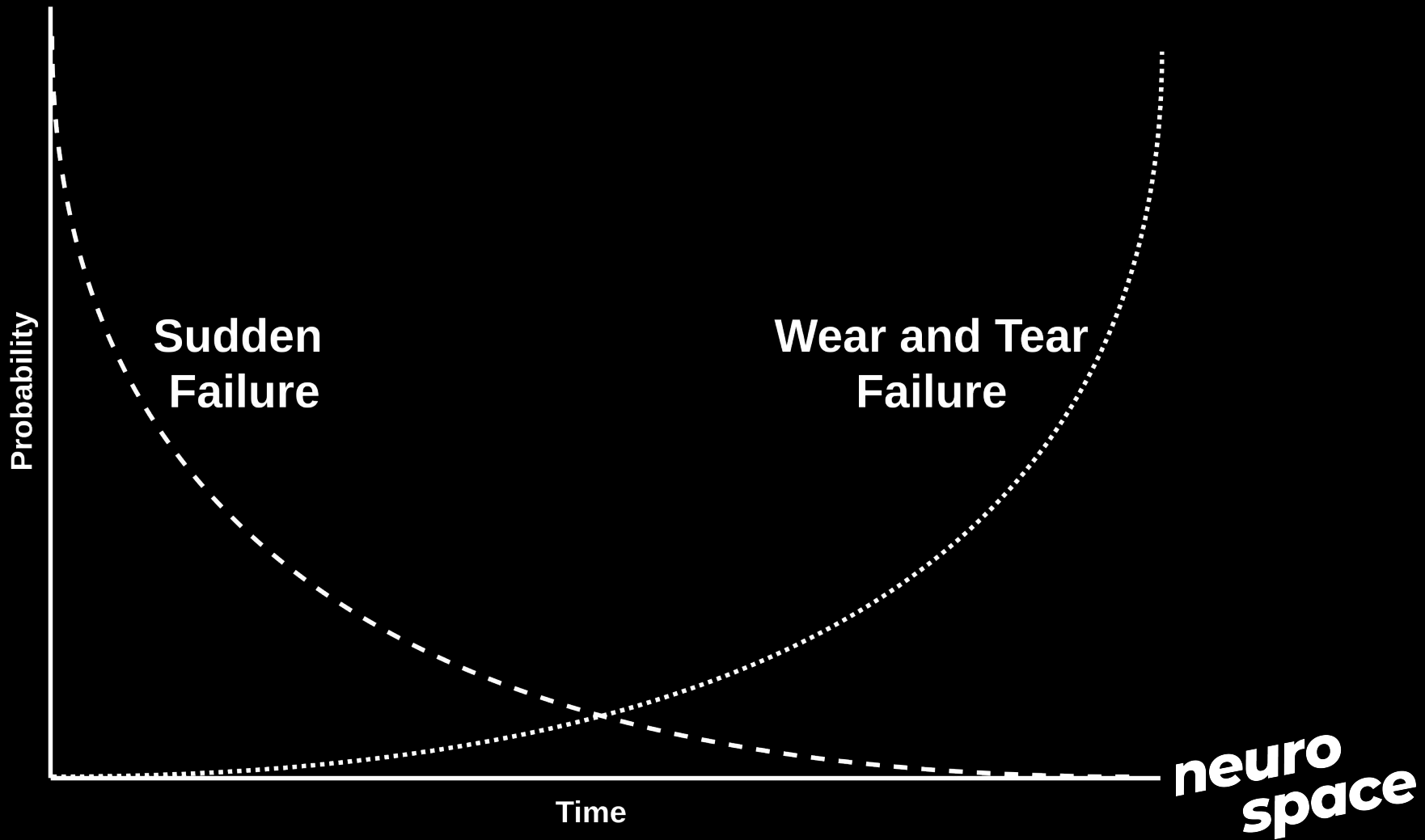
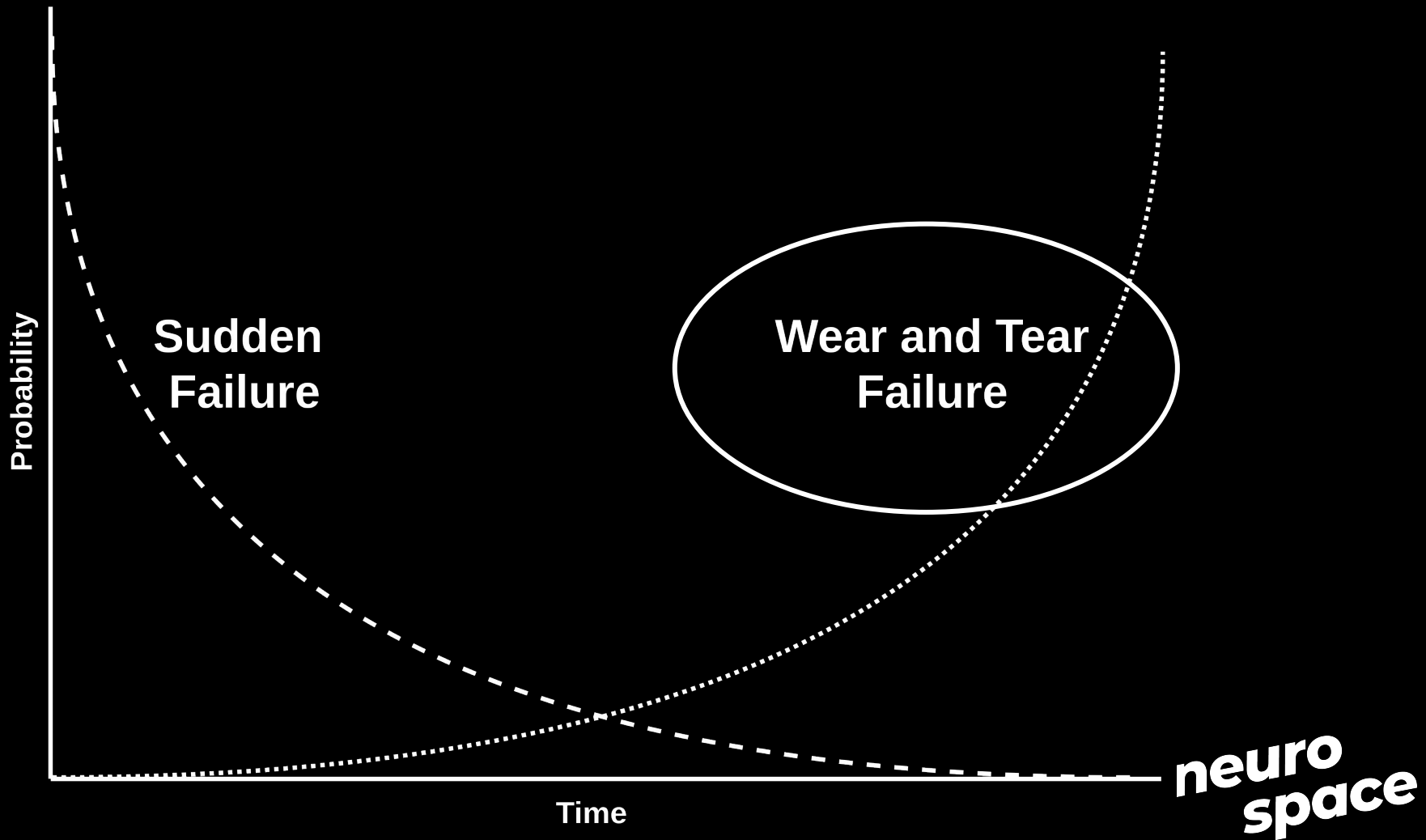


