In [1]:
```
# LSTM RNN model is used to examine model performance with two data sets with
 contrasting behavior
# Data:
    # dataset 1: used cars monthly sales in millions of dolars from 1992-01-01
to 2019-12-01
        # https://fred.stlouisfed.org/series/MRTSSM44112USN
    # dataset 2: gold price daily in USD from 2015-02-23 to 2020-02-21
        # https://fred.stlouisfed.org/series/GOLDPMGBD228NLBM
# Note: Here we use GPU computing, so processing time will be different for th
ose who use CPU computing
```

In [2]:
```
# import libraries

import torch
import torch.nn as nn

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
%matplotlib inline
sns.set(style = "whitegrid", font_scale = 1.2)

# for plotting datetime values with matplotlib
from pandas.plotting import register_matplotlib_converters
register_matplotlib_converters()

# ignore non-critical warnings
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
# read dataset 1 csv file

data_1 = pd.read_csv('used_car_sales.csv', index_col = 0, parse_dates = True)
# set date column as index
data_1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 336 entries, 1992-01-01 to 2019-12-01
Data columns (total 1 columns):
MRTSSM44112USN    336 non-null int64
dtypes: int64(1)
memory usage: 5.2 KB
```

In [4]:
```
# there are 336 non-null entries of type int64
```

In [5]:
```
# call first 10 entries

data_1.head(10)
```

Out[5]:

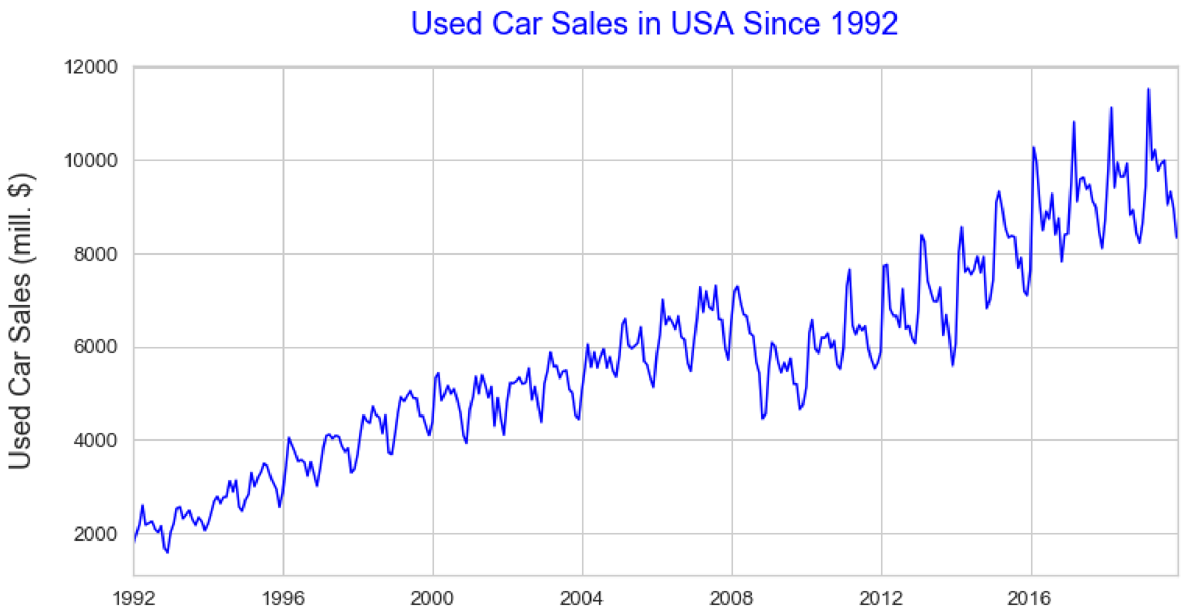
	MRTSSM44112USN
DATE	
1992-01-01	1744
1992-02-01	1990
1992-03-01	2177
1992-04-01	2601
1992-05-01	2171
1992-06-01	2207
1992-07-01	2251
1992-08-01	2087
1992-09-01	2016
1992-10-01	2149

In [6]:
```
# call last 10 entries

data_1.tail(10)
```

Out[6]:

	MRTSSM44112USN
DATE	
2019-03-01	11525
2019-04-01	10009
2019-05-01	10223
2019-06-01	9770
2019-07-01	9916
2019-08-01	9998
2019-09-01	9043
2019-10-01	9326
2019-11-01	8969
2019-12-01	8336

In [7]:
```
# plot data

plt.figure(figsize = (12,6))
plt.plot(data_1.index, data_1['MRTSSM44112USN'], c = 'blue')
plt.autoscale(axis='x',tight=True)
plt.ylabel('Used Car Sales (mill. $)', fontsize = 18, labelpad = 15)
plt.title('Used Car Sales in USA Since 1992', fontsize = 20, pad = 20, color =
'blue')
plt.show()
```



