```
In [1]:
          import tensorflow as tf
          import pandas as pd
          import numpy as np
          from sklearn.metrics import mean squared error
In [3]:
          import matplotlib.pyplot as plt
          def loss plot(history):
              plt.plot(history.history['loss'])
              plt.plot(history.history['val_loss'])
              plt.title('Model loss')
              plt.ylabel('loss')
              plt.xlabel('Epoch')
              plt.legend(['Train', 'Val'], loc='upper right')
               #plt.legend(['Train'], loc='upper right')
In [25]:
          data = pd.read_csv('data/q2_dataset.csv')
In [9]:
          data.head()
Out [9]:
                Date Close/Last
                                  Volume
                                          Open
                                                  High
                                                          Low
          0 07/08/20
                        $381.37 29272970 376.72 381.50
                                                       376.36
          1 07/07/20
                        $372.69
                                28106110 375.41 378.62 372.23
          2 07/06/20
                        $373.85 29663910 370.00 375.78
                                                       369.87
                        $364.11
          3 07/02/20
                                28510370
                                         367.85 370.47
                                                       363.64
          4 07/01/20
                        $364.11 27684310 365.12 367.36 363.91
In [8]:
          data.tail()
Out[8]:
                    Date Close/Last
                                      Volume
                                              Open
                                                      High
                                                              Low
          1254 07/15/2015
                            $126.82 33559770 125.72
                                                     127.15 125.58
                            $125.61 31695870 126.04 126.37 125.04
          1255 07/14/2015
          1256 07/13/2015
                            $125.66 41365600 125.03 125.76 124.32
          1257
                  07/10/15
                            $123.28 61292800 121.94 123.85
                                                            121.21
          1258
                 07/09/15
                            $120.07 78291510 123.85 124.06 119.22
In [ ]:
          type(data)
         pandas.core.frame.DataFrame
Out[ ]:
In [26]:
          list(data.columns)
          ['Date', 'Close/Last', 'Volume', 'Open', 'High', 'Low']
Out[26]:
```

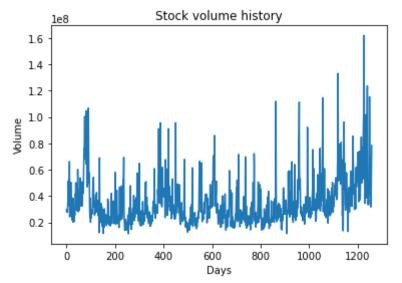
```
In [27]:
           data.columns = data.columns.str.strip()
           list(data.columns)
           ['Date', 'Close/Last', 'Volume', 'Open', 'High', 'Low']
Out[27]:
In [28]:
           data['target']= data['Open']
           data['Date'] =pd.to_datetime(data.Date)
           data=data.sort values(by='Date')
           data.reset_index(inplace=True, drop=True)
           data.head()
Out[28]:
                    Date Close/Last
                                       Volume
                                                 Open
                                                         High
                                                                 Low
                                                                      target
                                     78291510 123.85
              2015-07-09
                                                       124.06
                                                               119.22
                                                                      123.85
                             $120.07
           1
              2015-07-10
                            $123.28 61292800 121.94 123.85
                                                               121.21
                                                                       121.94
              2015-07-13
                            $125.66 41365600 125.03
                                                       125.76
                                                               124.32
                                                                      125.03
              2015-07-14
                             $125.61
                                     31695870 126.04
                                                       126.37
                                                               125.04
                                                                      126.04
                            $126.82 33559770 125.72
              2015-07-15
                                                        127.15
                                                              125.58
                                                                      125.72
In [19]:
           data.head(20)
Out[19]:
                     Date Close/Last
                                         Volume
                                                  Open
                                                           High
                                                                   Low
                                                                        target
               2015-07-09
                                                         124.06
            0
                              $120.07
                                       78291510 123.85
                                                                 119.22
                                                                        123.85
               2015-07-10
                              $123.28
                                       61292800
                                                  121.94
                                                         123.85
                                                                 121.21
                                                                        121.94
               2015-07-13
                              $125.66
                                       41365600 125.03
                                                         125.76
                                                                124.32 125.03
            2
                                       31695870 126.04
                                                         126.37 125.04 126.04
            3
               2015-07-14
                              $125.61
               2015-07-15
                              $126.82
                                       33559770
                                                 125.72
                                                         127.15
                                                                125.58
                                                                        125.72
                                                  127.74
                                                         128.57
                                                                         127.74
            5
               2015-07-16
                              $128.51
                                       35987630
                                                                 127.35
            6
               2015-07-17
                              $129.62
                                       45970470 129.08 129.62
                                                                128.31 129.08
            7
               2015-07-20
                              $132.07
                                       55204920
                                                 130.97
                                                         132.97
                                                                 130.70
                                                                        130.97
                                       73006780 132.85 132.92 130.32 132.85
               2015-07-21
                              $130.75
               2015-07-22
                              $125.22
                                     115288400 121.99 125.50
                                                                 121.99
                                                                        121.99
               2015-07-23
                              $125.16
                                       50832950 126.20
                                                         127.09
                                                                125.06
                                                                        126.20
                                       42090320 125.32
           11
               2015-07-24
                              $124.50
                                                         125.74
                                                                123.90
                                                                        125.32
           12
               2015-07-27
                              $122.77
                                       44371580 123.09
                                                         123.61
                                                                 122.12 123.09
               2015-07-28
                              $123.38
                                       33570380
                                                 123.38
                                                         123.91
                                                                 122.55
                                                                        123.38
           13
               2015-07-29
                              $122.99
                                                 123.15 123.50
                                                                 122.27
           14
                                       36912040
                                                                        123.15
               2015-07-30
                              $122.37
                                       33400950 122.32
                                                         122.57
                                                                 121.71 122.32
           15
           16
               2015-07-31
                              $121.30
                                       42832890 122.60 122.64
                                                                 120.91 122.60
                                      69639900 121.50 122.57
               2015-08-03
                              $118.44
                                                                 117.52 121.50
```

	Date	Close/Last	Volume	Open	High	Low	target
18	2015-08-04	\$114.64	123601900	117.42	117.70	113.25	117.42
19	2015-08-05	\$115.40	99202400	112.95	117.44	112.10	112.95

```
In []:
    from matplotlib import pyplot as plt
    plt.figure()
    plt.plot(data["Open"])
    plt.plot(data["High"])
    plt.plot(data["Low"])
    #plt.plot(data["Close"])
    plt.title('Stock price history')
    plt.ylabel('Price (USD)')
    plt.xlabel('Days')
    plt.legend(['Open','High','Low'], loc='upper left')
    plt.show()
```



```
In []:
    plt.figure()
    plt.plot(data["Volume"])
    plt.title('Stock volume history')
    plt.ylabel('Volume')
    plt.xlabel('Days')
    plt.show()
```



```
In [29]:
          #create features using columns from previous 3 days
          data['Volume_t-3'] = data.shift(3)['Volume']
          data['Volume t-2'] = data.shift(2)['Volume']
          data['Volume_t-1'] = data.shift(1)['Volume']
          data['Open_t-3'] = data.shift(3)['Open']
          data['Open_t-2'] = data.shift(2)['Open']
          data['Open_t-1'] = data.shift(1)['Open']
          data['High_t-3'] = data.shift(3)['High']
          data['High_t-2'] = data.shift(2)['High']
          data['High_t-1'] = data.shift(1)['High']
          data['Low t-3'] = data.shift(3)['Low']
          data['Low_t-2'] = data.shift(2)['Low']
          data['Low t-1'] = data.shift(1)['Low']
          data['target'] = data['Open']
          data.head()
```

Out[29]:		Date	Close/Last	Volume	Open	High	Low	target	Volume_t- 3	Volume_t- 2	Volume_
	0	2015- 07- 09	\$120.07	78291510	123.85	124.06	119.22	123.85	NaN	NaN	٨
	1	2015- 07-10	\$123.28	61292800	121.94	123.85	121.21	121.94	NaN	NaN	7829151
	2	2015- 07-13	\$125.66	41365600	125.03	125.76	124.32	125.03	NaN	78291510.0	6129280
	3	2015- 07-14	\$125.61	31695870	126.04	126.37	125.04	126.04	78291510.0	61292800.0	4136560
	4	2015- 07-15	\$126.82	33559770	125.72	127.15	125.58	125.72	61292800.0	41365600.0	3169587

```
In [30]:
    data = data.drop(['Close/Last','Volume','Open','High','Low'], axis = 1)
    data.head()
```

Out [30]: Date target Volume_t- Volume_t- Volume_t- Open_t- Open_t- Open_t- High_t- High 3 2 1 3

