AI for Finance - High Frequency Forecasting

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1. Introduction

In recent years, we have been the audience of a series of increasingly successful achievements of deep learning techniques. Deep neural networks were applied to tasks in which traditional machine learning algorithms wouldn't stand a chance – large-scale image classification, autonomous driving, and many others. Almost yearly, we can observe the introduction of a ri-visitation of some previous network architecture which makes it achieve state-of-the-art results on a specific task. With the constant improvement in commercially available Graphics Processing Units (GPU), the emergence of freely available processing power involving CPUs/GPUs (Google Colab, Kaggle, and so on) and the rapid development of different frameworks, deep learning continues to gain more and more attention amongst researchers and practitioners who want to apply the techniques to their business cases.
Deep learning proved to deliver great results with sequential data such as speech, audio, and video. That is why it naturally fits into working with sequential data such as time series—both univariate and multivariate. Financial time series are known to be erratic and complex, hence the reason why it is such a challenge to model them. Deep learning approaches are especially apt for the task, as they make no assumptions about the distribution of the underlying data and can be quite robust to noise.

In this final project, we are going to show one possible use case of deep learning in the financial domain – **forecasting high frequency time series**. For achieving this very specific - yet extremely flattering - field of application we focus on introducing three different approaches for time series forecasting. In particular, we provide a recipe for a **Multi Layer Perceptron**, a **Convolutional Neural Network**, and a **Recurrent Neural Network**. In the Conclusions' paragraph we will sum up performances and results of each and every architecture with the aim of understanding which is the most suitable for time series forecasting.

💡 **TIP 1**: for the best experience please run notebooks on GoogleColab!
💡 **TIP 2**: to save time and resources we also provide checkpoints for each training session. You can find them all in the `checkpoints` directory!
ℹ️ **NOTE**: the complete code is available in the repository on GitHub.

2. Data

Data used in this project are retrieved from the Refinitiv's Eikon platform (temporary subscription plan kindly provided by the University of Trento).

We extracted a historical list of daily prices with one minute frequency for the Apple (ticker: `AAPL`). Underneath is an example of the preprocessed dataframe structure:

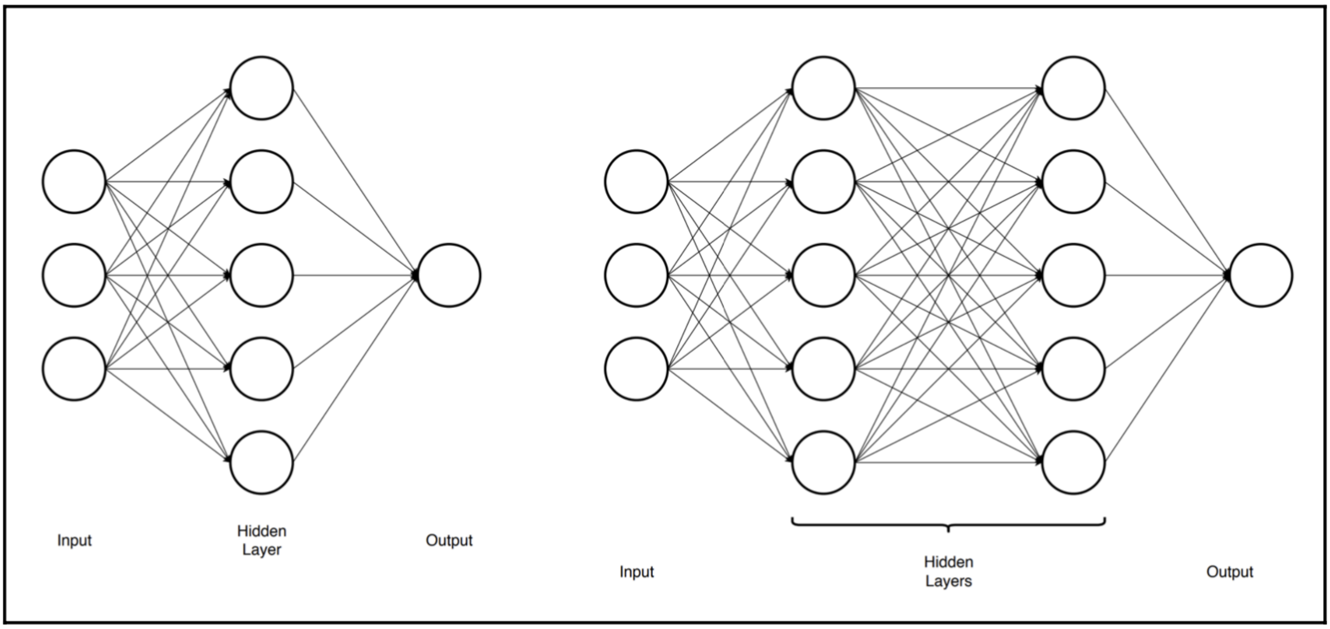
datetime	Close	%Chg	Volume
19:00:00	131.040000	1.345673e-03	152201.0
18:59:00	130.863900	-2.757830e-04	82634.0
18:58:00	130.900000	3.667056e-05	90831.0
18:57:00	130.895200	4.310648e-04	90186.0
18:56:00	130.838800	-4.766954e-04	113039.0
18:55:00	130.901200	8.556803e-05	105691.0
...	...	...	...