# Predictive maintenance







# challenge

So far, little (no) evidence exist that this is possible for small datasets (<70)

We need to give value as fast as possible, thus we wish to create a solid model with only 7 breakdowns

# Predictive maintenance on a water pump

# introduction to the dataset

<b>n</b>	220,320	100%
<b>n_normal</b>	205,836	approx. 93.42%
<b>n_recovering</b>	14,477	approx. 6.57%
<b>n_broken</b>	7	approx. 0.003%

52 sensors

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# time between failures (TBF)

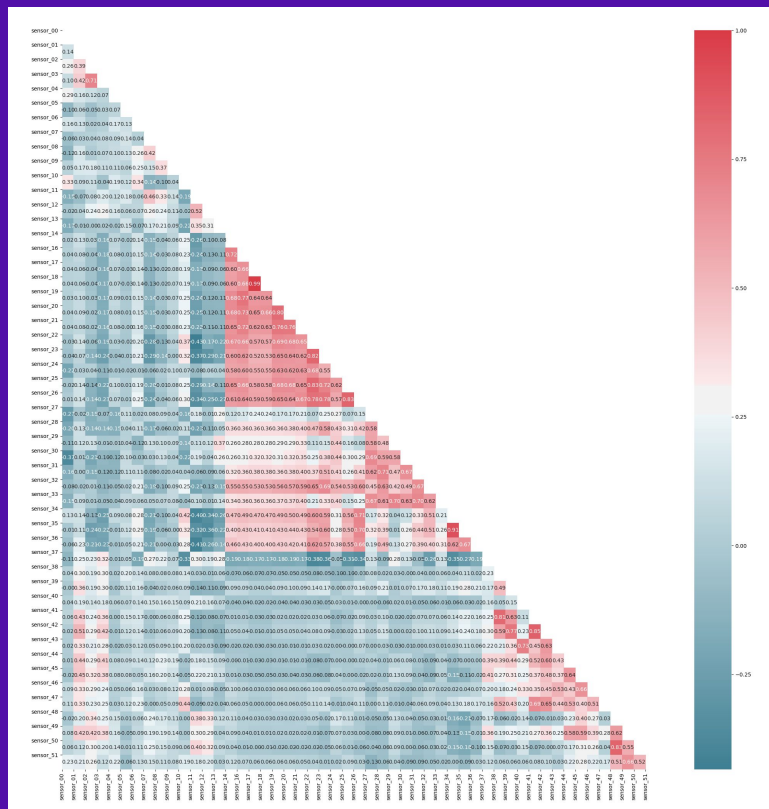
<b>1</b>	12 days
<b>2</b>	5 days
<b>3</b>	31 days
<b>4</b>	6 days
<b>5</b>	35 days
<b>6</b>	9 days
<b>7</b>	17.5 days