In [8]:
```
# plot shows highly cyclical data with a yearly cycle
# the big drop at 2008 corresponds to the 2008-2009 reccession
```

In [9]:
```
# read dataset 2 csv file

data_2 = pd.read_csv('GOLDPMGBD228NLBM.csv', index_col = 0, parse_dates = True
) # set date column as index

data_2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1305 entries, 2015-02-23 to 2020-02-21
Data columns (total 1 columns):
GOLDPMGBD228NLBM    1305 non-null object
dtypes: object(1)
memory usage: 20.4+ KB
```

In [10]:
```
# data have 1305 entries
# the data have missing entries since five years will result in 5 * 365 = 1825
data points
```

In [11]:
```
# call first 10 entries

data_2.head(10)
```

Out[11]:

DATE	GOLDPMGBD228NLBM
2015-02-23	1204.500
2015-02-24	1192.500
2015-02-25	1204.750
2015-02-26	1208.250
2015-02-27	1214.000
2015-03-02	1212.500
2015-03-03	1212.750
2015-03-04	1199.500
2015-03-05	1202.000
2015-03-06	1175.750

In [12]:
```
# call last 10 entries

data_2.tail(10)
```

Out[12]:

DATE	GOLDPMGBD228NLBM
2020-02-10	1573.20
2020-02-11	1570.50
2020-02-12	1563.70
2020-02-13	1575.05
2020-02-14	1581.40
2020-02-17	1580.80
2020-02-18	1589.85
2020-02-19	1604.20
2020-02-20	1619.00
2020-02-21	1643.30

In [13]:
```
# select gold prices column to work with

y = data_2.iloc[:, -1].values
y
```

Out[13]:
```
array(['1204.500', '1192.500', '1204.750', ..., '1604.20', '1619.00',
       '1643.30'], dtype=object)
```

In [14]:
```
# gold price values are in string format --> need to convert to floats
# however, strings of the type 'x.y' cannot be converted directly
# we will use split('.') and select only the digits before the decimal point
    # all values are >= 1000, thus the error introduced is negligible
```

In [15]:
```
# convert from strings to floats and at the same time check for missing values
and impute

count_null = 0 # set counter for null values

for i in range(len(y)):
    if y[i] == '.':
        y[i] = round(np.mean(y[i-10: i]), 1) # impute with 10-day running avg
        count_null = count_null + 1 # update null counter

    else:
        y[i] = y[i].split('.')[0] # split the string at '.' and drop the digit
s after the decimal point
        y[i] = float(y[i])

    print(i)
    print(y[i])
```

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1204.0
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1192.0
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1204.0
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1208.0
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1214.0
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1199.0
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1202.0
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1191.0
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1203.0
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1195.0
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In [16]:

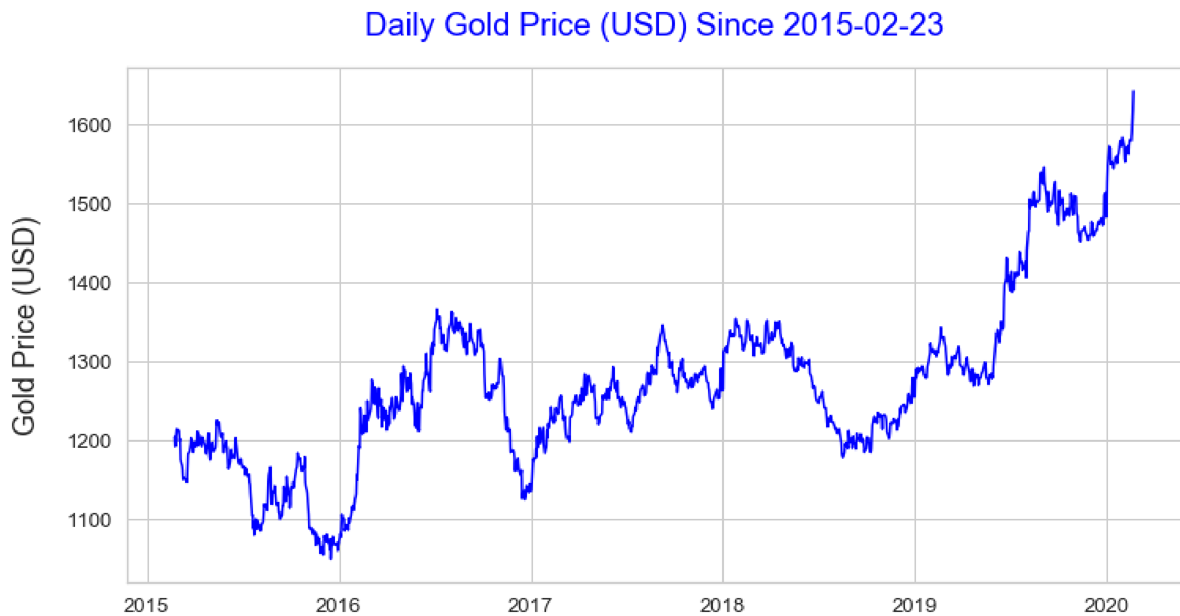
```
# print total null count
print(f'Total Null Count: {count_null}')
```

```
Total Null Count: 53
```