3. Multi Layer Perceptron (MLP)

Multi layer perceptrons (MLP) are one of the basic architectures of neural networks. At a very high level, they consist of three components:

- *input layer*: A vector of features.
- *hidden layers*: Each hidden layer consists of N neurons.
- *output layer*: Output of the network; depends on the task (regression/classification).

The input of each hidden layer is first transformed linearly (multiplication by weights and adding the bias term) and then non-linearly (by applying activation functions such as ReLU). Thanks to the non-linear activation, the network is able to model complex, non-linear relationships between the features and the target. A multilayer perceptron contains multiple hidden layers (also called dense layers or fully connected layers) stacked against each other. Beneath is a diagram presenting a network with a single hidden layer and an MLP with two layers:



Workflows concerning data preprocessing, data preparation (data-loaders, data-splitters), and plotting methods are shared by all recipes. What differs is, of course, the networks' architecture.

```
class MLP(nn.Module):
  def __init__(self, input_size):
      super(MLP, self).__init__()
      self.linear1 = nn.Linear(input_size, 8)
      self.linear2 = nn.Linear(8, 4)
      self.linear3 = nn.Linear(4, 1)
      self.dropout = nn.Dropout(p=0.2)

  def forward(self, x):
    x = self.linear1(x)
    x = F.relu(x)
    x = self.dropout(x)
    x = self.linear2(x)
    x = F.relu(x)
    x = self.dropout(x)
    x = self.linear3(x)
    return x
```

Multi layer perceptron's architecture is fairly simple. It is made up of three linear hidden layers of size `(input_size x 8)` , `(8 x 4)` , `(4 x 1)` respectively, and an output layer. Non-linearities are placed in between linear layers, and they are ReLUs. Dropout is a technique for reducing overfitting.