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<b>1</b>	12 days
<b>2</b>	5 days
<b>3</b>	31 days
<b>4</b>	6 days
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<b>7</b>	17.5 days

$\bar{X} = 16.5$  days

# heatmap (correlation)



neuro  
space

# approach

We use Python, Scikit-Learn, Talos, Pandas, Numpy, Tensorflow (Keras), Scipy, and Statsmodels

# approach

In all trials, the data is preprocessed the same way:

1. Split in train (3.5 breakdowns), validation (0.5 breakdown), and test (2 breakdowns)
2. Scaled by the help of StandardScaler
3. Noise reduced by the help of Principal Component Analysis, `n_components=10`
4. Those models that were hypertuned, has the option to use MSE or MAE

**Testing** four different algorithms

# summary

Machine learning model	Train loss	Validation loss	Test loss
Dense Neural Network	0.0715973	0.041526	0.1066
Support Vector Regression	1.871	N.C	0.0422
Long-Short-Term-Memory	0.05777	0.0669	0.0497
Random Forest Regression	5.3386e-05	0.0430	0.0431

# summary

Machine learning model	Train loss	Validation loss	Test loss
Dense Neural Network	0.0715973	0.041526	0.1066
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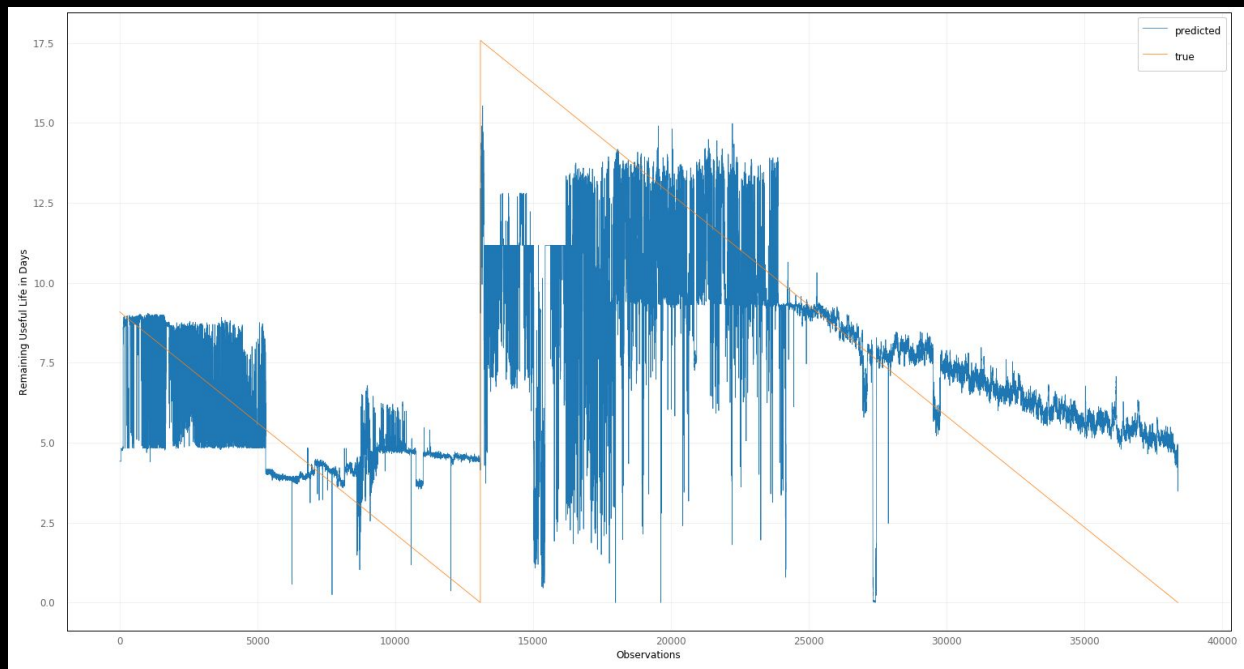
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# neural network with Talos

```
103 p = {'activation1':[relu, elu, tanh, sigmoid],  
104      'activation2':[relu, elu, tanh, sigmoid],  
105      'activation3': [sigmoid],  
106      'optimizer': ['Adam', "RMSprop"],  
107      'losses': ['mse', 'mae'],  
108      'first_hidden_layer': [12, 10, 8, 6],  
109      'second_hidden_layer': [2, 4, 6],  
110      'batch_size': [100, 1000],  
111      'epochs': [10, 15, 25, 50]}  
112
```