In [17]:

```
# number of nulls is 53 which is small relative to the total number of data po
ints
```

In [18]:
```
# plot gold prices

plt.figure(figsize = (12,6))
plt.plot(data_2.index, y, color = 'blue')
plt.ylabel('Gold Price (USD)', fontsize = 18, labelpad = 15)
plt.title('Daily Gold Price (USD) Since 2015-02-23', fontsize = 20, pad = 20,
color ='blue')
plt.show()
```



In [19]:
```
# in contrast with dataset 1, values here do not have clear cyclical nature an
d rather resemble "random walk"
```

In [20]:
```
# Prepare data
```

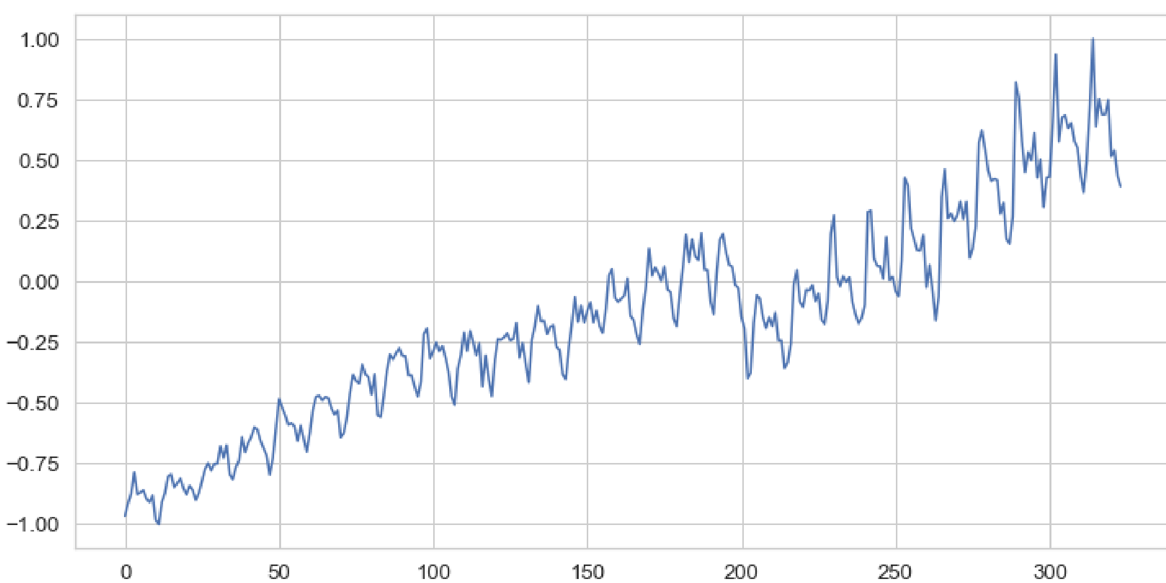
In [21]:
```
# get values from both datasets assigned as y_1 and y_2

# values from dataset 1
y_1 = data_1.iloc[:, -1].values.astype(float)

# values from dataset 2
y_2 = y[0:1290]
# for convenience we select 1290 out of 1305 points to use with a window size
 of 30 (one month) later on
```

In [22]:
```
# create train and test sets from y_1 and y_2

# dataset 1
test_size_1 = 12 # test size corresponds to 1 year

train_set_1 = y_1[:-test_size_1]
test_set_1 = y_1[-test_size_1:]

# dataset 2
test_size_2 = 30 # test size corresponds to 1 month

train_set_2 = y_2[:-test_size_2]
test_set_2 = y_2[-test_size_2:]
```