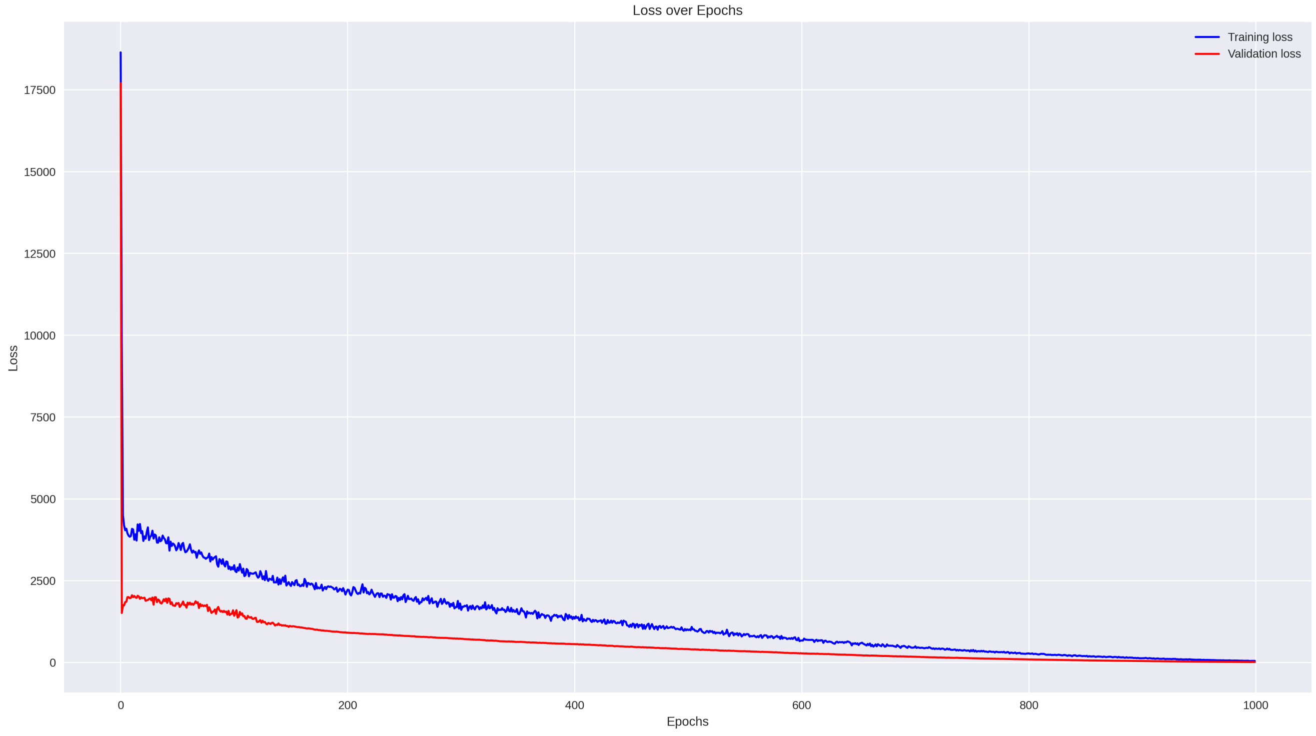
3.1. MPL Architecture

There are two approaches to defining networks in PyTorch and, in this section, we present the one based on defining a class, which inherits from `nn.Module` . By inheriting, we mean that it will automatically possess a series of required methods, and we only need to define a few selected ones (we can also overwrite the default methods if there is such a need). The first method is the `__init__` method, in which we store all the operations that we want to carry out. As a rule, we should store all the trainable operations here such as fully connected layers (`Linear`), and the `dropout` layer with its assigned.

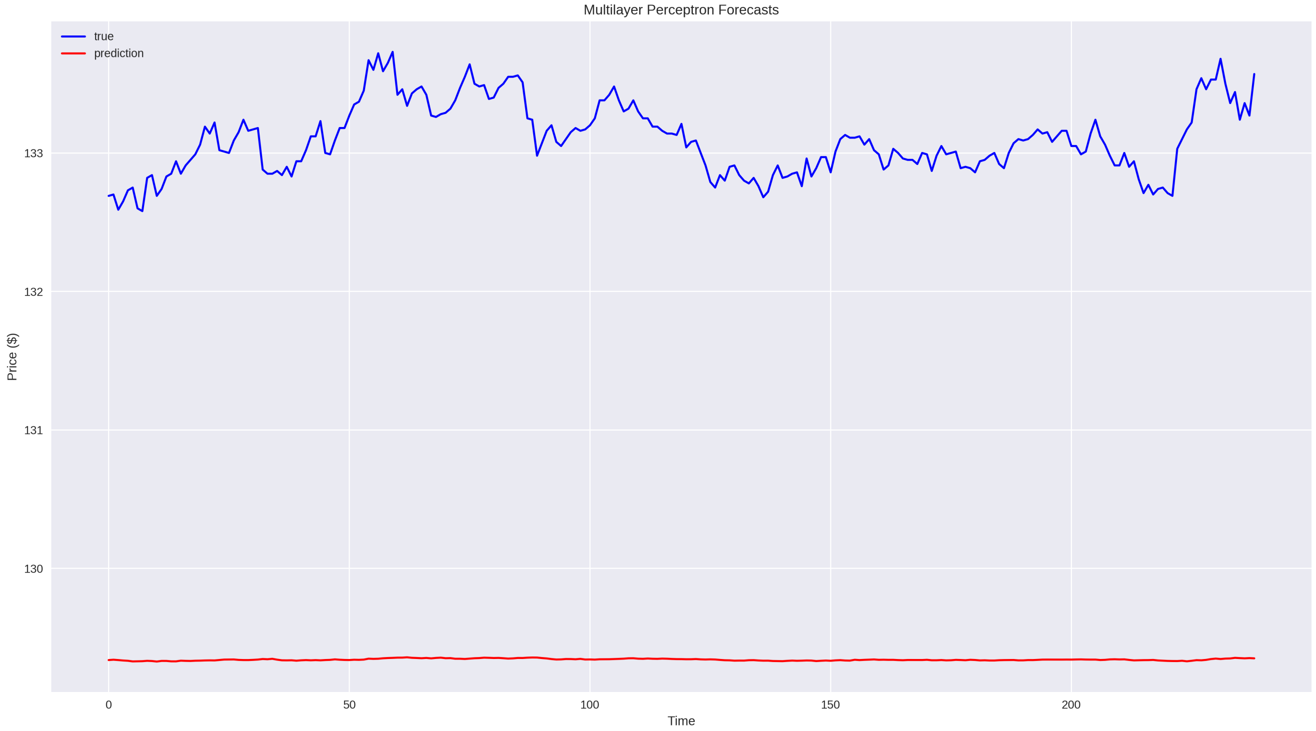
```
MLP(
  (linear1): Linear(in_features=1, out_features=8, bias=True)
  (linear2): Linear(in_features=8, out_features=4, bias=True)
  (linear3): Linear(in_features=4, out_features=1, bias=True)
  (dropout): Dropout(p=0.2, inplace=False)
)
```

ℹ️ Here you can find an in depth explanation of how dropout works.