3/2021						RNN_Report					
		Date	target	Volume_t- 3	Volume_t- 2	Volume_t-1	Open_t- 3	Open_t- 2	Open_t- 1	High_t- 3	Higl
	0	2015- 07- 09	123.85	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
	1	2015- 07-10	121.94	NaN	NaN	78291510.0	NaN	NaN	123.85	NaN	1
	2	2015- 07-13	125.03	NaN	78291510.0	61292800.0	NaN	123.85	121.94	NaN	124
	3	2015- 07-14	126.04	78291510.0	61292800.0	41365600.0	123.85	121.94	125.03	124.06	12:
	4	2015- 07-15	125.72	61292800.0	41365600.0	31695870.0	121.94	125.03	126.04	123.85	12
In [31]:	d	ata.is	na().sı	um()							
Out[31]:		te rget lume t	()) 3							

Volume_t-3 2 Volume_t-2 Volume_t-1 1 Open_t-3 3 Open_t-2 2 Open_t-1 1 High_t-3 3 $High_t-2$ 2 High t−1 1 Low_t-3 3 2 Low_t-2 Low_t-1 1 dtype: int64

In [32]:

#drop columns with null values data = data.dropna() data.reset_index(inplace=True, drop=True) data.head()

Out[32]:		Date	target	Volume_t- 3	Volume_t- 2	Volume_t-1	Open_t- 3	Open_t- 2	Open_t- 1	High_t- 3	Hig
	0	2015- 07-14	126.04	78291510.0	61292800.0	41365600.0	123.85	121.94	125.03	124.06	12
	1	2015- 07-15	125.72	61292800.0	41365600.0	31695870.0	121.94	125.03	126.04	123.85	12
	2	2015- 07-16	127.74	41365600.0	31695870.0	33559770.0	125.03	126.04	125.72	125.76	12
	3	2015- 07-17	129.08	31695870.0	33559770.0	35987630.0	126.04	125.72	127.74	126.37	12
	4	2015- 07- 20	130.97	33559770.0	35987630.0	45970470.0	125.72	127.74	129.08	127.15	12

```
In [33]:
          list(data.columns)
          ['Date',
Out[33]:
           'target',
           'Volume_t-3',
           'Volume_t-2',
           'Volume_t-1',
           'Open_t-3',
           'Open_t-2',
           'Open t-1',
           'High_t-3',
           'High_t-2',
           'High_t-1',
           'Low_t-3',
           'Low_t-2',
           'Low_t-1']
In [34]:
           data = data[[
            'Date',
            'Volume_t-3',
            'Volume t-2',
            'Volume_t-1',
            'Open_t-3',
            'Open_t-2',
            'Open_t-1',
            'High_t-3',
            'High_t-2',
            'High_t-1',
            'Low_t-3',
            'Low t-2',
            'Low t-1',
            'target']]
           data.head()
```

Out[34]:		Date	Volume_t- 3	Volume_t- 2	Volume_t-1	Open_t- 3	Open_t- 2	Open_t- 1	High_t- 3	High_t- 2	Hi
	0	2015- 07-14	78291510.0	61292800.0	41365600.0	123.85	121.94	125.03	124.06	123.85	1
	1	2015- 07-15	61292800.0	41365600.0	31695870.0	121.94	125.03	126.04	123.85	125.76	1
	2	2015- 07-16	41365600.0	31695870.0	33559770.0	125.03	126.04	125.72	125.76	126.37	•
	3	2015- 07-17	31695870.0	33559770.0	35987630.0	126.04	125.72	127.74	126.37	127.15	1
	4	2015- 07- 20	33559770.0	35987630.0	45970470.0	125.72	127.74	129.08	127.15	128.57	1

Dataset Creation

We sorted the dataset in ascending order, since our intention is to predict the opening price from the **previous** three days. Using the pandas shift function which shifts the index by desired number of periods, we were able to create new features by specifying the index that was

needed. For example, to get the Volume from three days prior, we shift by 3 - data.shift(3) ['Volume']. This process was repeated for all necessary columns and indices.

```
In [35]:
           len(data)
          1256
Out[35]:
In [36]:
           from sklearn.model selection import train test split
           #split the data into train and test set
           train, test = train_test_split(data, test_size=0.30, random_state=0)
           #save the data
           train.to_csv('train_data_RNN.csv',index=False)
           test.to_csv('test_data_RNN.csv',index=False)
 In [ ]:
           type(train)
          pandas.core.frame.DataFrame
 Out[]:
In [38]:
           train.head()
                                                                    Open_t-
Out[38]:
                                     Volume_t-
                                                            Open_t-
                                                                              Open_t-
                                                                                       High_t-
                                                                                               High_t-
                       Volume_t-3
                                                Volume_t-1
                 Date
                                                                           2
                                                                                             3
                                                                                                     2
                 2018-
           689
                   04-
                        34581850.0
                                    26750260.0
                                               34949690.0
                                                             164.88
                                                                       172.58
                                                                                170.97
                                                                                        172.01
                                                                                                 174.23
                   09
                 2020-
          1134
                        42621540.0
                                    35217270.0
                                                30521720.0
                                                             307.24
                                                                      310.60
                                                                                311.64
                                                                                        310.43
                                                                                                 312.67
                 01-14
                 2019-
           901
                        28204640.0
                                    31644240.0
                                                23793830.0
                                                              174.65
                                                                      172.40
                                                                               168.99
                                                                                        175.57
                                                                                                 173.94
                 02-11
                 2017-
           579
                        17633730.0
                                    21175670.0
                                                16916650.0
                                                             156.29
                                                                       156.91
                                                                                157.23
                                                                                        157.42
                                                                                                 157.55
                 10-27
                 2016-
           367
                        21337310.0 23724430.0
                                                26043820.0
                                                                       116.80
                                                                                116.35
                                                              116.74
                                                                                        117.50
                                                                                                 117.40
In [40]:
           data train = pd.read csv('train data RNN.csv')
           data test = pd.read csv('test data RNN.csv')
```

Preprocessing

Scaling the data

The range of the data is widely varied. The values of Volume are very high and could skew the model. Normalizing data helps the algorithm in converging i.e. to find local/ global minimum efficiently. We utilise the Minmax scaler to keep feature values between 0 and 1.

Scaled values of X are created using the following formula:

```
X_{std} = (X - X.min(axis=0)) / (X.max(axis=0) - X.min(axis=0))
```

```
X_scaled = X_std * (max - min) + min
```

We also tried the Standard scaler, however there was no significant difference in training or test loss with this scaler.

Splitting Features and Target

The target is the opening price of the day we wish to predict.

```
In [41]:
            #separate features and target
            X_train = data_train.drop(['Date', 'target'], axis = 1)
            y_train = data_train['target']
            X_test_date = data_test
            X_test = data_test.drop(['Date', 'target'], axis = 1)
            y test = data test['target']
 In [ ]:
            X train
 Out[]:
                              Volume_t-
                                                               Open_t-
                                                                        Open_t-
                                                                                  High_t-
                                                                                           High_t-
                                                      Open_t-
                                                                                                   High_t
                Volume_t-3
                                         Volume_t-1
                                                                     2
                                         34949690.0
                34581850.0
                             26750260.0
                                                       164.88
                                                                 172.58
                                                                          170.97
                                                                                   172.01
                                                                                            174.23
                                                                                                     172.4
                42621540.0
                             35217270.0
                                          30521720.0
                                                       307.24
                                                                 310.60
                                                                          311.64
                                                                                   310.43
                                                                                            312.67
                                                                                                     317.0
                28204640.0
                             31644240.0
                                         23793830.0
                                                        174.65
                                                                 172.40
                                                                          168.99
                                                                                   175.57
                                                                                            173.94
                                                                                                     170.6
             3
                 17633730.0
                             21175670.0
                                          16916650.0
                                                       156.29
                                                                 156.91
                                                                          157.23
                                                                                   157.42
                                                                                            157.55
                                                                                                     157.8
                 21337310.0
                            23724430.0
                                         26043820.0
                                                                          116.35
                                                                                            117.40
             4
                                                        116.74
                                                                 116.80
                                                                                   117.50
                                                                                                     116.5
                20182050.0 20670830.0
                                         15955820.0
                                                                 191.78
                                                                                   192.55
                                                                                            192.43
           874
                                                       189.69
                                                                          190.68
                                                                                                     191.9
                36487930.0
                             38016810.0
           875
                                         52954070.0
                                                        211.15
                                                                 216.88
                                                                          219.05
                                                                                   215.18
                                                                                            220.45
                                                                                                    222.3
           876
                28803760.0
                             33511990.0
                                         36486560.0
                                                       303.22
                                                                305.64
                                                                          308.10
                                                                                   305.17
                                                                                            310.35
                                                                                                     317.0
                35907770.0 25402270.0
                                                                153.80
           877
                                          21983410.0
                                                        151.78
                                                                          153.89
                                                                                   153.92
                                                                                            154.72
                                                                                                     154.2
           878 39824200.0 41464880.0
                                                                                            170.02
                                                                                                     171.7
                                          38116290.0
                                                       173.68
                                                                 167.25
                                                                          167.81
                                                                                   175.15
          879 rows × 12 columns
In [42]:
            X test
                                                      Open_t-
                                                                                  High_t-
Out [42]:
                                                               Open_t-
                                                                        Open_t-
                                                                                           High_t-
                                                                                                   High_t
                                         Volume_t-1
                Volume_t-3 Volume_t-2
```