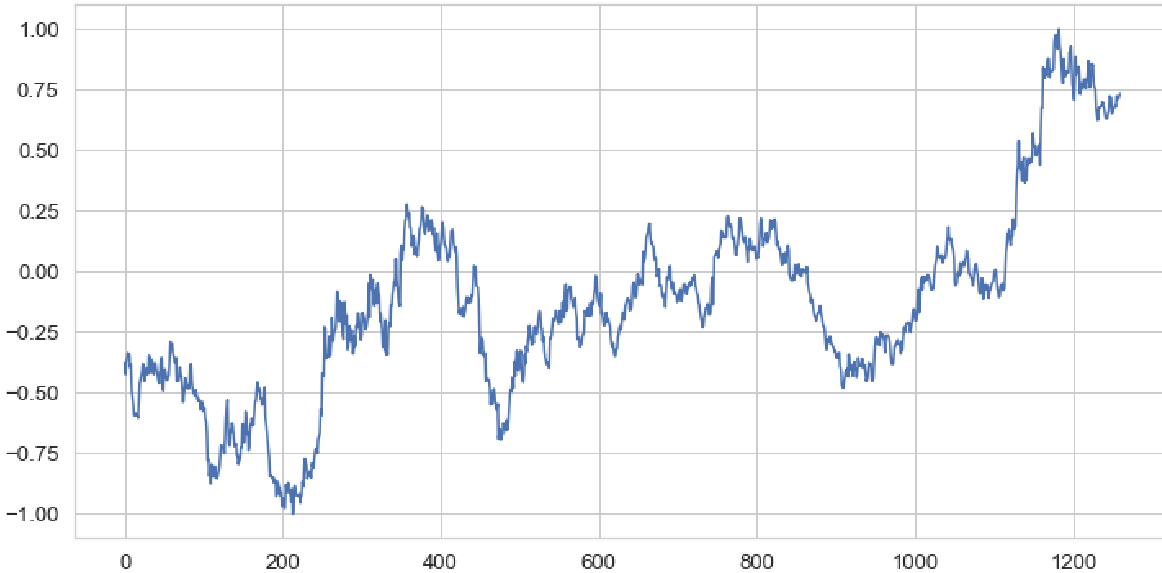
In [23]:
```
# NNs perform better with normalized data --> normalize data using MinMaxScale
r
    # normalize train_set only to avoid information leakage from test_set

from sklearn.preprocessing import MinMaxScaler

# instantiate a scaler with a feature range from -1 to 1
scaler_1 = MinMaxScaler(feature_range=(-1, 1)) # for dataset 1
scaler_2 = MinMaxScaler(feature_range=(-1, 1)) # for dataset 2
```

In [24]:
```
# normalize the training sets

train_set_1 = scaler_1.fit_transform(train_set_1.reshape(-1, 1))

train_set_2 = scaler_2.fit_transform(train_set_2.reshape(-1, 1))
```

In [25]:
```
# plot normalized train set 1

plt.figure(figsize = (12,6))
plt.plot(train_set_1)
plt.show()
```



In [26]:
```
# plot normalized train set 2

plt.figure(figsize = (12,6))
plt.plot(train_set_2)
plt.show()
```



In [27]:
```
# normalized data is bound within -1 and 1, while preserving the ratio between data points
```

In [28]:
```
# Prepare data for LSTM model
```

In [29]:
```
# first, check if GPU computing is available
# torch.cuda.is_available() checks and returns a Boolean True if a GPU is available, else it'll return False

is_cuda = torch.cuda.is_available()

# set device to GPU or CPU depending on the outcome --> we will use this device variable later on in our code
if is_cuda:
    device = torch.device("cuda")
else:
    device = torch.device("cpu")
```

In [30]:
```
# convert train_set_1 and train_set_2 to tensors and set window sizes for both sets
train_set_1 = torch.FloatTensor(train_set_1).view(-1)
train_set_2 = torch.FloatTensor(train_set_2).view(-1)

# window size for dataset 1
window_size_1 = 12 # 1 year

# window size for dataset 2
window_size_2 = 30 # 1 month
```

In [31]:
```
# define function to create seq/label tuples

def input_data(seq, ws):  # ws is the window size
    out = []
    L = len(seq)
    for i in range(L-ws):
        window = seq[i:i+ws]
        label = seq[i+ws:i+ws+1]
        out.append((window, label))
    return out
```

In [32]:
```
# apply the input_data function to train_set_1 and train_set_2

train_data_1 = input_data(train_set_1, window_size_1)
train_data_2 = input_data(train_set_2, window_size_2)
```

In [33]:
```
len(train_data_1)  # this should equal 336 - 12 - 12
```

Out[33]:
```
312
```

In [34]:
```
# show first element of train_data_1
train_data_1[0]
```

Out[34]:
```
(tensor([-0.9663, -0.9148, -0.8756, -0.7868, -0.8768, -0.8693, -0.8601, -0.89
44,
         -0.9093, -0.8815, -0.9824, -1.0000]),
 tensor([-0.9081]))
```

In [35]:
```
# first tensor is the input data for the model
# second tensor is the target value to be predicted by model based on input da
ta
```