3.2. MLP Losses



3.3. MLP Prediction

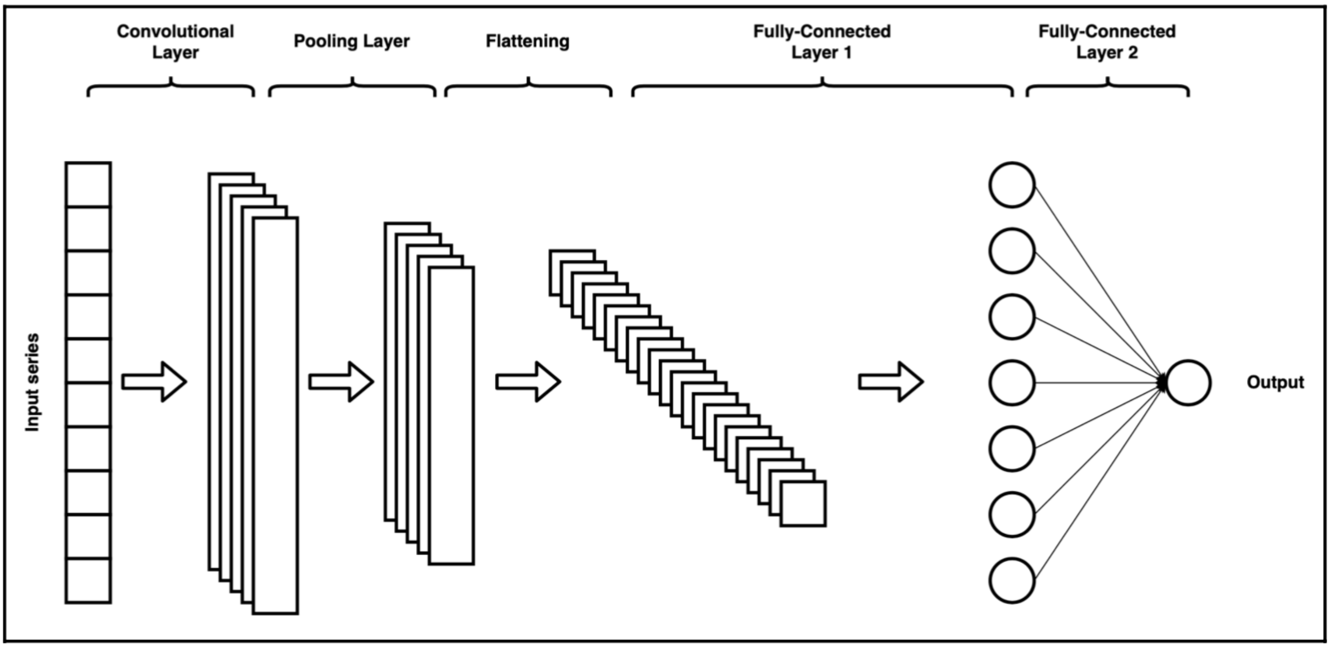


4. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNN) were developed and remained very popular in the image classification domain. However, they can also be applied to 1-dimensional problems, such as predicting the next value in a sequence, be it a time series or the next word in a sentence.
The elements that constitute a typical CNN architecture are as follows:

- *convolutional layer*: The goal of this layer is to apply convolutional filtering to extract potential features.
- *pooling layer*: This layer reduces the size of the image or series while preserving the important characteristics identified by the convolutional layer.
- *fully connected layer*: Usually, there is more than one fully connected layer at the end of the network to map features into classes or values.

In the following diagram, we present a simplified schema of a mono-dimensional CNN:




```
class Flatten(nn.Module):
  def forward(self, x):
      return x.view(x.size()[0], -1)
model = nn.Sequential(OrderedDict([
    ('conv_1', nn.Conv1d(1, 32, 3, padding=1)),
    ('max_pool_1', nn.MaxPool1d(2)),
    ('relu_1', nn.ReLU()),
    ('flatten', Flatten()),
    ('fc_1', nn.Linear(192, 50)),
    ('relu_2', nn.ReLU()),
    ('dropout_1', nn.Dropout(0.4)),
    ('fc_2', nn.Linear(50, 1))
]))
```