3

127.74

145.13

113.38

184.28

2

130.97

145.01

113.25

186.51

129.08

147.17

113.63

183.08

3

129.62

148.28

114.72

185.47

128.57

147.16

114.18

184.99

45970470.0

25674500.0

35678360.0

55204920.0

24725210.0

50061580.0

22526310.0 30684390.0

0 35987630.0

35421310.0

50278030.0

29773430.0

132.9

146.1

115.5

191.9

Volume_t-3 Volume_t-2 Volume_t-1

	4	26560420	.0 261788	840.0 317	35810.0	109.5	1 110.2	3 109.9	95 110.7	3 110.98	3 110.4
	•••		•••			•	•				
	372	64678220	.0 53168	580.0 561	57370.0	112.1	3 111.9	4 111.0	07 112.6	8 112.80	0 111.9
	373	33935720	.0 69281	360.0 540	17920.0	208.7	3 216.4	2 213.9	90 210.1	6 221.3	7 218.0
	374	24833800	.0 25080	500.0 201	17070.0	145.8	7 145.5	0 147.9	97 146.1	8 148.49	9 149.3
	375	53812480	.0 32503	750.0 452	47890.0	284.69	277.9	5 276.2	28 286.9	5 281.68	3 277.2
	376	69032740	.0 246778	880.0 121	19710.0	282.2	3 280.5	3 284.6	9 282.6	5 284.2	5 284.8
	377 rd	ows × 12 c	olumns								
In [43]:	y_t:	rain									
Out[43]:	0	169.8									
	1 2	316.7 171.0									
	3	159.2	9								
	4	115.5	9								
	874	192.4	5								
	875	209.5									
	876	317.8									
	877 878	153.2 167.8									
	0/0)								
				879, dty	pe: fl	oat64					
- []				: 879, dty	pe: fl	oat64					
In [44]:		: target		: 879, dty	pe: fl	oat64					
In [44]: Out[44]:	y_to	: target est	, Length:	: 879, dty	pe: fl	oat64					
	y_te	: target est 132.8 144.4	, Length:	: 879, dty	pe: fl	oat64					
	y_to	: target est	Length:	: 879, dty	rpe: fl	oat64					
	y_te	: target est 132.8 144.4 116.4	, Length:	: 879, dty	ype: fl	oat64					
	y_tc 0 1 2 3 4	: target 132.8 144.4 116.4 191.8 108.9	, Length:	: 879, dty	ype: fl	oat64					
	y_te	: target 132.8 144.4 116.4 191.8 108.9 112.0	, Length:	: 879, dty	ype: fl	oat64					
	y_tc 0 1 2 3 4	: target 132.8 144.4 116.4 191.8 108.9	, Length:	: 879, dty	ype: fl	oat64					
	y_to 0 1 2 3 4 372 373 374 375	132.8 144.4 116.4 191.8 108.9 112.0 205.5 148.8 273.6	, Length: 5 9 4 1 1 2 3 2 1	: 879, dty	ype: fl	oat64					
	y_tc 0 1 2 3 4 372 373 374 375 376	132.8 144.4 116.4 191.8 108.9 112.0 205.5 148.8 273.6 284.8	, Length: 5 9 4 1 1 2 3 2 1								
	y_tc 0 1 2 3 4 372 373 374 375 376	132.8 144.4 116.4 191.8 108.9 112.0 205.5 148.8 273.6 284.8	, Length: 5 9 4 1 1 2 3 2 1	: 879, dty							
	Name y_t 0 1 2 3 4 372 373 374 375 376 Name	132.8 144.4 116.4 191.8 108.9 112.0 205.5 148.8 273.6 284.8	, Length: 5 9 4 1 1 2 3 2 1								
Out[44]:	Name y_t 0 1 2 3 4 372 373 374 375 376 Name	: target 132.8 144.4 116.4 191.8 108.9 112.0 205.5 148.8 273.6 284.8 : target est_date	, Length: 5 9 4 1 1 2 3 2 1 2 2		/pe: fl		Open_t-	Open_t2	Open_t- 1	High_t- 3	High_t- 2
Out[44]:	Name y_t 0 1 2 3 4 372 373 374 375 376 Name	: target 132.8 144.4 116.4 191.8 108.9 112.0 205.5 148.8 273.6 284.8 : target Pate Vo	, Length: 5 9 4 1 1 2 3 2 1 2 2	: 377, dty	ype: fl	oat64					

Open_t- Open_t- High_t- High_t- High_t

2

	Date	Volume_t-3	Volume_t-2	Volume_t-1	Open_t- 3	Open_t- 2	Open_t- 1	High_t- 3	High_t- 2
2	2015- 09-25	50278030.0	35678360.0	50061580.0	113.38	113.63	113.25	114.18	114.72
3	2019- 06-10	29773430.0	22526310.0	30684390.0	184.28	183.08	186.51	184.99	185.47
4	2016- 04- 08	26560420.0	26178840.0	31735810.0	109.51	110.23	109.95	110.73	110.98
•••									•••
372	2015- 12-17	64678220.0	53168580.0	56157370.0	112.18	111.94	111.07	112.68	112.80
373	2019- 08-02	33935720.0	69281360.0	54017920.0	208.76	216.42	213.90	210.16	221.37
374	2017- 07-17	24833800.0	25080500.0	20117070.0	145.87	145.50	147.97	146.18	148.49
375	2020- 04-22	53812480.0	32503750.0	45247890.0	284.69	277.95	276.28	286.95	281.68
376	2019- 12-26	69032740.0	24677880.0	12119710.0	282.23	280.53	284.69	282.65	284.25

377 rows × 14 columns

```
In [46]:
          #scale the data
          #scaling the dataset using minmaxscaler
          from sklearn.preprocessing import MinMaxScaler
          scaler=MinMaxScaler(feature range=(0,1))
          X train=scaler.fit transform(X train)
          X test=scaler.transform(X test)
In [50]:
          X train[:10]
         array([[0.15426342, 0.12644697, 0.15606877, 0.26949793, 0.29492857,
                 0.28369714, 0.28620284, 0.29059167, 0.28161701, 0.27437691,
                 0.29461484, 0.27707898],
                [0.20767603, 0.19602151, 0.12662877, 0.78186072, 0.78785714,
                 0.77656704, 0.77930961, 0.77786773, 0.7855027 , 0.78971724,
                 0.78024251, 0.783580771,
                [0.11189569, 0.16666145, 0.08189741, 0.30466079, 0.29428571,
                 0.27675975, 0.29888497, 0.28957094, 0.27527444, 0.30381869,
                 0.28840942, 0.27785848],
                [0.04166663, 0.08063982, 0.03617348, 0.23858197, 0.23896429,
                 0.23555587, 0.23422749, 0.23188202, 0.23056282, 0.24314969,
                 0.23466476, 0.23661553],
                [0.06627179, 0.10158332, 0.0968568 , 0.09623898, 0.09571429,
                 0.09232332, 0.09201667, 0.09056351, 0.0865656 , 0.09914735,
                 0.09739658, 0.09084789],
                [0.06032861, 0.23632515, 0.11907544, 0.29656289, 0.29867857,
                 0.29739673, 0.29019273, 0.29038049, 0.29806587, 0.29944614,
                 0.29597004, 0.30067675],
                [0.10418206, 0.2385764 , 0.12959566, 0.31034731, 0.30571429,
```

0.29935882, 0.30750597, 0.3035796, 0.30723122, 0.31161638,

```
0.28815977, 0.29947206],
                [0.1531356 , 0.10127863, 0.09360209, 0.10199748, 0.10714286,
                 0.10300971, 0.10177764, 0.10147478, 0.09904164, 0.10475878,
                 0.10784593, 0.10406406],
                [0.11052279, 0.34197841, 0.68454705, 0.05398596, 0.04967857,
                 0.02102239, 0.04980229, 0.04797438, 0.02453389, 0.05480251,
                 0.05149786, 0.02012543],
                [0.04760117, 0.07985845, 0.04767943, 0.1903905, 0.19325]
                 0.19175922, 0.18909195, 0.19105276, 0.18881338, 0.19468736,
                 0.19222539, 0.19267973]
In [51]:
          #numpy array conversion
          X train=np.array(X train)
          X_test=np.array(X_test)
In [52]:
          # reshape input to be [samples, time steps, features] which is required for LSTM
          X_train =X_train.reshape(X_train.shape[0],X_train.shape[1] , 1)
          X test = X test.reshape(X test.shape[0], X test.shape[1] , 1)
In [54]:
          X train.shape
Out[54]: (879, 12, 1)
In [55]:
          X test.shape
Out[55]: (377, 12, 1)
```

Design Steps

RNNs were not chosen because of the vanishing gradient problem. Long short-term memory (LSTM) is a deep learning system that avoids the vanishing gradient problem. LSTM is normally augmented by recurrent gates called "forget gates".LSTM prevents backpropagated errors from vanishing or exploding. Instead, errors can flow backwards through unlimited numbers of virtual layers unfolded in space.