In [36]:
```
len(train_data_2)  # this should equal 1290 - 30 - 30
```

Out[36]:
```
1230
```

In [37]:
```
# show first element of train_data_2
train_data_2[0]
```

Out[37]:
```
(tensor([-0.3763, -0.4245, -0.3763, -0.3602, -0.3360, -0.3441, -0.3441, -0.39
64,
         -0.3843, -0.4930, -0.5211, -0.5453, -0.5936, -0.5855, -0.5855, -0.59
36,
         -0.5936, -0.6056, -0.5292, -0.4608, -0.4487, -0.4286, -0.4125, -0.38
03,
         -0.4125, -0.4527, -0.4447, -0.4044, -0.4004, -0.4245]),
 tensor([-0.4209]))
```

In [38]:
```
# Define the LSTM model
```

In [39]:
```
class LSTMnetwork(nn.Module):
    def __init__(self, input_size = 1, hidden_size = 256, output_size = 1): #
 use LSTM layer of size 256
        super().__init__()
        self.hidden_size = hidden_size

        # add an LSTM layer:
        self.lstm = nn.LSTM(input_size, hidden_size)

        # add a fully-connected layer:
        self.linear = nn.Linear(hidden_size, output_size)

        # initialize h0 and c0 -- use .to(device) to select GPU or CPU computa
tion, respectively
        self.hidden = (torch.zeros(1, 1, self.hidden_size).to(device),
                       torch.zeros(1, 1, self.hidden_size).to(device))

    def forward(self, seq):
        lstm_out, self.hidden = self.lstm(seq.view(len(seq), 1, -1), self.hidd
en)
        pred = self.linear(lstm_out.view(len(seq), -1))
        return pred[-1]  # we only want the last value
```

In [40]:
```
# Training
```

In [41]:
```
# define train_model function to be used with the two datasets

def train_model(epochs, train_data):

    # instantiate model, define loss and optimization functions

    torch.manual_seed(42)
    model = LSTMnetwork()

    model.to(device) # use .to(device) to select GPU or CPU computation, respe
ctively

    criterion = nn.MSELoss() # use MSE

    # optimizer has to be defined after model has been associated with the dev
ice!
    optimizer = torch.optim.Adam(model.parameters(), lr=0.001) # use Adam opti
mizer


    # start training

    start_time = time.time()
    for epoch in range(epochs):

        # extract the sequence & label from the training data
        for seq, y_train in train_data:

            # reset the parameters and hidden states -- use .to(device) to sel
ect GPU or CPU computation, respectively
            optimizer.zero_grad()
            model.hidden = (torch.zeros(1, 1, model.hidden_size).to(device),
                            torch.zeros(1, 1, model.hidden_size).to(device))
            y_pred = model(seq.to(device))

            loss = criterion(y_pred, y_train.to(device))
            loss.backward()
            optimizer.step()

        # print training result every 10 epochs starting with 1st epoch
        if epoch%10 == 0:
            print(f'Epoch: {epoch+1:2} Loss: {loss.item():10.8f}')

    print(f'\nDuration: {time.time() - start_time:.0f} seconds')
    return model
```

In [42]:
```
# define model_predictions function to be used with both datasets

def model_predictions(model, future, preds, window_size):

    # set the model to evaluation mode
    model.eval()

    for i in range(future):
        seq = torch.FloatTensor(preds[-window_size:])
        with torch.no_grad():
            model.hidden = (torch.zeros(1, 1, model.hidden_size).to(device),
                            torch.zeros(1, 1, model.hidden_size).to(device))
            preds.append(model(seq.to(device)).item())
```

In [43]:
```
import time

epochs = 200

# train model with train_data_1
train_data = train_data_1

model_1 = train_model(epochs, train_data) # provide separate name for model in
case it will be used later on
```

```
Epoch:  1 Loss: 0.02258122
Epoch: 11 Loss: 0.01771832
Epoch: 21 Loss: 0.00304347
Epoch: 31 Loss: 0.00054948
Epoch: 41 Loss: 0.01037953
Epoch: 51 Loss: 0.00080097
Epoch: 61 Loss: 0.00018010
Epoch: 71 Loss: 0.00063973
Epoch: 81 Loss: 0.00016539
Epoch: 91 Loss: 0.00000044
Epoch: 101 Loss: 0.00001165
Epoch: 111 Loss: 0.00004981
Epoch: 121 Loss: 0.00000134
Epoch: 131 Loss: 0.00000192
Epoch: 141 Loss: 0.00000058
Epoch: 151 Loss: 0.00008903
Epoch: 161 Loss: 0.00176829
Epoch: 171 Loss: 0.00005219
Epoch: 181 Loss: 0.00018570
Epoch: 191 Loss: 0.00011390

Duration: 325 seconds
```