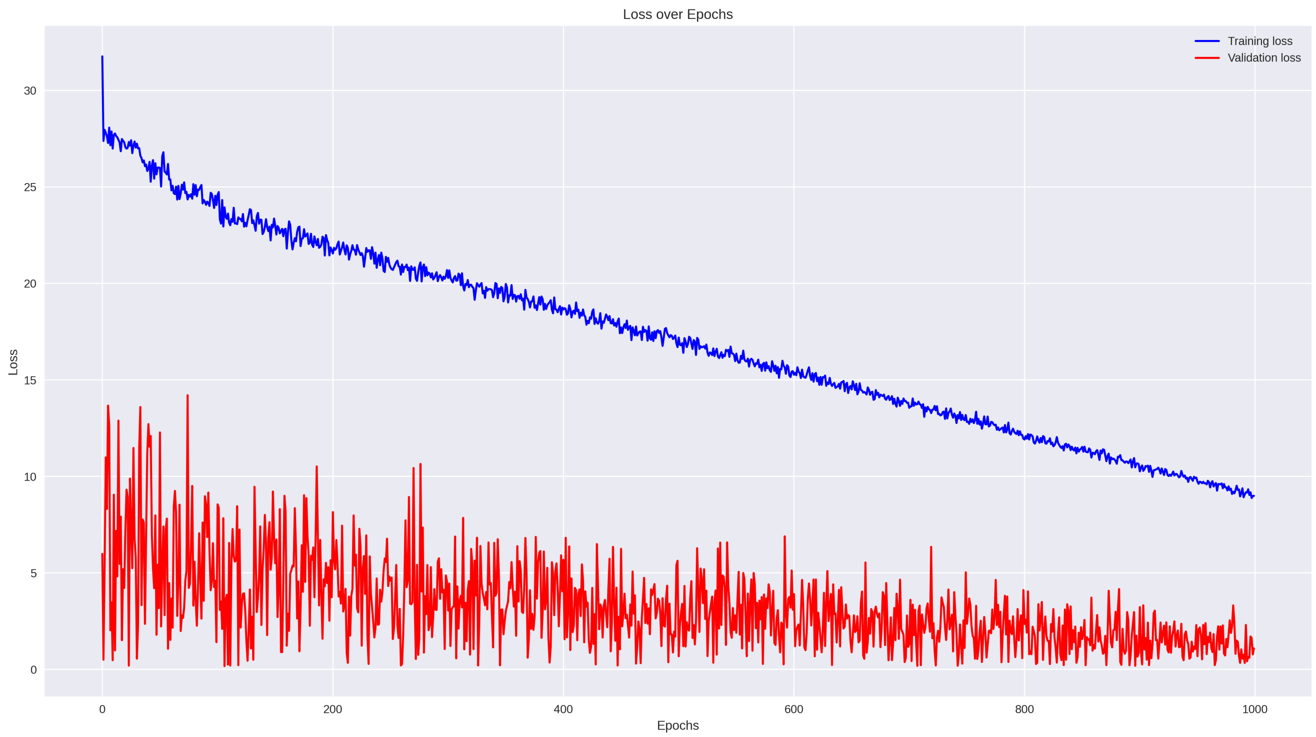
4.1. CNN Architecture

The general outline of the training loop is very similar to the one used in the previous recipe, so we only describe the novelties. Within the training loop, we had to reshape the features/targets coming from the DataLoader objects. That is because `nn.Conv1d` expects a 3-dimensional input, with the dimensions being *number of batches*, *channels*, *length of series*. Alternatively, we could have defined a custom Dataset/DataLoader, which would have returned the inputs of the correct size. For this recipe, we used the RMSE as the loss function simply by extracting the square root of MSE through `torch.sqrt` .

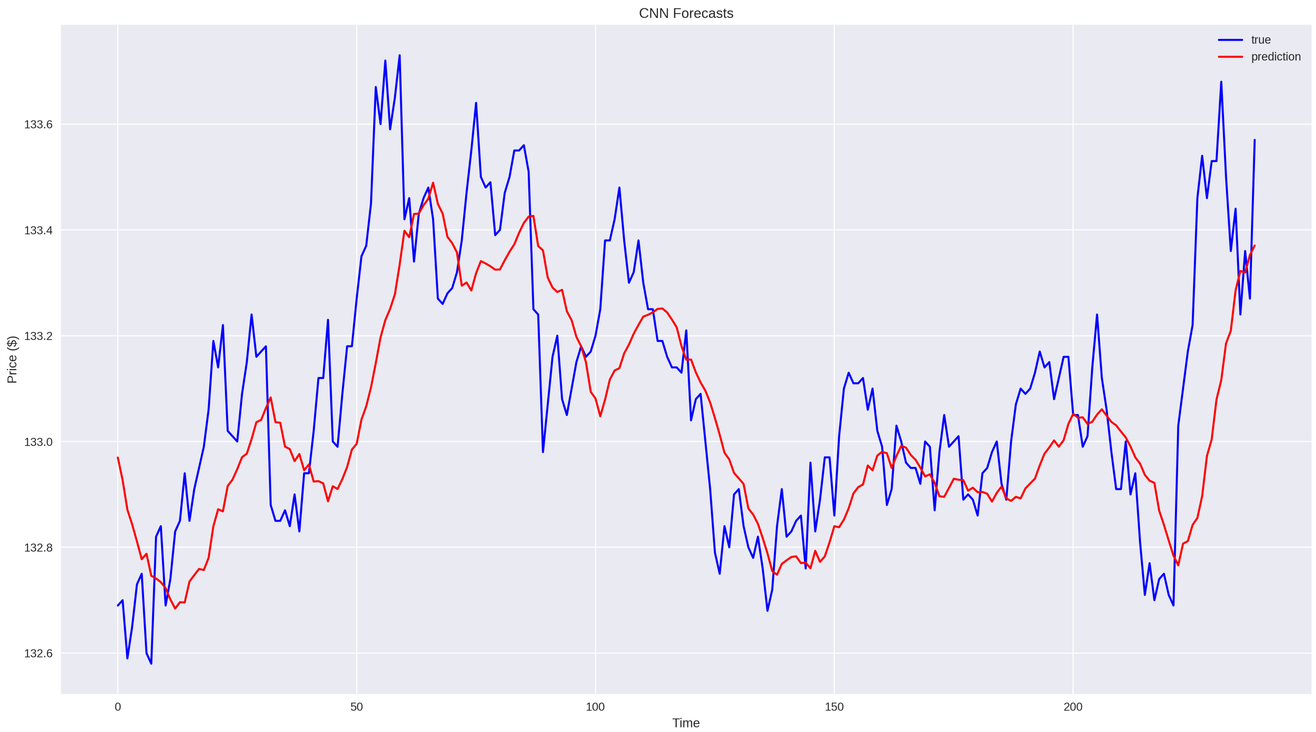
```
Sequential(
  (conv_1): Conv1d(1, 32, kernel_size=(3,), stride=(1,), padding=(1,))
  (max_pool_1): MaxPool1d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (relu_1): ReLU()
  (flatten): Flatten()
  (fc_1): Linear(in_features=192, out_features=50, bias=True)
  (relu_2): ReLU()
  (dropout_1): Dropout(p=0.4, inplace=False)
  (fc_2): Linear(in_features=50, out_features=1, bias=True)
)
```

