RUL-Based Policy as Classification

An Alternative Formulation

Let's consider an alternative formulation for our policy

- Rather than building a RUL estimator
- ...And triggering maintenance when the estimate is too low

...We could train a single model to do all the work instead

Such a model may work as follows

- If the RUL is larger than θ, the output is 1 (all fine)
- Otherwise, the output is 0 (we need to stop)

Rather than a numerical quantity, we have a discrete one

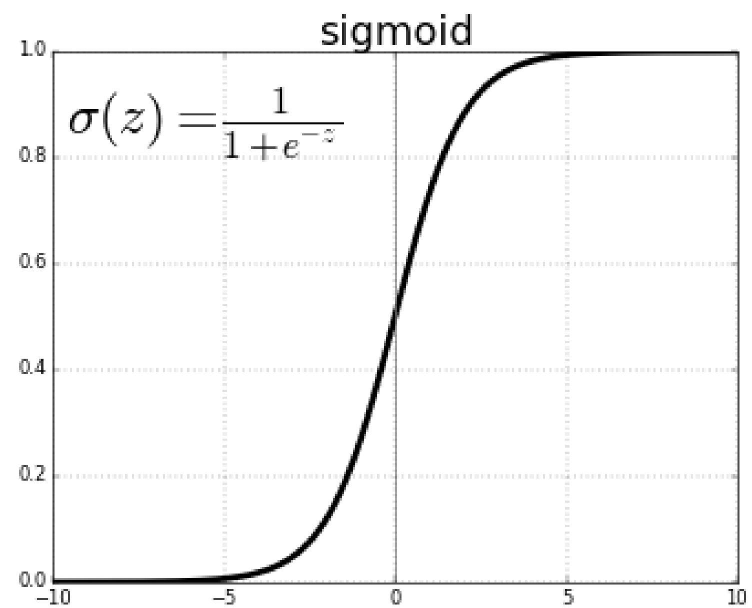
We say that our model is a classifier

- A typical classifier would be an image recognizer
- ...But this one fits the definition, too

NN Classifier

As we have seen, we can easily define a NN classifier

...By using a sigmoid activation function on the output layer



With this change, we can view the NN output as a probability

Specifically, as the probability that the class is 1

- If this is > 0.5, we say the class is 1
- If it is < 0.5, then the class is 0

NN Classifier

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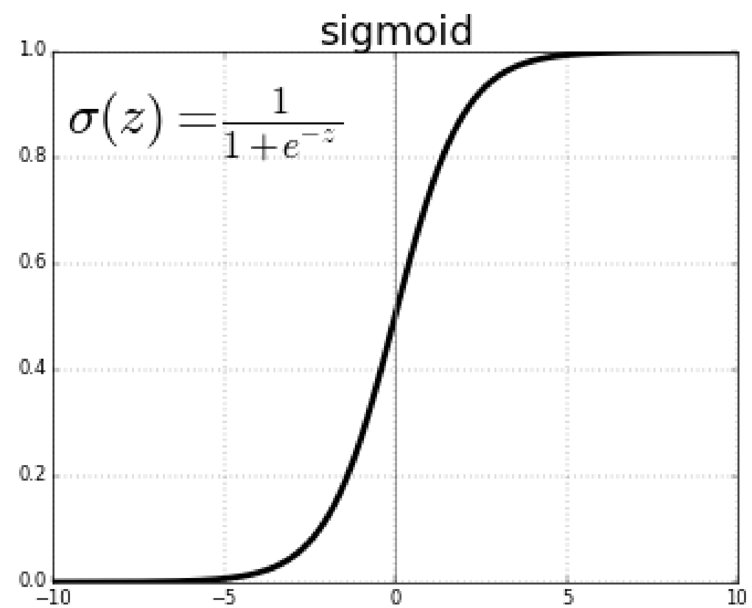


Our ground truth changes

- Rather than targets (i.e. numerical quantities to estimate)
- We have categorical values (a.k.a. labels)

Labels vs Targets

Our ground truth changes

- Rather than targets (i.e. numerical quantities to estimate)
- We have categorical values (a.k.a. labels)