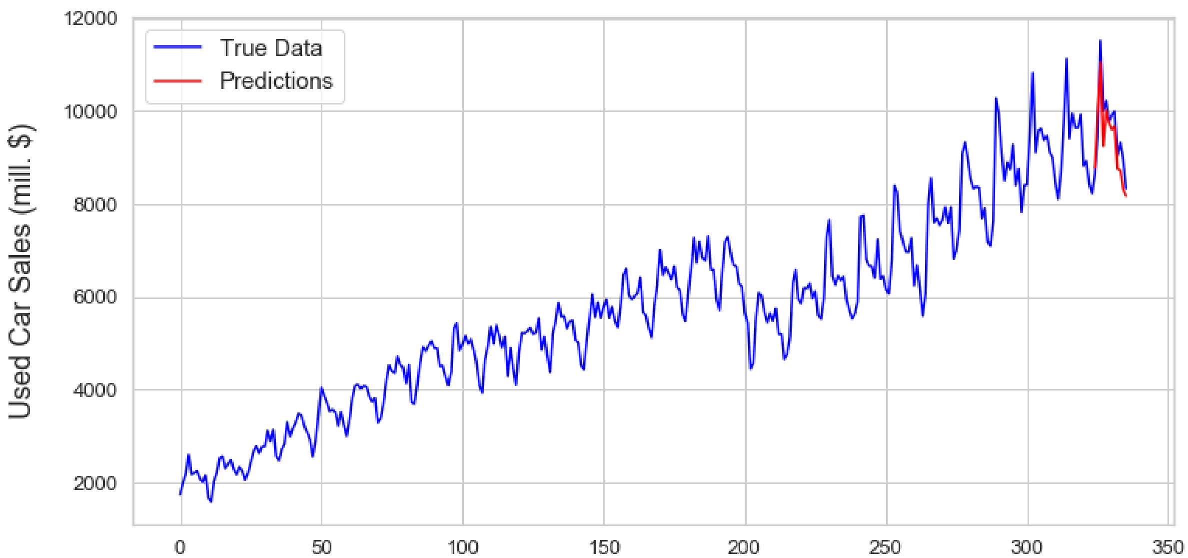
In [44]:
```
# make predictions for train_set_1

future = 12
window_size = window_size_1
preds = train_set_1[-window_size:].tolist()

model_predictions(model_1, future, preds, window_size)
```

In [45]:
```
preds
```

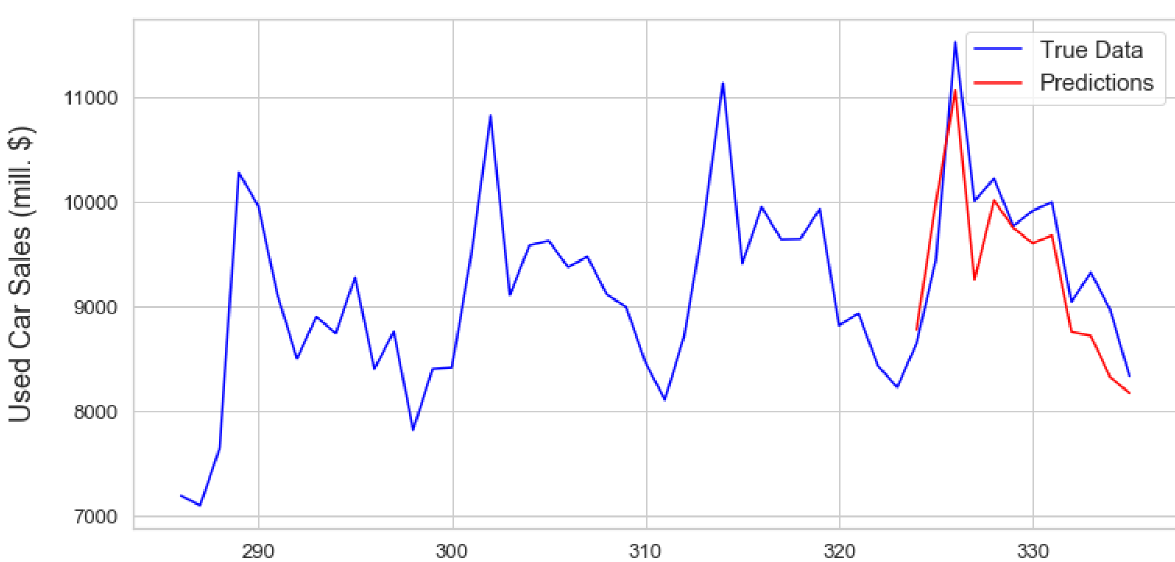
Out[45]:
```
[0.4943973124027252,
 0.7203895449638367,
 1.0,
 0.6391245126724243,
 0.7526442408561707,
 0.6879254579544067,
 0.6887632012367249,
 0.7486647963523865,
 0.5155513882637024,
 0.5398470759391785,
 0.4353335499763489,
 0.39176878333091736,
 0.5067726373672485,
 0.7620344758033752,
 0.9861121773719788,
 0.6068530082702637,
 0.7663792967796326,
 0.7105640172958374,
 0.679915189743042,
 0.6957989931106567,
 0.5026361346244812,
 0.4948640465736389,
 0.4121510982513428,
 0.3802984952926636]
```