ℹ️ **NOTE**: you can find more about CNNs here.

4.2. CNN Losses

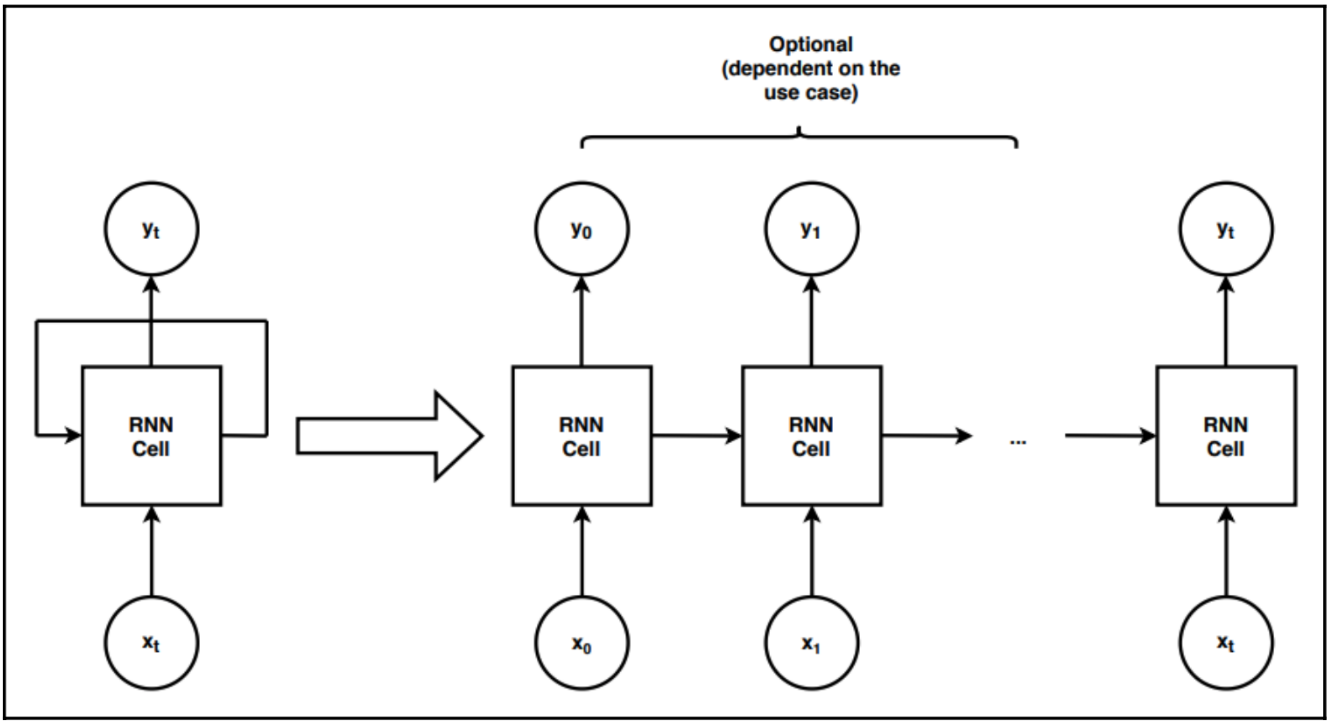


4.3. CNN Prediction



5. Recurrent Neural Network (RNN)

Recurrent Neural Networks (RNNs) are a special type of neural network designed to work with sequential data. They are popular for time series forecasting as well as for solving NLP problems such as machine translation, text generation, and speech recognition. There are numerous extensions of the RNNs, such as Long-Short Term Memory (LSTM) networks and Gated Recurrent Unit (GRU) networks, which are currently holding the state-of-the-art title.
The following diagram shows a typical vanilla RNN schema:



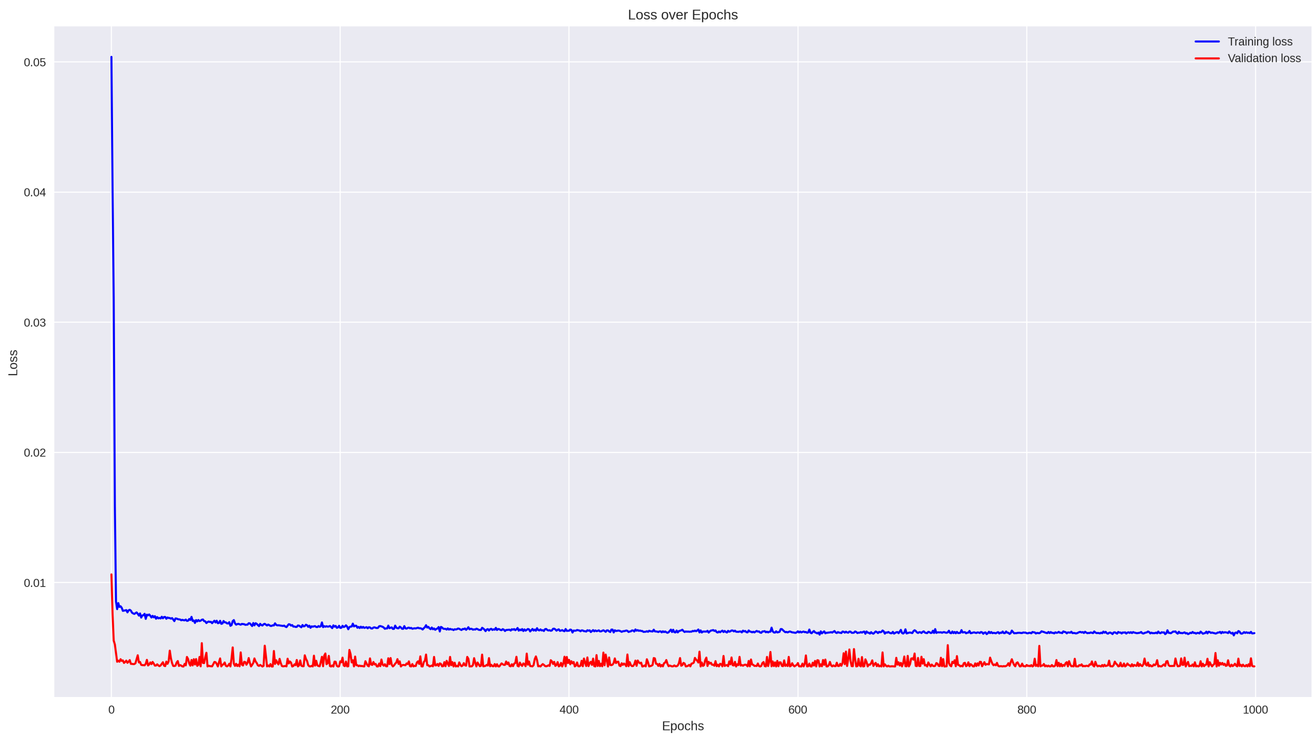

```
class RNN(nn.Module):
  def __init__(self, input_size, hidden_size, n_layers, output_size):
    super(RNN, self).__init__()
    self.rnn = nn.RNN(input_size, hidden_size,
                      n_layers, batch_first=True,
                      nonlinearity='relu')
    self.fc = nn.Linear(hidden_size, output_size)

  def forward(self, x):
    output, _ = self.rnn(x)
    output = self.fc(output[:, -1, :])
    return output
```

The network architecture adopted in this section features six neurons in the hidden layer, one RNN layer, and returns one feature as output. As loss function we use both Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). We use Adam as the optimizer.