Gated recurrent units (GRUs) are a gating mechanism in recurrent neural networks introduced in 2014. They are used in the full form and several simplified variants. They have fewer parameters than LSTM, as they lack an output gate.

LSTMs and GRUs take 3D input so data was reshaped. We considered various RNN architectures but the following gave the best performance for our problem.

Step 1: Model Architecture

```
MODEL 1
```

```
LSTM LAYER 1 - 50 units --> Dropout 0.2 --> LSTM LAYER 2 - 50 units --> Dropout 0.2 --> LSTM LAYER 3 - 50 units --> Dropout 0.2 --> Dense Layer - 1 unit
```

This model uses three LSTM layers. 20 % of the nodes at each layer are unused to avoid overfitting and improve model performance.

MODEL 2

GRU Layer 75 units --> GRU Layer 30 units --> GRU Layer 30 units --> Dropout 0.2 --> Dense Layer - 1 layer

This model uses three GRU layers. 20 % of the nodes at the final GRU layer are unused to avoid overfitting and improve model performance.

Step 2: Optimizers considered

Adagrad - Resulted in poor model performance. Model did not train.

Stochastic Gradient Descents - Resulted in poor model performance. Model did not train.

Adam: Model performed well with this. It is also recommended as the best optimizer for LSTMs as referenced in [1]

Step 3: Number of Epochs

Epochs	Model 1 Training Loss	Model 2 Training Loss
100	13621	18898
256	4851	8759
512	4203	4312
800	1033	2159
1500	189	292

Step 4: Runtime

Model 1 - 13 min 26s for 1500 epochs Model 2 - 12 min 26s for 1500 epochs

Model 2 has a shorter run time, perhaps because of the smaller width in its 2nd and 3rd layer.

Step 5: Loss Metric

Mean Squared Error.

```
from keras.models import Sequential
  from keras.layers import Dense, Dropout, Activation, Embedding
  from keras.layers import LSTM, SimpleRNN, GRU, Bidirectional
  from keras import callbacks
  from keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau, C
```

Model #1

```
In [57]: model = tf.keras.models.Sequential([
    # Shape [batch, time, features] => [batch, time, lstm_units]
```

```
tf.keras.layers.Dropout(0.2),
          tf.keras.layers.LSTM(50, return_sequences=True),
          tf.keras.layers.Dropout(0.2),
          tf.keras.layers.LSTM(50),
          tf.keras.layers.Dropout(0.2),
          # Shape => [batch, time, features]
          tf.keras.layers.Dense(units=1, activation='linear')
       ])
In [58]:
       model.compile(loss='mean_squared_error',optimizer='adam')
       monitor = EarlyStopping(monitor='val loss', min delta=1e-3, patience=5, verbose=
In [59]:
       model.summary()
      Model: "sequential"
      Layer (type)
                           Output Shape
                                             Param #
      1stm (LSTM)
                           (None, 12, 50)
                                              10400
                           (None, 12, 50)
      dropout (Dropout)
      1stm 1 (LSTM)
                           (None, 12, 50)
                                              20200
      dropout 1 (Dropout)
                           (None, 12, 50)
      1stm 2 (LSTM)
                           (None, 50)
                                             20200
      dropout_2 (Dropout)
                                              0
                           (None, 50)
      dense (Dense)
                           (None, 1)
                                             51
      ______
      Total params: 50,851
      Trainable params: 50,851
      Non-trainable params: 0
In [60]:
       %%time
       history = model.fit(X train,y train,validation split=0.05,epochs=1500,batch size
      Epoch 1/1500
      loss: 33627.8398
      Epoch 2/1500
      oss: 31396.8242
      Epoch 3/1500
      oss: 30665.1504
      Epoch 4/1500
      oss: 30262.4941
      Epoch 5/1500
      oss: 29956.0996
      Epoch 6/1500
```