In [46]:
```
# invert the normalization for the predicted values to be able to compare to t
est data

preds_1 = scaler_1.inverse_transform(np.array(preds[future:]).reshape(-1, 1))
# use the coresponding scaler
```

In [47]:
```
# plot y_1 and preds_1 to compare predictions to data

plt.figure(figsize = (12,6))
plt.plot(y_1, c = 'blue', label = 'True Data')
plt.plot(np.arange(len(y_1) - future, len(y_1)), preds_1, c = 'red', label =
'Predictions')
plt.ylabel('Used Car Sales (mill. $)', fontsize = 18, labelpad = 15)
plt.legend(fontsize = 15)
plt.show()
```



In [48]:
```
# plot only last portion of graph for more detail view

plt.figure(figsize = (12,6))
plt.plot(np.arange(len(y_1) - 50, len(y_1)), y_1[-50:], c = 'blue', label = 'T
rue Data')
plt.plot(np.arange(len(y_1) - future, len(y_1)), preds_1, c = 'red', label =
'Predictions')
plt.ylabel('Used Car Sales (mill. $)', fontsize = 18, labelpad = 15)
plt.legend(fontsize = 15)
plt.show()
```



In [49]:
```
# model predictions matches well data
# we note, however, that similar result can be obtained simply by appropriate
 averaging and translating the closest data cycles
```

In [50]:
```
# repeat the same process with dataset 2
```

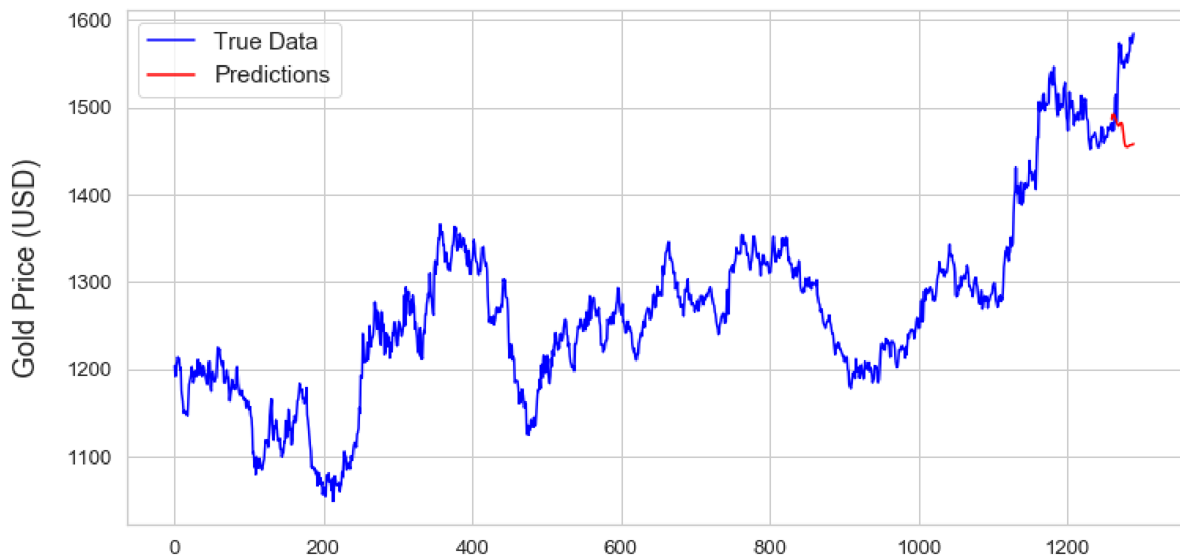
In [51]:
```
# train model with train_data_2
train_data = train_data_2

model_2 = train_model(epochs, train_data)
```

```
Epoch:  1 Loss: 0.00132558
Epoch: 11 Loss: 0.00002865
Epoch: 21 Loss: 0.00001599
Epoch: 31 Loss: 0.00171120
Epoch: 41 Loss: 0.00000009
Epoch: 51 Loss: 0.00002835
Epoch: 61 Loss: 0.00002389
Epoch: 71 Loss: 0.00090776
Epoch: 81 Loss: 0.00011469
Epoch: 91 Loss: 0.00009155
Epoch: 101 Loss: 0.00002225
Epoch: 111 Loss: 0.00004643
Epoch: 121 Loss: 0.00026000
Epoch: 131 Loss: 0.00033497
Epoch: 141 Loss: 0.00008077
Epoch: 151 Loss: 0.00012586
Epoch: 161 Loss: 0.00000982
Epoch: 171 Loss: 0.00009436
Epoch: 181 Loss: 0.00024117
Epoch: 191 Loss: 0.00010930

Duration: 1435 seconds
```