# neural network with Talos



# summary

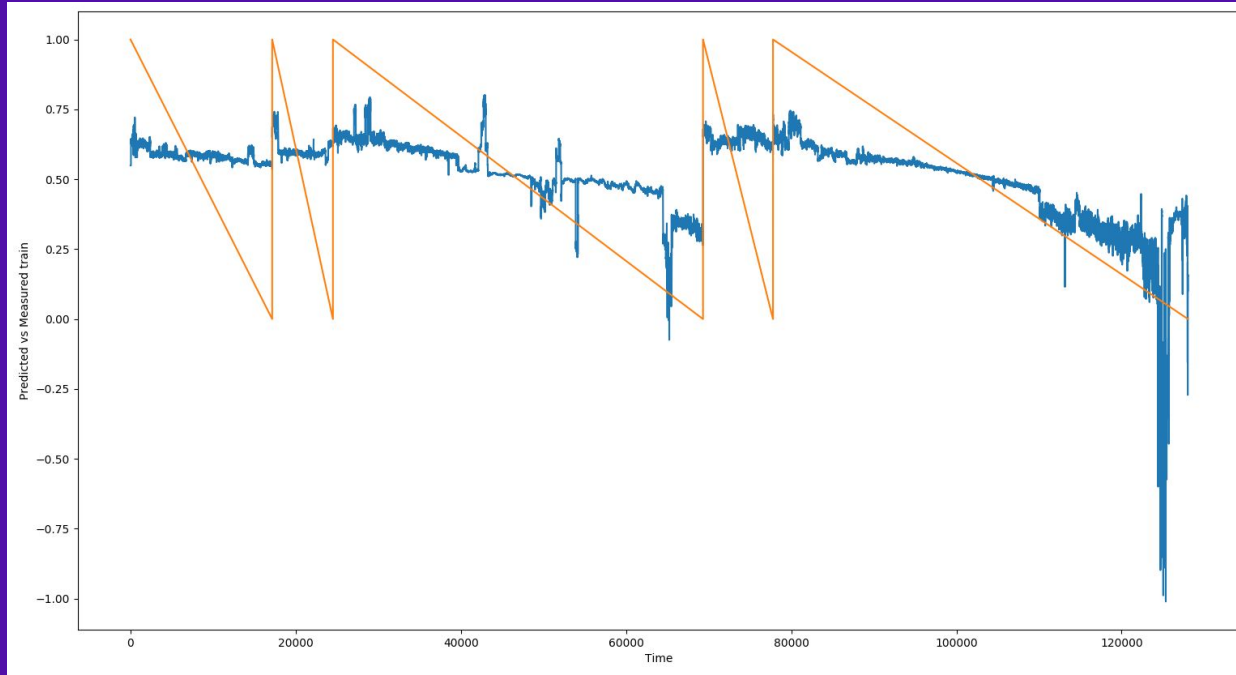
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# support vector regression