We obtain them by just comparing the RUL with our chosen θ

In [2]:
```
class_thr = 18
tr_lbl = (tr['rul'] >= class_thr)
ts_lbl = (ts['rul'] >= class_thr)
```

The resulting vector contain the outcome of the comparison

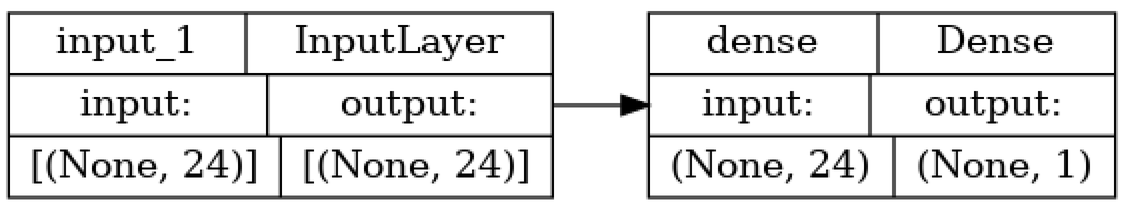
- I.e. `tr_lbl` contains `True` if the RUL was larger than θ
- ...And `False` otherwise

A Logistic Regression Model

We will start by building the simpler possible NN classifier

In [3]:
```
hidden = []
nn = util.build_ml_model(input_size=len(dt_in), output_size=1, hidden=hidden, output_activation=
util.plot_ml_model(nn)
```

Out[3]:



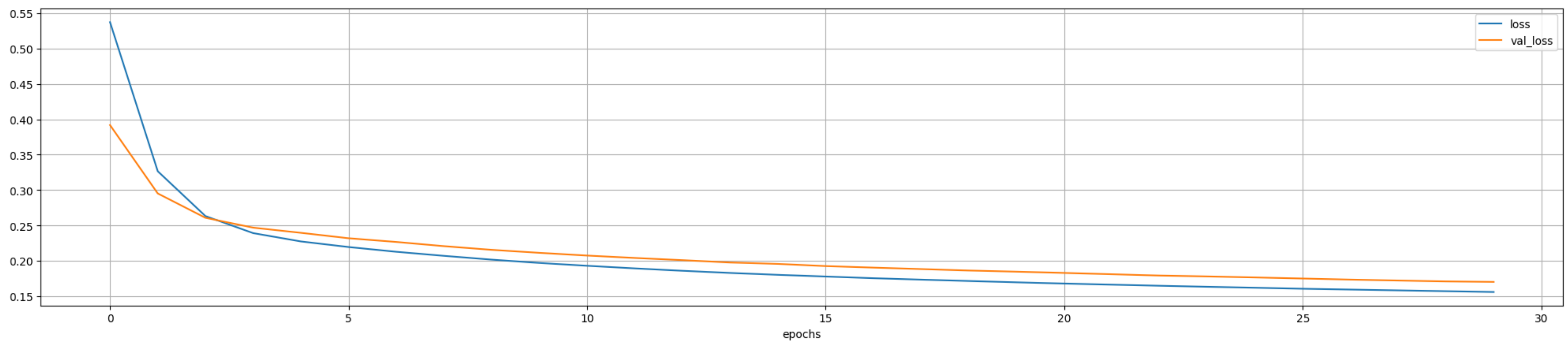
- It's the same as our Liner Regressor
- ...Except that we have a sigmoid activation on the output function

This is called a Logistic Regressor

A Logistic Regression Model

Next, we trigger the training process

```
In [4]: history = util.train_ml_model(nn, tr_s[dt_in], tr_lbl, epochs=30, validation_split=0.2, loss='bi
        util.plot_training_history(history, figsize=figsize)
```



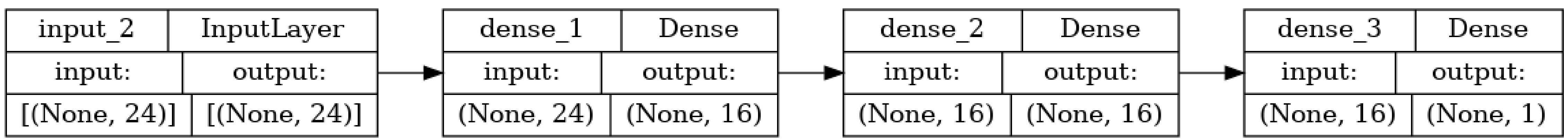

```
Final loss: 0.1560 (training), 0.1703 (validation)
```