tf.keras.layers.LSTM(50, return sequences=True, input shape=(12,1)),

```
oss: 29674.6270
Epoch 7/1500
oss: 29407.0371
Epoch 8/1500
oss: 29148.5254
Epoch 9/1500
oss: 28899.8750
Epoch 10/1500
oss: 28652.4551
Epoch 11/1500
oss: 28410.8457
Epoch 12/1500
oss: 28174.4082
Epoch 13/1500
oss: 27942.5742
Epoch 14/1500
oss: 27711.4121
Epoch 15/1500
oss: 27483.4805
Epoch 16/1500
oss: 27264.5332
Epoch 17/1500
oss: 27048.5605
Epoch 18/1500
oss: 26830.2109
Epoch 19/1500
oss: 26615.3750
Epoch 20/1500
oss: 26402.8672
Epoch 21/1500
oss: 26184.5918
Epoch 22/1500
oss: 25970.9512
Epoch 23/1500
oss: 25758.2988
Epoch 24/1500
oss: 25549.0742
Epoch 25/1500
oss: 25346.2793
Epoch 26/1500
```

```
oss: 25143.7500
Epoch 27/1500
oss: 24941.0547
Epoch 28/1500
oss: 24745.0918
Epoch 29/1500
oss: 24547.5293
Epoch 30/1500
oss: 24350.4043
Epoch 31/1500
oss: 24158.0195
Epoch 32/1500
oss: 23959.4551
Epoch 33/1500
oss: 23768.1582
Epoch 34/1500
oss: 23575.8633
Epoch 35/1500
oss: 23387.3418
Epoch 36/1500
oss: 23199.3555
Epoch 37/1500
oss: 23008.4434
Epoch 38/1500
oss: 22825.5840
Epoch 39/1500
oss: 22643.9219
Epoch 40/1500
oss: 22460.5078
Epoch 41/1500
oss: 22282.1465
Epoch 42/1500
oss: 22099.6602
Epoch 43/1500
oss: 21921.8555
Epoch 44/1500
oss: 21743.0645
Epoch 45/1500
oss: 21567.2676
Epoch 46/1500
oss: 21393.4863
```

```
Epoch 47/1500
oss: 21220.3613
Epoch 48/1500
oss: 21047.7930
Epoch 49/1500
oss: 20881.2754
Epoch 50/1500
oss: 20716.1191
Epoch 51/1500
oss: 20549.9941
Epoch 52/1500
oss: 20380.5723
Epoch 53/1500
oss: 20214.0098
Epoch 54/1500
oss: 20048.6230
Epoch 55/1500
oss: 19886.3418
Epoch 56/1500
oss: 19723.2793
Epoch 57/1500
oss: 19565.8379
Epoch 58/1500
oss: 19410.0293
Epoch 59/1500
oss: 19251.8496
Epoch 60/1500
oss: 19094.4199
Epoch 61/1500
oss: 18938.0000
Epoch 62/1500
oss: 18784.2539
Epoch 63/1500
oss: 18629.3047
Epoch 64/1500
oss: 18476.5527
Epoch 65/1500
oss: 18322.8770
Epoch 66/1500
oss: 18170.5000
Epoch 67/1500
```

```
oss: 18018.5605
Epoch 68/1500
oss: 17872.8613
Epoch 69/1500
oss: 17725.9824
Epoch 70/1500
oss: 17581.5840
Epoch 71/1500
oss: 17439.9395
Epoch 72/1500
oss: 17294.0391
Epoch 73/1500
oss: 17150.1172
Epoch 74/1500
oss: 17004.0898
Epoch 75/1500
oss: 16862.5547
Epoch 76/1500
oss: 16720.9004
Epoch 77/1500
oss: 16584.2227
Epoch 78/1500
oss: 16446.8027
Epoch 79/1500
oss: 16311.0459
Epoch 80/1500
oss: 16174.5664
Epoch 81/1500
oss: 16037.9883
Epoch 82/1500
oss: 15905.8564
Epoch 83/1500
oss: 15773.8350
Epoch 84/1500
oss: 15641.8975
Epoch 85/1500
oss: 15511.8867
Epoch 86/1500
oss: 15382.7969
Epoch 87/1500
```

```
oss: 15253.4072
Epoch 88/1500
oss: 15122.2588
Epoch 89/1500
oss: 14995.8584
Epoch 90/1500
oss: 14872.0869
Epoch 91/1500
oss: 14751.7666
Epoch 92/1500
oss: 14624.8252
Epoch 93/1500
oss: 14497.1787
Epoch 94/1500
oss: 14375.4229
Epoch 95/1500
oss: 14256.3477
Epoch 96/1500
oss: 14138.7559
Epoch 97/1500
oss: 14020.9648
Epoch 98/1500
oss: 13904.1816
Epoch 99/1500
oss: 13788.0635
Epoch 100/1500
oss: 13673.6191
Epoch 101/1500
oss: 13556.3691
Epoch 102/1500
oss: 13444.2285
Epoch 103/1500
oss: 13329.1846
Epoch 104/1500
oss: 13218.4414
Epoch 105/1500
oss: 13107.8271
Epoch 106/1500
oss: 12995.8398
Epoch 107/1500
oss: 12881.6748
```

```
Epoch 108/1500
oss: 12766.7148
Epoch 109/1500
oss: 12657.7441
Epoch 110/1500
oss: 12551.9180
Epoch 111/1500
oss: 12446.5752
Epoch 112/1500
oss: 12342.8037
Epoch 113/1500
oss: 12240.5312
Epoch 114/1500
oss: 12134.3760
Epoch 115/1500
oss: 12035.3623
Epoch 116/1500
oss: 11933.8760
Epoch 117/1500
oss: 11831.4502
Epoch 118/1500
oss: 11729.7041
Epoch 119/1500
14/14 [================== ] - 0s 31ms/step - loss: 11631.2578 - val 1
oss: 11632.3633
Epoch 120/1500
oss: 11533.9150
Epoch 121/1500
oss: 11434.7803
Epoch 122/1500
oss: 11337.9297
Epoch 123/1500
oss: 11242.7412
Epoch 124/1500
oss: 11147.4834
Epoch 125/1500
oss: 11052.0469
Epoch 126/1500
oss: 10959.3916
Epoch 127/1500
oss: 10867.6738
Epoch 128/1500
```

```
oss: 10771.5430
Epoch 129/1500
oss: 10681.8340
Epoch 130/1500
oss: 10594.5742
Epoch 131/1500
oss: 10504.7793
Epoch 132/1500
oss: 10415.0713
Epoch 133/1500
oss: 10326.3320
Epoch 134/1500
oss: 10236.4102
Epoch 135/1500
oss: 10146.6680
Epoch 136/1500
oss: 10060.8037
Epoch 137/1500
oss: 9975.5332
Epoch 138/1500
oss: 9892.6279
Epoch 139/1500
ss: 9811.0479
Epoch 140/1500
ss: 9730.0547
Epoch 141/1500
ss: 9651.5879
Epoch 142/1500
ss: 9571.6572
Epoch 143/1500
ss: 9487.6191
Epoch 144/1500
ss: 9409.3955
Epoch 145/1500
ss: 9333.4609
Epoch 146/1500
ss: 9254.3193
Epoch 147/1500
ss: 9175.3574
Epoch 148/1500
```

```
ss: 9099.1484
Epoch 149/1500
ss: 9025.4756
Epoch 150/1500
ss: 8950.4609
Epoch 151/1500
ss: 8877.1865
Epoch 152/1500
ss: 8801.5938
Epoch 153/1500
ss: 8729.9805
Epoch 154/1500
ss: 8653.6670
Epoch 155/1500
ss: 8579.5303
Epoch 156/1500
ss: 8509.7598
Epoch 157/1500
ss: 8440.9883
Epoch 158/1500
ss: 8373.3838
Epoch 159/1500
ss: 8305.4336
Epoch 160/1500
ss: 8236.1055
Epoch 161/1500
ss: 8168.9971
Epoch 162/1500
ss: 8103.6777
Epoch 163/1500
ss: 8039.3813
Epoch 164/1500
ss: 7975.7280
Epoch 165/1500
ss: 7911.1206
Epoch 166/1500
ss: 7845.9043
Epoch 167/1500
ss: 7780.3833
Epoch 168/1500
ss: 7717.4502
```

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Epoch 169/1500
ss: 7654.9448
Epoch 170/1500
ss: 7594.0605
Epoch 171/1500
ss: 7534.4346
Epoch 172/1500
ss: 7473.7983
Epoch 173/1500
ss: 7411.3823
Epoch 174/1500
ss: 7352.6265
Epoch 175/1500
ss: 7291.4473
Epoch 176/1500
ss: 7232.5083
Epoch 177/1500
ss: 7172.7734
Epoch 178/1500
ss: 7113.0703
Epoch 179/1500
ss: 7056.9785
Epoch 180/1500
ss: 6996.1699
Epoch 181/1500
ss: 6936.6592
Epoch 182/1500
ss: 6878.7017
Epoch 183/1500
ss: 6824.9956
Epoch 184/1500
ss: 6771.8096
Epoch 185/1500
ss: 6716.2563
Epoch 186/1500
ss: 6664.9238
Epoch 187/1500
ss: 6611.8394
Epoch 188/1500
ss: 6556.5317
Epoch 189/1500
```

```
ss: 6505.4160
Epoch 190/1500
ss: 6458.6255
Epoch 191/1500
ss: 6410.8105
Epoch 192/1500
ss: 6361.2109
Epoch 193/1500
ss: 6312.9297
Epoch 194/1500
ss: 6265.1582
Epoch 195/1500
ss: 6218.5952
Epoch 196/1500
ss: 6173.4473
Epoch 197/1500
ss: 6123.1704
Epoch 198/1500
ss: 6076.8130
Epoch 199/1500
ss: 6032.7656
Epoch 200/1500
ss: 5987.3833
Epoch 201/1500
ss: 5943.0776
Epoch 202/1500
ss: 5900.4731
Epoch 203/1500
ss: 5857.5312
Epoch 204/1500
ss: 5816.7446
Epoch 205/1500
ss: 5775.7778
Epoch 206/1500
ss: 5733.4253
Epoch 207/1500
ss: 5691.4482
Epoch 208/1500
ss: 5651.6519
Epoch 209/1500
```

```
ss: 5612.8174
Epoch 210/1500
ss: 5573.4922
Epoch 211/1500
ss: 5534.4531
Epoch 212/1500
ss: 5495.0205
Epoch 213/1500
ss: 5454.0249
Epoch 214/1500
ss: 5418.0859
Epoch 215/1500
ss: 5381.5605
Epoch 216/1500
ss: 5346.5723
Epoch 217/1500
ss: 5310.2739
Epoch 218/1500
ss: 5270.4478
Epoch 219/1500
ss: 5232.9458
Epoch 220/1500
ss: 5198.7305
Epoch 221/1500
ss: 5163.4668
Epoch 222/1500
ss: 5127.5420
Epoch 223/1500
ss: 5091.5605
Epoch 224/1500
ss: 5057.9863
Epoch 225/1500
ss: 5025.2739
Epoch 226/1500
ss: 4991.3018
Epoch 227/1500
ss: 4956.0972
Epoch 228/1500
ss: 4922.9438
Epoch 229/1500
ss: 4890.0840
```

```
Epoch 230/1500
ss: 4859.4360
Epoch 231/1500
ss: 4827.0820
Epoch 232/1500
ss: 4795.8369
Epoch 233/1500
ss: 4764.8223
Epoch 234/1500
ss: 4730.2583
Epoch 235/1500
ss: 4697.9053
Epoch 236/1500
ss: 4665.4106
Epoch 237/1500
ss: 4633.7881
Epoch 238/1500
ss: 4600.6699
Epoch 239/1500
ss: 4569.8955
Epoch 240/1500
ss: 4535.4746
Epoch 241/1500
ss: 4506.1792
Epoch 242/1500
ss: 4474.4043
Epoch 243/1500
ss: 4444.7832
Epoch 244/1500
ss: 4415.6792
Epoch 245/1500
ss: 4388.0151
Epoch 246/1500
ss: 4362.1973
Epoch 247/1500
ss: 4337.3149
Epoch 248/1500
ss: 4313.1274
Epoch 249/1500
ss: 4286.9209
Epoch 250/1500
```