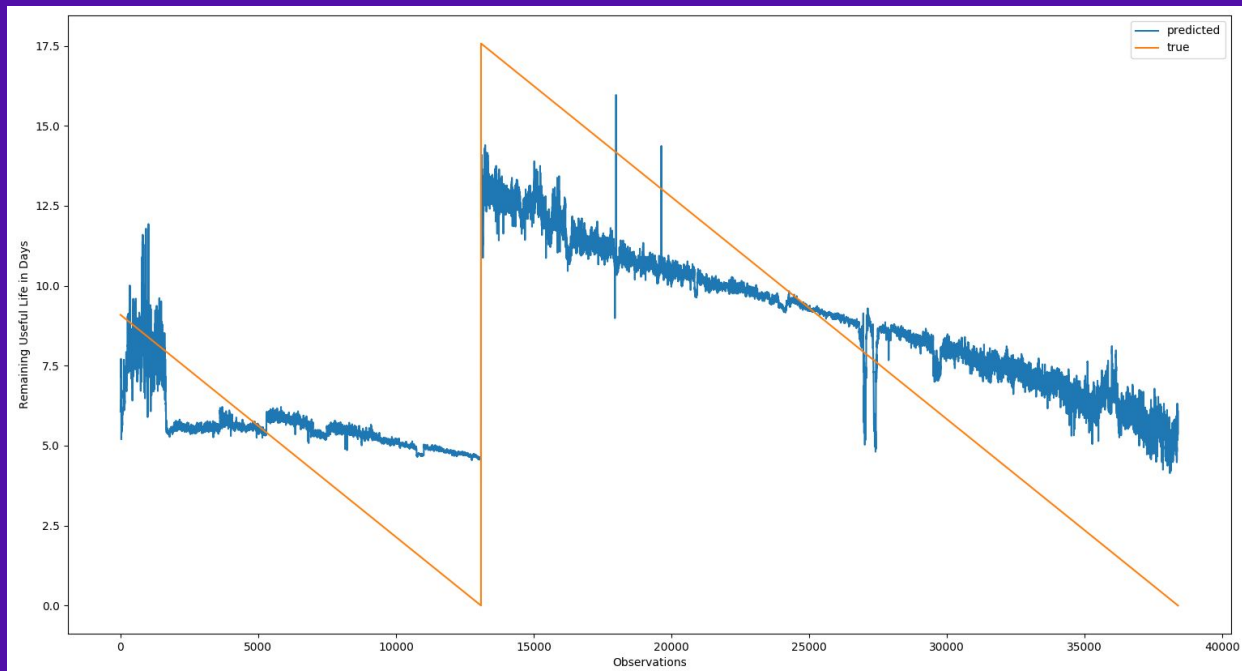
GridSearchCV for hypertune optimization

According to Scikit-learn SVR is hard to scale when dataset is large  
( $n > 10,000$ )