An MLP Classifier Model

Now, let's try with a deeper model

In [5]:
```
hidden = [16, 16]
nn2 = util.build_ml_model(input_size=len(dt_in), output_size=1, hidden=hidden, output_activatio
util.plot_ml_model(nn2)
```

Out[5]:



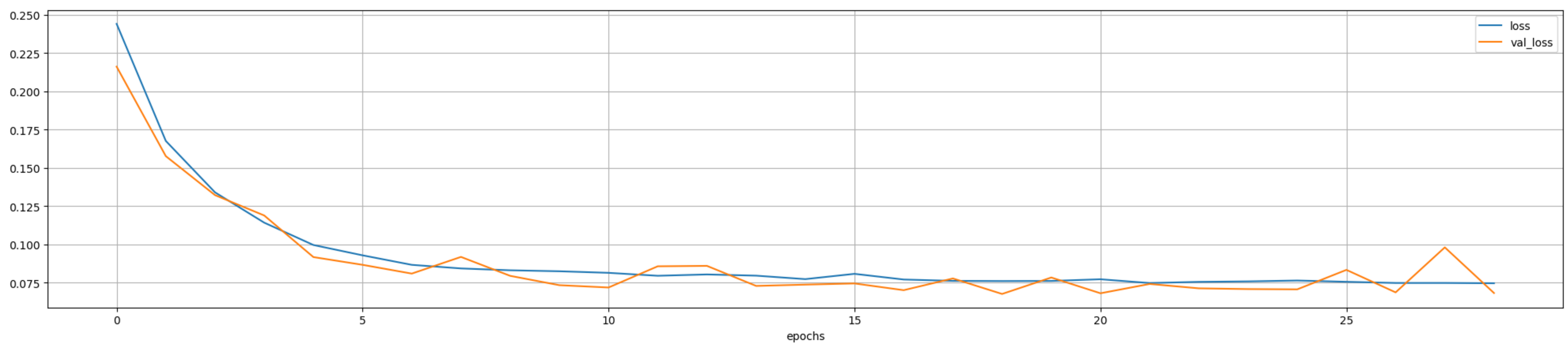
Once again, we have introduced two hidden layers

- We can view each layer as a function which transforms its input
- The last layer then is a Logistic Regressor on the transformed data

An MLP Classifier Model

Let's perform training and check the results

In [6]:
```
history = util.train_ml_model(nn2, tr_s[dt_in], tr_lbl, epochs=30, validation_split=0.2, loss='b
util.plot_training_history(history, figsize=figsize)
```



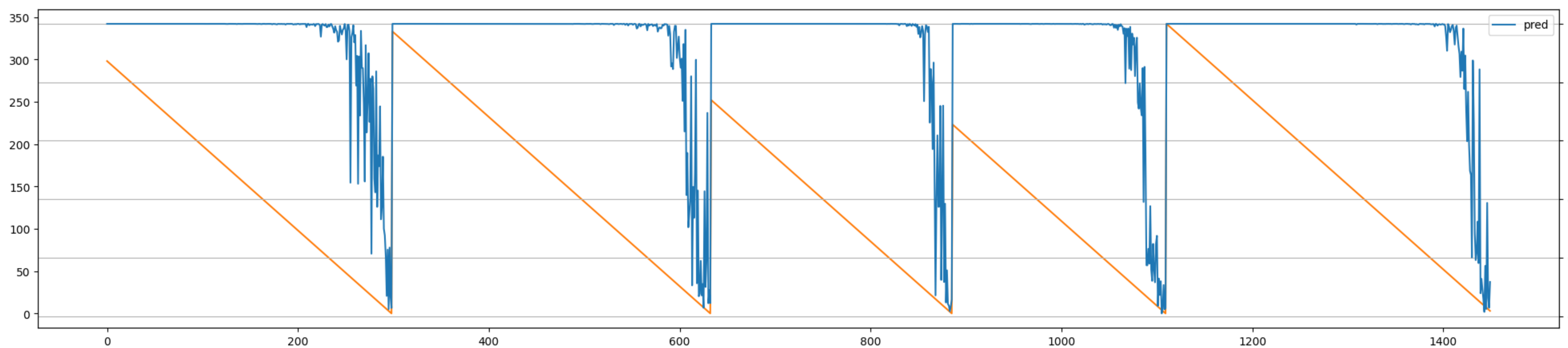

```
Final loss: 0.0747 (training), 0.0682 (validation)
```