```
ss: 4263.2544
Epoch 251/1500
ss: 4241.1616
Epoch 252/1500
ss: 4214.4824
Epoch 253/1500
ss: 4191.0210
Epoch 254/1500
ss: 4167.3555
Epoch 255/1500
ss: 4142.9546
Epoch 256/1500
ss: 4119.1958
Epoch 257/1500
ss: 4098.9141
Epoch 258/1500
ss: 4076.8870
Epoch 259/1500
ss: 4057.4829
Epoch 260/1500
ss: 4036.9741
Epoch 261/1500
ss: 4018.0115
Epoch 262/1500
ss: 3997.5959
Epoch 263/1500
ss: 3976.3408
Epoch 264/1500
14/14 [==============================] - 0s 31ms/step - loss: 4690.0864 - val lo
ss: 3952.7437
Epoch 265/1500
ss: 3933.1475
Epoch 266/1500
ss: 3916.6350
Epoch 267/1500
ss: 3896.8345
Epoch 268/1500
ss: 3879.6443
Epoch 269/1500
ss: 3863.1860
Epoch 270/1500
```

```
ss: 3846.1047
Epoch 271/1500
ss: 3827.3076
Epoch 272/1500
ss: 3808.9670
Epoch 273/1500
ss: 3790.1665
Epoch 274/1500
ss: 3774.8669
Epoch 275/1500
ss: 3757.8752
Epoch 276/1500
ss: 3743.9065
Epoch 277/1500
ss: 3729.5276
Epoch 278/1500
ss: 3714.3772
Epoch 279/1500
ss: 3699.3267
Epoch 280/1500
ss: 3685.1487
Epoch 281/1500
ss: 3670.8389
Epoch 282/1500
ss: 3655.6135
Epoch 283/1500
ss: 3643.6062
Epoch 284/1500
ss: 3630.3867
Epoch 285/1500
ss: 3619.3157
Epoch 286/1500
ss: 3605.2117
Epoch 287/1500
ss: 3593.1797
Epoch 288/1500
ss: 3582.0220
Epoch 289/1500
ss: 3569.8984
Epoch 290/1500
ss: 3557.9456
```

```
Epoch 291/1500
ss: 3547.3779
Epoch 292/1500
ss: 3536.5232
Epoch 293/1500
ss: 3523.1162
Epoch 294/1500
ss: 3511.0576
Epoch 295/1500
14/14 [=============] - Os 32ms/step - loss: 4493.4438 - val_lo
ss: 3496.1975
Epoch 296/1500
ss: 3483.0859
Epoch 297/1500
ss: 3472.5315
Epoch 298/1500
ss: 3461.1299
Epoch 299/1500
ss: 3451.5127
Epoch 300/1500
ss: 3441.0674
Epoch 301/1500
ss: 3430.9294
Epoch 302/1500
ss: 3419.9333
Epoch 303/1500
ss: 3410.1975
Epoch 304/1500
ss: 3402.0610
Epoch 305/1500
ss: 3394.3438
Epoch 306/1500
ss: 3383.4478
Epoch 307/1500
ss: 3375.5381
Epoch 308/1500
ss: 3367.2607
Epoch 309/1500
ss: 3360.1260
Epoch 310/1500
ss: 3353.8259
Epoch 311/1500
```