# support vector regression (train+validation)



# support vector regression (test)



# summary

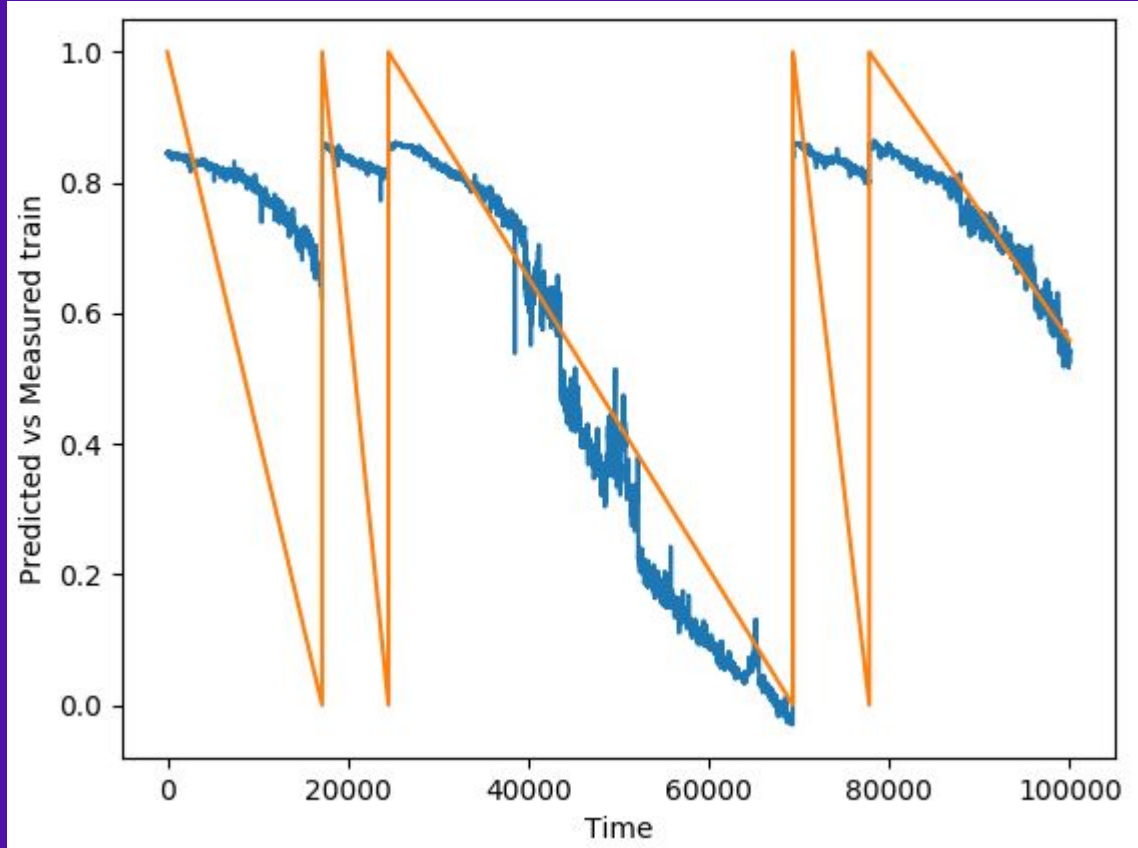
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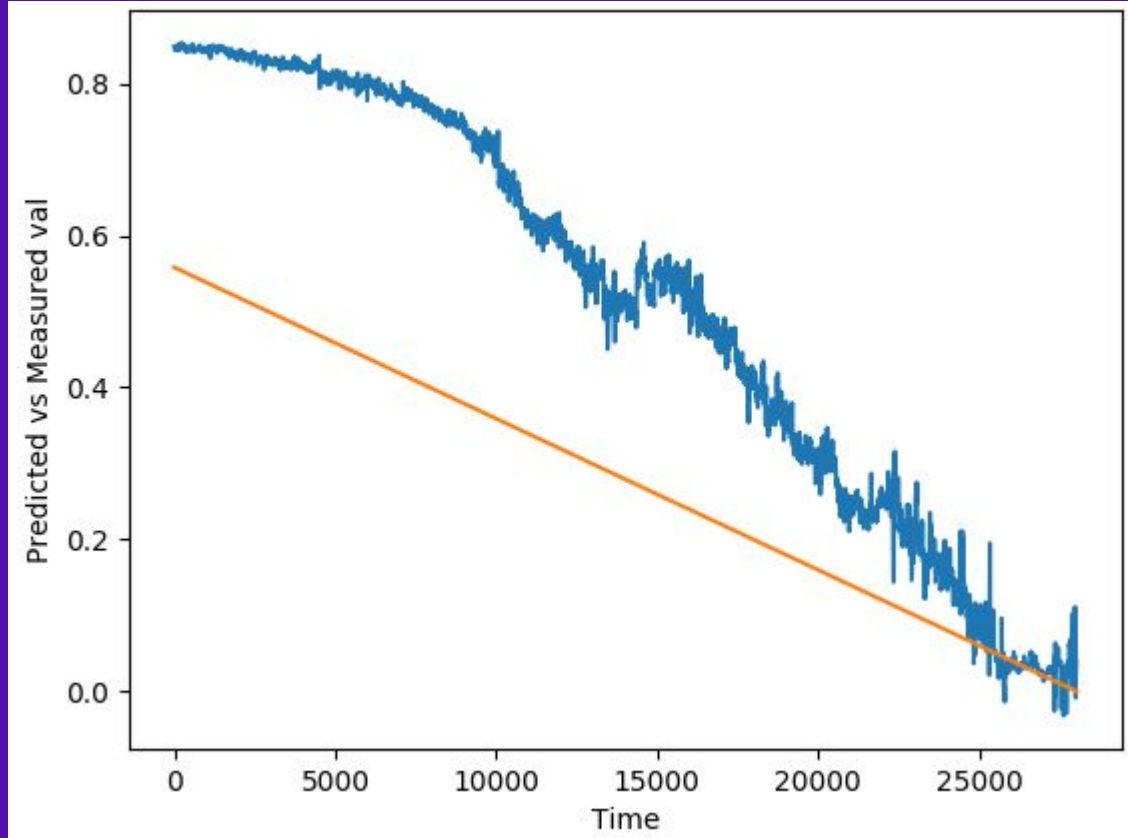
# long-short-term-memory