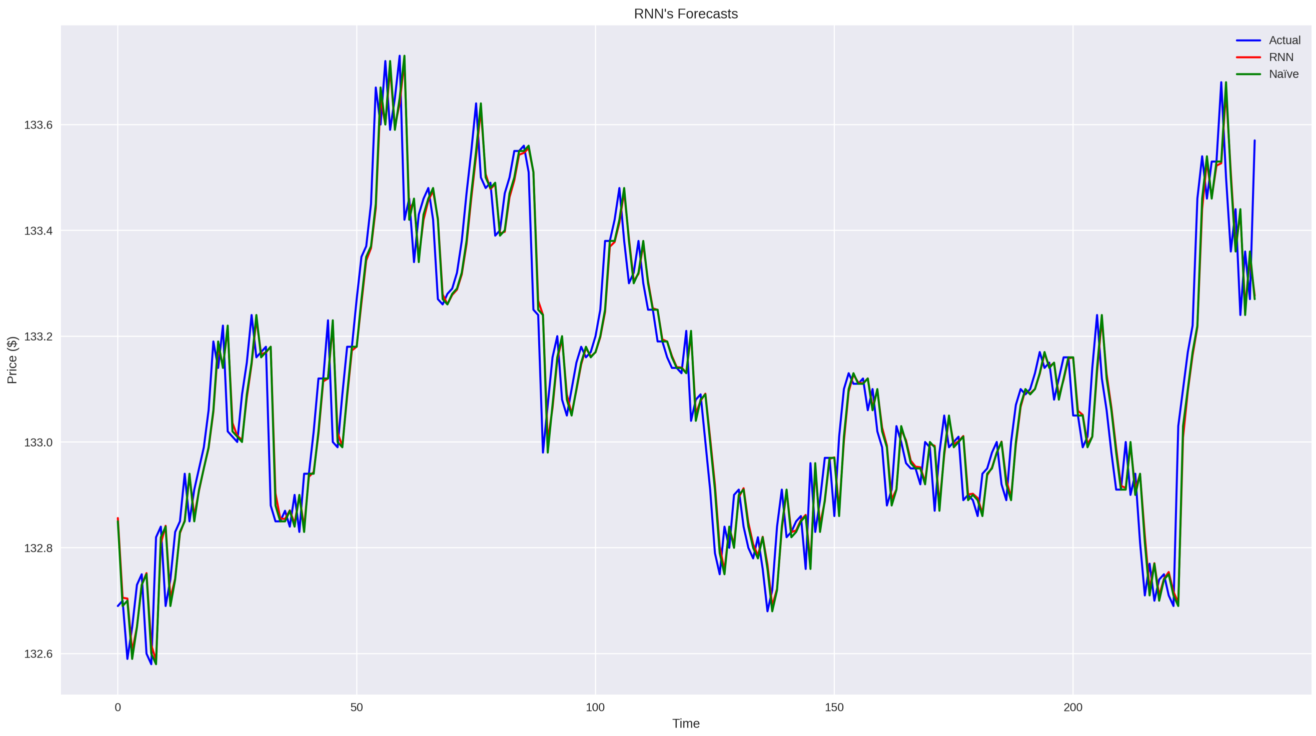
5.1 RNN Architecture

```
RNN(
  (rnn): RNN(1, 6, batch_first=True)
  (fc): Linear(in_features=6, out_features=1, bias=True)
)
```

5.2. RNN Losses



5.3. RNN Prediction



6. Conclusion

To sum up, the three recipes proposed in this project aim at achieving the same results with different strategies.
In the previous projects (Project 3, Project 4, and Project 5) we used regression techniques to perform tasks strictly related to prediction. In this final project we finally introduce deep learning techniques to perform high frequency predictions for 12 periods (meaning 12 minutes) in advance.

MLP shows not enough explanatory power for such a task. Its prediction of the time series, due entirely to its linear constraints, is a straight line (see *MLP Prediction*). And it is not sufficient for high frequency forecasting.

CNN, on the other hand, does a pretty good job predicting the overall development of the price changes. It happens on a smoother curve compared to the ground truth, hence sparks are approximated with curved local maximum and local minimum peaks (see *CNN Prediction*). Unfortunately, such a model could never be of help in the real world scenario. The general development of the cost curve is not interesting, what is interesting instead is to **sharply** predict the value of a price several periods in advance.
Approaches for more advanced CNN models are out there already and one is called *multi-headed models*. The underlying idea is to train different specifications of the convolutional parts of the network, concatenate them at the flattening stage, and feed the joined output to the fully connected layer(s). The main benefit of using multi-headed models is the flexibility they provide, which (depending on the use case) can result in a substantial boost in performance.

RNN's prediction is stunningly impressive. It looks almost a perfect replica of the ground truth (see *RNN Prediction*). Despite its fairly simple architecture, the model provides proof of evidence of its remarkable explanation power for time series forecasting whenever compared to its colleagues MLP and CNN.

I would like to conclude with a central theorem of machine learning which - to me - is as granted as meaningful: the ***No Free Lunch Theorem*** (Wolpert, 1996) which basically states that ***no machine learning algorithm is universally any better than any other***. The most sophisticated algorithm we can conceive of has the same average performance (over all possible tasks) as merely predicting that every point belongs to the same class.
All this to say that RNN might excel in tasks such as series forecasting, but may be cancelled out by a CNN in an image classification task.