A deeper network in this case works much better

Inspecting the Predictions

Let's check our raw predictions (probabilities) over time

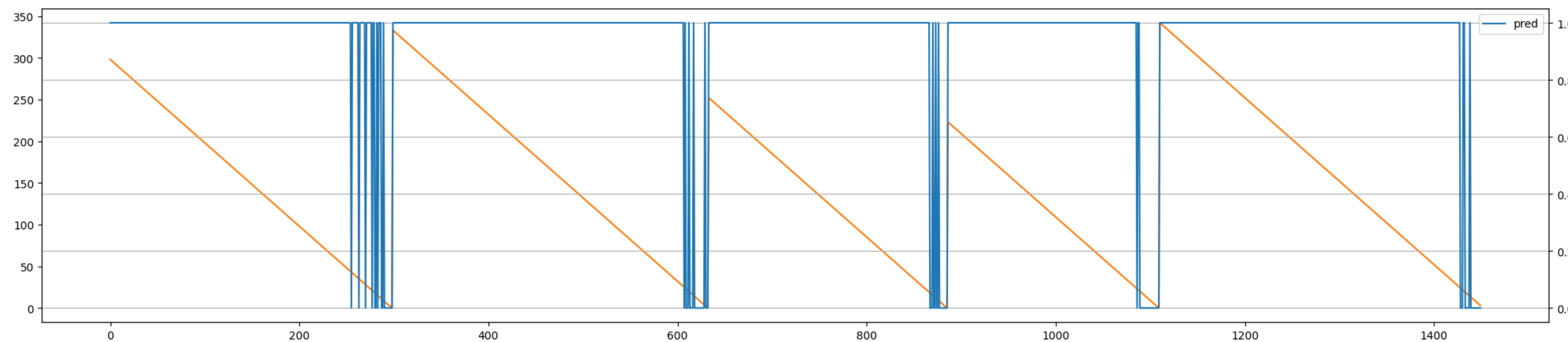
In [8]:
```
ts_prob2 = nn2.predict(ts_s[dt_in], verbose=0).ravel()
stop = 1450
util.plot_rul(ts_prob2[:stop], ts['rul'][:stop], same_scale=False, figsize=figsize)
```



Inspecting the Predictions

After rounding is applied, this is what we get

In [10]:
```
ts_pred2 = np.round(nn2.predict(ts_s[dt_in], verbose=0).ravel())
util.plot_rul(ts_pred2[:stop], ts['rul'][:stop], same_scale=False, figsize=figsize)
```



Evaluating the Policy

We can evaluate the classifier directly

...Because it defines the whole policy, with no need for additional calibration

```
In [11]: tr_pred2 = np.round(nn2.predict(tr_s[dt_in], verbose=0).ravel())
         ts_pred2 = np.round(nn2.predict(ts_s[dt_in], verbose=0).ravel())

         tr_c2, tr_f2, tr_s2 = cmodel.cost(tr['machine'].values, tr_pred2, 0.5, return_margin=True)
         ts_c2, ts_f2, ts_s2 = cmodel.cost(ts['machine'].values, ts_pred2, 0.5, return_margin=True)

         print(f'Cost: {tr_c2} (training), {ts_c2} (test)')
         print(f'Avg. fails: {tr_f2/len(tr_mcn)} (training), {ts_f2/len(ts_mcn)} (test)')
         print(f'Avg. slack: {tr_s2/len(tr_mcn):.2f} (training), {ts_s2/len(ts_mcn):.2f} (test)')
```

```
Cost: -16121 (training), -6076 (test)
Avg. fails: 0.0 (training), 0.0 (test)
Avg. slack: 29.84 (training), 27.67 (test)
```

Which is comparable with our earlier results