We used basic optimization principles of trial and error

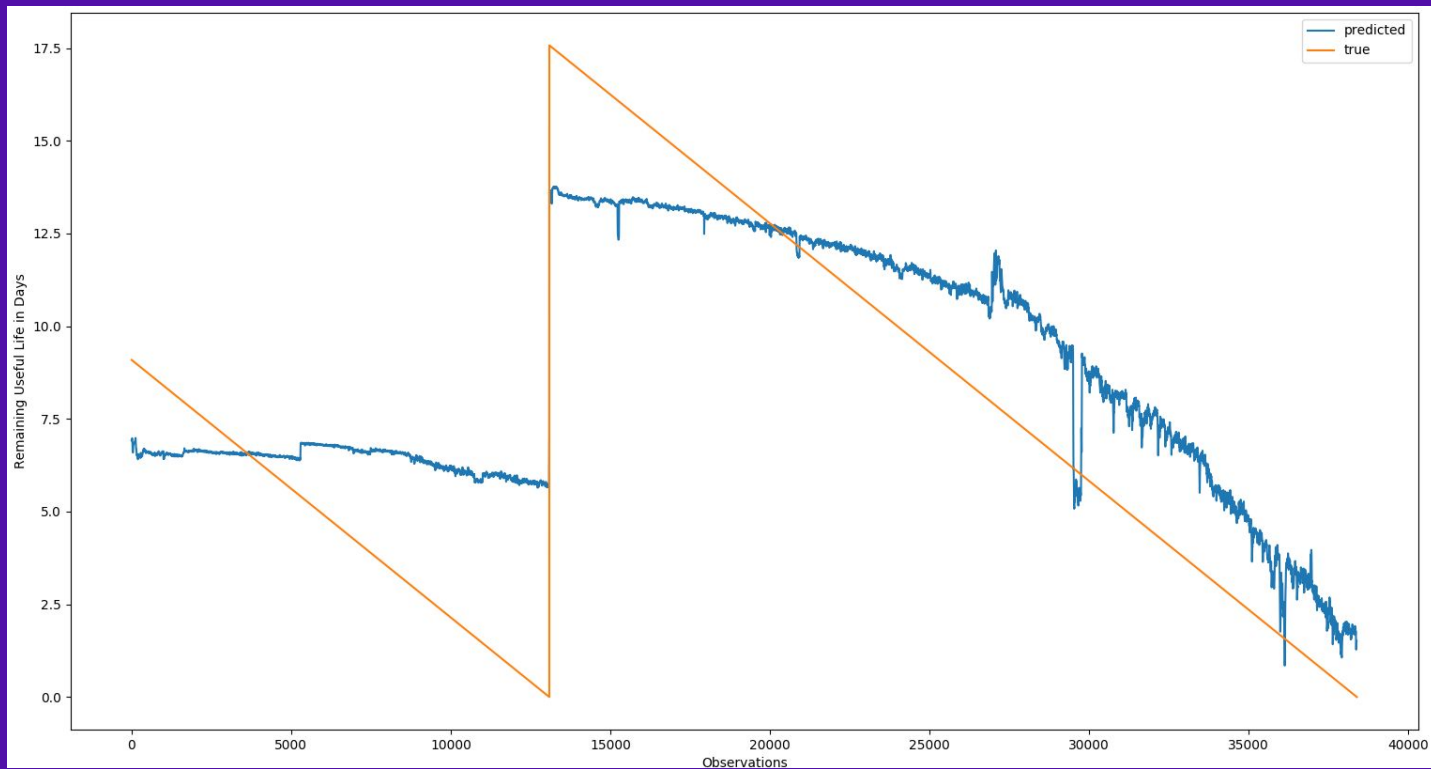
# long-short-term-memory (train)



# long-short-term-memory (validation)



# long-short-term-memory (test)



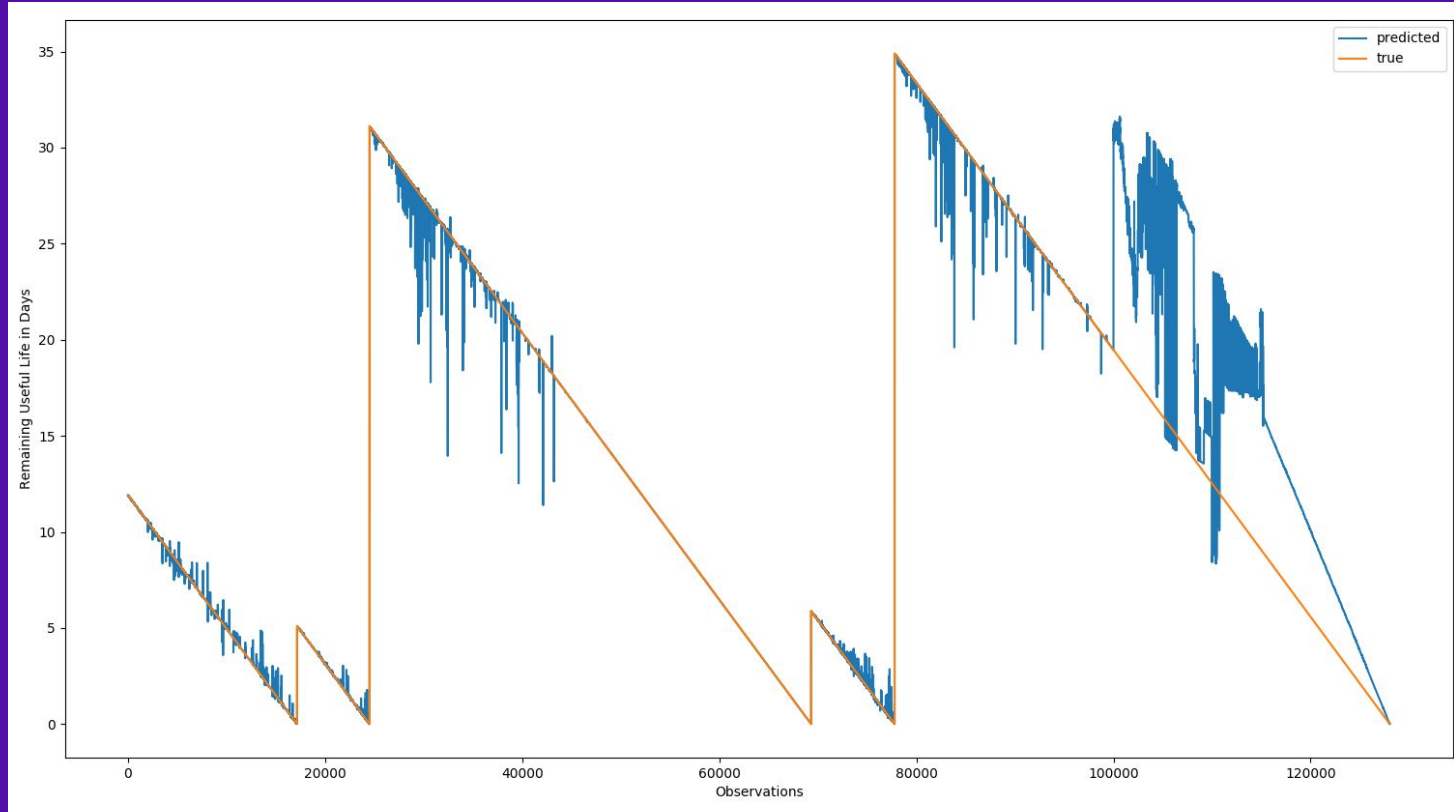
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# random forest regression