```
ss: 3346.5823
Epoch 312/1500
ss: 3339.3416
Epoch 313/1500
ss: 3330.5984
Epoch 314/1500
ss: 3320.8240
Epoch 315/1500
ss: 3313.1604
Epoch 316/1500
ss: 3305.4790
Epoch 317/1500
ss: 3297.4773
Epoch 318/1500
ss: 3290.6829
Epoch 319/1500
ss: 3282.8733
Epoch 320/1500
ss: 3277.0740
Epoch 321/1500
ss: 3272.7861
Epoch 322/1500
ss: 3267.1956
Epoch 323/1500
ss: 3259.1077
Epoch 324/1500
ss: 3253.5713
Epoch 325/1500
14/14 [=========================] - 0s 34ms/step - loss: 4211.4277 - val lo
ss: 3247.1846
Epoch 326/1500
ss: 3242.9851
Epoch 327/1500
ss: 3237.0940
Epoch 328/1500
ss: 3232.3936
Epoch 329/1500
ss: 3227.3857
Epoch 330/1500
ss: 3221.1211
Epoch 331/1500
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ss: 3218.4243
Epoch 332/1500
ss: 3214.6985
Epoch 333/1500
ss: 3210.2109
Epoch 334/1500
ss: 3205.9609
Epoch 335/1500
ss: 3201.0537
Epoch 336/1500
ss: 3196.9080
Epoch 337/1500
ss: 3193.8296
Epoch 338/1500
ss: 3190.6506
Epoch 339/1500
ss: 3187.0049
Epoch 340/1500
ss: 3183.5210
Epoch 341/1500
ss: 3179.4900
Epoch 342/1500
ss: 3174.2725
Epoch 343/1500
ss: 3169.9829
Epoch 344/1500
ss: 3165.3792
Epoch 345/1500
ss: 3161.6475
Epoch 346/1500
ss: 3158.1218
Epoch 347/1500
ss: 3153.7834
Epoch 348/1500
ss: 3149.2368
Epoch 349/1500
ss: 3146.6431
Epoch 350/1500
ss: 3143.5291
Epoch 351/1500
ss: 3140.9578
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Epoch 352/1500
ss: 3138.4656
Epoch 353/1500
ss: 3134.4763
Epoch 354/1500
ss: 3131.1577
Epoch 355/1500
ss: 3127.6804
Epoch 356/1500
14/14 [=============] - Os 34ms/step - loss: 4249.2495 - val_lo
ss: 3125.2842
Epoch 357/1500
ss: 3122.9226
Epoch 358/1500
ss: 3118.4553
Epoch 359/1500
ss: 3116.6243
Epoch 360/1500
ss: 3114.7461
Epoch 361/1500
ss: 3112.9211
Epoch 362/1500
ss: 3109.8420
Epoch 363/1500
ss: 3105.2712
Epoch 364/1500
ss: 3102.1025
Epoch 365/1500
ss: 3099.8804
Epoch 366/1500
ss: 3098.5078
Epoch 367/1500
ss: 3097.2148
Epoch 368/1500
ss: 3096.6560
Epoch 369/1500
ss: 3096.2585
Epoch 370/1500
ss: 3093.1414
Epoch 371/1500
ss: 3092.0649
Epoch 372/1500
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ss: 3090.5688
Epoch 373/1500
ss: 3089.8303
Epoch 374/1500
ss: 3087.7046
Epoch 375/1500
ss: 3085.9299
Epoch 376/1500
ss: 3084.5146
Epoch 377/1500
ss: 3083.8118
Epoch 378/1500
ss: 3081.9033
Epoch 379/1500
ss: 3081.3123
Epoch 380/1500
ss: 3078.9495
Epoch 381/1500
ss: 3079.5952
Epoch 382/1500
ss: 3078.4646
Epoch 383/1500
ss: 3077.2112
Epoch 384/1500
ss: 3074.9617
Epoch 385/1500
ss: 3074.6025
Epoch 386/1500
ss: 3073.7234
Epoch 387/1500
ss: 3071.7952
Epoch 388/1500
ss: 3069.4443
Epoch 389/1500
ss: 3068.9084
Epoch 390/1500
ss: 3069.3523
Epoch 391/1500
ss: 3068.8743
Epoch 392/1500
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ss: 3068.1318
Epoch 393/1500
ss: 3067.9187
Epoch 394/1500
ss: 3065.2471
Epoch 395/1500
ss: 3064.4446
Epoch 396/1500
ss: 3062.3596
Epoch 397/1500
ss: 3060.9709
Epoch 398/1500
ss: 3060.1492
Epoch 399/1500
ss: 3058.2883
Epoch 400/1500
ss: 3056.3623
Epoch 401/1500
ss: 3054.7634
Epoch 402/1500
ss: 3053.6509
Epoch 403/1500
ss: 3052.6157
Epoch 404/1500
ss: 3051.9111
Epoch 405/1500
ss: 3052.2148
Epoch 406/1500
ss: 3051.6331
Epoch 407/1500
ss: 3050.7642
Epoch 408/1500
ss: 3050.7307
Epoch 409/1500
ss: 3050.6140
Epoch 410/1500
ss: 3050.4709
Epoch 411/1500
ss: 3050.5984
Epoch 412/1500
ss: 3049.9780
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Epoch 413/1500
ss: 3049.1006
Epoch 414/1500
ss: 3047.8547
Epoch 415/1500
ss: 3047.9749
Epoch 416/1500
ss: 3047.3064
Epoch 417/1500
ss: 3047.2102
Epoch 418/1500
ss: 3048.5610
Epoch 419/1500
ss: 3048.0615
Epoch 420/1500
ss: 3047.7837
Epoch 421/1500
ss: 3047.8804
Epoch 422/1500
ss: 3047.5859
Epoch 423/1500
ss: 3046.9470
Epoch 424/1500
ss: 3046.3689
Epoch 425/1500
ss: 3045.5859
Epoch 426/1500
ss: 3045.5393
Epoch 427/1500
ss: 3044.2212
Epoch 428/1500
ss: 3044.4382
Epoch 429/1500
ss: 3043.8662
Epoch 430/1500
ss: 3044.1409
Epoch 431/1500
ss: 3045.3181
Epoch 432/1500
ss: 3045.4297
Epoch 433/1500
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ss: 3044.3484
Epoch 434/1500
ss: 3043.2703
Epoch 435/1500
ss: 3041.9897
Epoch 436/1500
ss: 3040.7725
Epoch 437/1500
ss: 3040.2634
Epoch 438/1500
ss: 3040.2109
Epoch 439/1500
ss: 3039.9358
Epoch 440/1500
ss: 3040.9084
Epoch 441/1500
ss: 3041.5193
Epoch 442/1500
ss: 3041.2080
Epoch 443/1500
ss: 3041.8345
Epoch 444/1500
ss: 3042.2073
Epoch 445/1500
ss: 3041.3938
Epoch 446/1500
ss: 3041.3252
Epoch 447/1500
ss: 3039.1484
Epoch 448/1500
ss: 3037.2351
Epoch 449/1500
ss: 3037.2781
Epoch 450/1500
ss: 3037.1094
Epoch 451/1500
ss: 3037.7493
Epoch 452/1500
ss: 3038.0688
Epoch 453/1500
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ss: 3038.9639
Epoch 454/1500
ss: 3036.7241
Epoch 455/1500
ss: 3036.1006
Epoch 456/1500
ss: 3035.6846
Epoch 457/1500
ss: 3034.5171
Epoch 458/1500
ss: 3034.1868
Epoch 459/1500
ss: 3033.7805
Epoch 460/1500
ss: 3034.7820
Epoch 461/1500
ss: 3035.8875
Epoch 462/1500
ss: 3035.1201
Epoch 463/1500
ss: 3035.2288
Epoch 464/1500
ss: 3036.3154
Epoch 465/1500
ss: 3037.4326
Epoch 466/1500
ss: 3038.6541
Epoch 467/1500
ss: 3036.6382
Epoch 468/1500
ss: 3037.2549
Epoch 469/1500
ss: 3039.2898
Epoch 470/1500
ss: 3040.1052
Epoch 471/1500
ss: 3040.5330
Epoch 472/1500
ss: 3040.2273
Epoch 473/1500
ss: 3037.3618
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Epoch 474/1500
ss: 3036.3657
Epoch 475/1500
ss: 3036.2329
Epoch 476/1500
ss: 3037.4751
Epoch 477/1500
ss: 3036.8311
Epoch 478/1500
ss: 3037.2891
Epoch 479/1500
ss: 3037.4385
Epoch 480/1500
ss: 3037.3313
Epoch 481/1500
ss: 3038.2478
Epoch 482/1500
ss: 3036.7556
Epoch 483/1500
ss: 3036.3750
Epoch 484/1500
ss: 3035.4517
Epoch 485/1500
ss: 3035.9163
Epoch 486/1500
ss: 3034.4861
Epoch 487/1500
ss: 3034.6189
Epoch 488/1500
ss: 3034.3523
Epoch 489/1500
ss: 3033.5732
Epoch 490/1500
ss: 3033.5266
Epoch 491/1500
ss: 3034.5078
Epoch 492/1500
ss: 3034.8931
Epoch 493/1500
ss: 3034.3569
Epoch 494/1500
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ss: 3034.1174
Epoch 495/1500
ss: 3032.9893
Epoch 496/1500
ss: 3033.7710
Epoch 497/1500
ss: 3033.2432
Epoch 498/1500
ss: 3034.9382
Epoch 499/1500
ss: 3036.5686
Epoch 500/1500
ss: 3037.1990
Epoch 501/1500
ss: 3036.7615
Epoch 502/1500
ss: 3036.6760
Epoch 503/1500
ss: 3036.9014
Epoch 504/1500
ss: 3037.6616
Epoch 505/1500
ss: 3036.2158
Epoch 506/1500
ss: 3035.4595
Epoch 507/1500
ss: 3035.5913
Epoch 508/1500
ss: 3035.1338
Epoch 509/1500
ss: 3036.2358
Epoch 510/1500
ss: 3036.1069
Epoch 511/1500
ss: 3035.6626
Epoch 512/1500
ss: 3035.0686
Epoch 513/1500
ss: 3035.9880
Epoch 514/1500
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ss: 3037.9768
Epoch 515/1500
ss: 3036.5515
Epoch 516/1500
ss: 3035.2927
Epoch 517/1500
ss: 3033.5977
Epoch 518/1500
ss: 3033.0493
Epoch 519/1500
ss: 3032.2439
Epoch 520/1500
ss: 3032.8486
Epoch 521/1500
ss: 3034.2158
Epoch 522/1500
ss: 3034.7478
Epoch 523/1500
ss: 3035.8938
Epoch 524/1500
ss: 3037.1992
Epoch 525/1500
ss: 3038.9346
Epoch 526/1500
ss: 3039.1257
Epoch 527/1500
ss: 3039.5039
Epoch 528/1500
ss: 3040.3342
Epoch 529/1500
ss: 3040.5344
Epoch 530/1500
ss: 3040.6743
Epoch 531/1500
ss: 3039.2422
Epoch 532/1500
ss: 3037.1006
Epoch 533/1500
ss: 3035.7900
Epoch 534/1500
ss: 3033.7549
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Epoch 535/1500
ss: 3033.7451
Epoch 536/1500
ss: 3034.0640
Epoch 537/1500
ss: 3035.1460
Epoch 538/1500
ss: 3035.5999
Epoch 539/1500
14/14 [=============] - Os 34ms/step - loss: 4226.3647 - val_lo