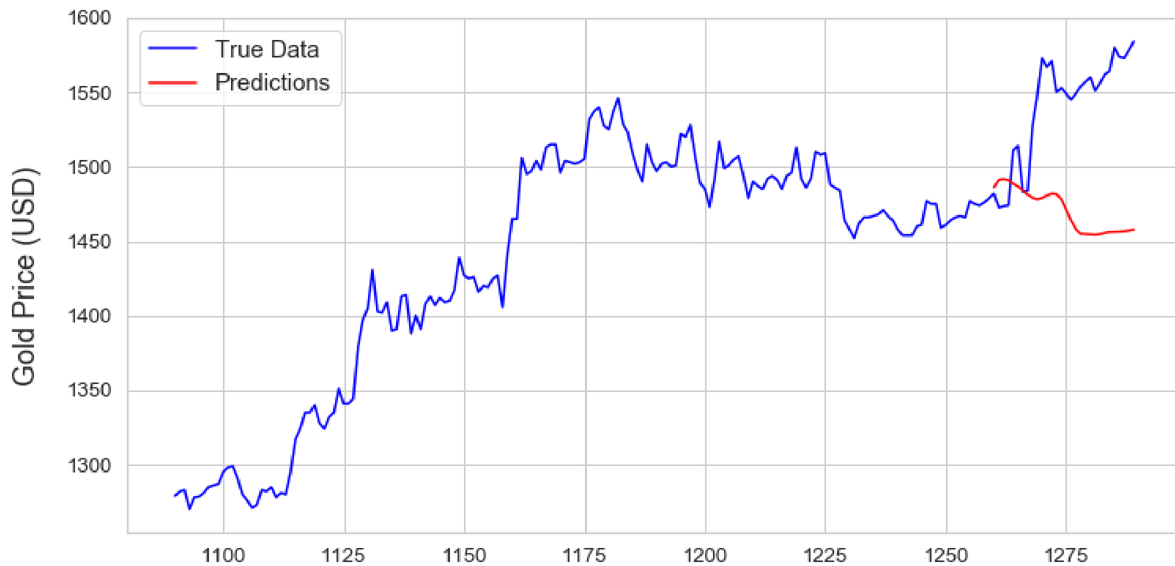
In [52]:
```
# make predictions for train_set_2

future = 30
window_size = window_size_2
preds = train_set_2[-window_size:].tolist()

model_predictions(model_2, future, preds, window_size)
```

In [53]:
```
# invert the normalization for the predicted values to be able to compare to t
est data

preds_2 = scaler_2.inverse_transform(np.array(preds[future:]).reshape(-1, 1))
# use the coresponding scaler
```

In [54]:
```
# plot y_2 and preds_2 to compare predictions to data

plt.figure(figsize = (12,6))
plt.plot(y_2, c = 'blue', label = 'True Data')
plt.plot(np.arange(len(y_2) - future, len(y_2)), preds_2, c = 'red', label =
'Predictions')
plt.ylabel('Gold Price (USD)', fontsize = 18, labelpad = 15)
plt.legend(fontsize = 15)
plt.show()
```



In [55]:
```
# plot only last portion of graph for more detail view

plt.figure(figsize = (12,6))
plt.plot(np.arange(len(y_2) - 200, len(y_2)), y_2[-200:], c = 'blue', label =
'True Data')
plt.plot(np.arange(len(y_2) - future, len(y_2)), preds_2, c = 'red', label =
'Predictions')
plt.ylabel('Gold Price (USD)', fontsize = 18, labelpad = 15)
plt.legend(fontsize = 15)
plt.show()
```



In [56]:
```
# predictions diverge dramatically from data
# extensive research on LSTM models used for predicting "random walk" type of
 data (e.g. stock prices) showed similar results
```

In [57]:
```
# Conclusion:
    # 1) LSTM model provides good predictions for data with well-defined cycli
cal behavior
            # we note that for such data much simpler mathematical operations
 would provide equally good predictions

    # 2) LSTM (and other versions of RNNs) model does not provide good predict
ions for data with random behavior
            # this finding is supported by numerous other studies

    # For data with random behavior different types of analysis are needed for
providing good predictions (if at all possible)
```