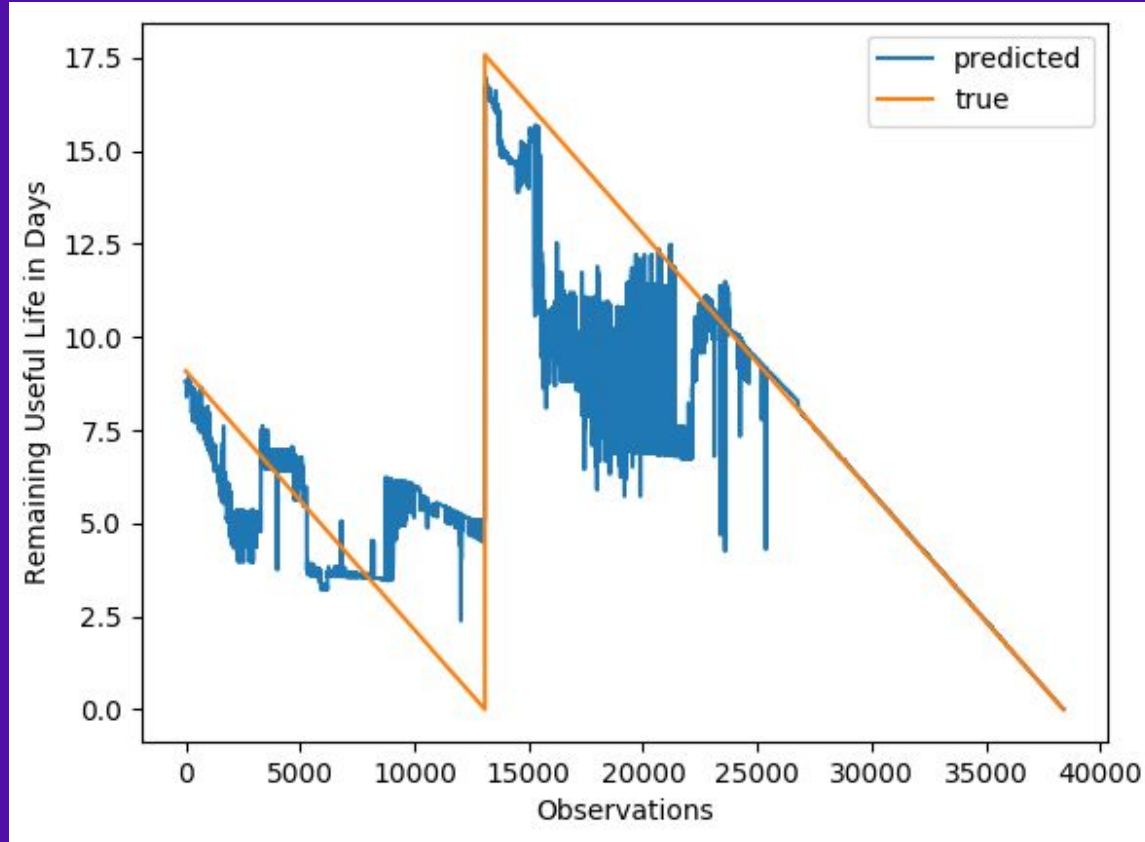
We used GridSearchCV for parameter Hypertuning

# random forest regression (train and validation)



neuro  
space

# random forest regression (test)





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