ss: 3034.9084
Epoch 540/1500
ss: 3034.3579
Epoch 541/1500
ss: 3035.4150
Epoch 542/1500
ss: 3034.9873
Epoch 543/1500
ss: 3034.6221
Epoch 544/1500
ss: 3033.8687
Epoch 545/1500
ss: 3033.7625
Epoch 546/1500
ss: 3034.2166
Epoch 547/1500
ss: 3035.0640
Epoch 548/1500
ss: 3034.5857
Epoch 549/1500
ss: 3033.5276
Epoch 550/1500
ss: 3030.0608
Epoch 551/1500
ss: 3029.0774
Epoch 552/1500
ss: 3029.5234
Epoch 553/1500
ss: 3028.1541
Epoch 554/1500
ss: 3028.8525
Epoch 555/1500
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ss: 3028.4617
Epoch 556/1500
ss: 3027.0820
Epoch 557/1500
ss: 3026.8623
Epoch 558/1500
ss: 3025.9312
Epoch 559/1500
ss: 3027.3943
Epoch 560/1500
ss: 3028.5618
Epoch 561/1500
ss: 3029.2944
Epoch 562/1500
ss: 3028.4155
Epoch 563/1500
ss: 3027.8896
Epoch 564/1500
ss: 3027.6064
Epoch 565/1500
ss: 3025.8672
Epoch 566/1500
ss: 3026.2146
Epoch 567/1500
ss: 3029.2188
Epoch 568/1500
ss: 3030.5349
Epoch 569/1500
ss: 3031.5623
Epoch 570/1500
ss: 3031.6155
Epoch 571/1500
ss: 3033.0344
Epoch 572/1500
ss: 3035.1272
Epoch 573/1500
ss: 3035.0298
Epoch 574/1500
ss: 3034.7532
Epoch 575/1500
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ss: 3035.2458
Epoch 576/1500
ss: 3033.5376
Epoch 577/1500
ss: 3032.9646
Epoch 578/1500
ss: 3034.0806
Epoch 579/1500
ss: 3034.4915
Epoch 580/1500
ss: 3036.2461
Epoch 581/1500
ss: 3037.2712
Epoch 582/1500
ss: 3037.4399
Epoch 583/1500
ss: 3036.1709
Epoch 584/1500
ss: 3037.3601
Epoch 585/1500
ss: 3039.3352
Epoch 586/1500
ss: 3040.5525
Epoch 587/1500
ss: 3042.8647
Epoch 588/1500
ss: 3042.3330
Epoch 589/1500
ss: 3043.6514
Epoch 590/1500
ss: 3042.3708
Epoch 591/1500
ss: 3041.5947
Epoch 592/1500
ss: 3037.4126
Epoch 593/1500
ss: 3037.2236
Epoch 594/1500
ss: 3039.0227
Epoch 595/1500
ss: 3040.2302
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Epoch 596/1500
ss: 3040.0811
Epoch 597/1500
ss: 3039.5984
Epoch 598/1500
ss: 3038.9829
Epoch 599/1500
ss: 3040.2458
Epoch 600/1500
ss: 3041.4045
Epoch 601/1500
ss: 3041.0056
Epoch 602/1500
ss: 3039.4412
Epoch 603/1500
ss: 3040.2178
Epoch 604/1500
ss: 3040.7170
Epoch 605/1500
ss: 3041.8525
Epoch 606/1500
ss: 3040.2061
Epoch 607/1500
ss: 3039.3765
Epoch 608/1500
ss: 3038.8545
Epoch 609/1500
ss: 3039.4592
Epoch 610/1500
ss: 3039.3665
Epoch 611/1500
ss: 3041.4546
Epoch 612/1500
ss: 3041.3938
Epoch 613/1500
ss: 3038.3569
Epoch 614/1500
ss: 3039.3440
Epoch 615/1500
ss: 3039.9397
Epoch 616/1500
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ss: 3038.2249
Epoch 617/1500
ss: 3037.5889
Epoch 618/1500
ss: 3036.2734
Epoch 619/1500
ss: 3036.8835
Epoch 620/1500
ss: 3037.8672
Epoch 621/1500
ss: 3037.8271
Epoch 622/1500
ss: 3036.0654
Epoch 623/1500
ss: 3036.1838
Epoch 624/1500
14/14 [=============] - 0s 34ms/step - loss: 4060.0767 - val_lo
ss: 3035.7900
Epoch 625/1500
ss: 3037.8396
Epoch 626/1500
ss: 3035.5662
Epoch 627/1500
ss: 3034.0042
Epoch 628/1500
ss: 3032.2737
Epoch 629/1500
ss: 3032.9587
Epoch 630/1500
14/14 [==============================] - 0s 34ms/step - loss: 4182.2534 - val lo
ss: 3034.4087
Epoch 631/1500
14/14 [==============] - 1s 38ms/step - loss: 4076.1445 - val_lo
ss: 3036.3477
Epoch 632/1500
ss: 3037.4158
Epoch 633/1500
ss: 3037.9534
Epoch 634/1500
ss: 3035.3772
Epoch 635/1500
ss: 3034.5100
Epoch 636/1500
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ss: 3035.6091
Epoch 637/1500
ss: 3031.2922
Epoch 638/1500
ss: 3031.5508
Epoch 639/1500
ss: 3030.5344
Epoch 640/1500
ss: 3030.5586
Epoch 641/1500
ss: 3031.8579
Epoch 642/1500
ss: 3033.4424
Epoch 643/1500
ss: 3029.8291
Epoch 644/1500
ss: 3028.6509
Epoch 645/1500
ss: 3030.0369
Epoch 646/1500
ss: 3029.8904
Epoch 647/1500
ss: 3031.0427
Epoch 648/1500
ss: 3031.3601
Epoch 649/1500
ss: 3033.4626
Epoch 650/1500
ss: 3034.6953
Epoch 651/1500
ss: 3033.5117
Epoch 652/1500
ss: 3034.0422
Epoch 653/1500
ss: 3033.2561
Epoch 654/1500
ss: 3032.0166
Epoch 655/1500
ss: 3032.3867
Epoch 656/1500
ss: 3033.8765
```

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Epoch 657/1500
ss: 3034.0857
Epoch 658/1500
ss: 3032.1697
Epoch 659/1500
ss: 3032.6494
Epoch 660/1500
ss: 3033.1938
Epoch 661/1500
ss: 3033.7336
Epoch 662/1500
ss: 3035.6306
Epoch 663/1500
ss: 3035.0349
Epoch 664/1500
ss: 3035.2290
Epoch 665/1500
ss: 3034.9221
Epoch 666/1500
ss: 3034.1755
Epoch 667/1500
ss: 3033.6448
Epoch 668/1500
ss: 3033.5493
Epoch 669/1500
ss: 3034.7585
Epoch 670/1500
ss: 3036.6743
Epoch 671/1500
ss: 3034.9272
Epoch 672/1500
ss: 3035.0859
Epoch 673/1500
ss: 3034.3181
Epoch 674/1500
ss: 3035.6931
Epoch 675/1500
14/14 [============== ] - 0s 34ms/step - loss: 4144.6899 - val lo
ss: 3037.9321
Epoch 676/1500
ss: 3039.0498
Epoch 677/1500
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ss: 3038.9751
Epoch 678/1500
ss: 3038.9141
Epoch 679/1500
ss: 3038.5374
Epoch 680/1500
ss: 3036.6182
Epoch 681/1500
ss: 3037.6882
Epoch 682/1500
ss: 3036.7334
Epoch 683/1500
ss: 3035.4453
Epoch 684/1500
ss: 3034.4600
Epoch 685/1500
14/14 [=============] - 0s 34ms/step - loss: 4077.0969 - val_lo
ss: 3034.0330
Epoch 686/1500
ss: 3033.6179
Epoch 687/1500
ss: 3032.9939
Epoch 688/1500
ss: 3034.6604
Epoch 689/1500
ss: 3036.3318
Epoch 690/1500
ss: 3036.4924
Epoch 691/1500
ss: 3038.1750
Epoch 692/1500
ss: 3036.7471
Epoch 693/1500
ss: 3037.4468
Epoch 694/1500
ss: 3037.9773
Epoch 695/1500
ss: 3036.1650
Epoch 696/1500
ss: 3034.9680
Epoch 697/1500
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ss: 3035.2517
Epoch 698/1500
ss: 3036.6882
Epoch 699/1500
ss: 3036.4968
Epoch 700/1500
ss: 3035.2603
Epoch 701/1500
ss: 3034.9929
Epoch 702/1500
ss: 3035.2493
Epoch 703/1500
ss: 3032.8650
Epoch 704/1500
ss: 3031.3313
Epoch 705/1500
ss: 3030.6882
Epoch 706/1500
ss: 3032.5444
Epoch 707/1500
ss: 3033.6899
Epoch 708/1500
ss: 3033.1172
Epoch 709/1500
ss: 3034.0627
Epoch 710/1500
ss: 3035.4048
Epoch 711/1500
ss: 3035.9790
Epoch 712/1500
ss: 3034.7180
Epoch 713/1500
ss: 3035.0173
Epoch 714/1500
ss: 3037.1396
Epoch 715/1500
ss: 3037.6899
Epoch 716/1500
ss: 2994.3552
Epoch 717/1500
ss: 2359.6458
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Epoch 718/1500
ss: 2185.8545
Epoch 719/1500
ss: 2138.2207
Epoch 720/1500
ss: 2076.1189
Epoch 721/1500
ss: 2027.9641
Epoch 722/1500
ss: 1988.4979
Epoch 723/1500
ss: 1936.3901
Epoch 724/1500
ss: 1898.4957
Epoch 725/1500
ss: 1859.1106
Epoch 726/1500
ss: 1822.2841
Epoch 727/1500
ss: 1780.7714
Epoch 728/1500
ss: 1756.1058
Epoch 729/1500
ss: 1718.6335
Epoch 730/1500
ss: 1679.5078
Epoch 731/1500
ss: 1648.2024
Epoch 732/1500
ss: 1620.5637
Epoch 733/1500
ss: 1590.1735
Epoch 734/1500
ss: 1566.2585
Epoch 735/1500
ss: 1541.2225
Epoch 736/1500
ss: 1514.5977
Epoch 737/1500
ss: 1490.8981
Epoch 738/1500
```

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ss: 1470.3688
Epoch 739/1500
ss: 1454.6069
Epoch 740/1500
ss: 1422.0093
Epoch 741/1500
ss: 1407.5975
Epoch 742/1500
ss: 1373.1398
Epoch 743/1500
ss: 1353.8805
Epoch 744/1500
ss: 1336.7159
Epoch 745/1500
ss: 1311.6266
Epoch 746/1500
14/14 [=============] - Os 35ms/step - loss: 1766.5663 - val_lo
ss: 1303.3069
Epoch 747/1500
ss: 1282.9122
Epoch 748/1500
ss: 1265.7587
Epoch 749/1500
ss: 1239.1500
Epoch 750/1500
ss: 1220.5328
Epoch 751/1500
ss: 1203.5995
Epoch 752/1500
ss: 1184.3229
Epoch 753/1500
ss: 1174.5472
Epoch 754/1500
ss: 1154.0918
Epoch 755/1500
ss: 1144.4512
Epoch 756/1500
ss: 1127.5020
Epoch 757/1500
ss: 1125.4772
Epoch 758/1500
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ss: 1093.2318
Epoch 759/1500
ss: 1078.8688
Epoch 760/1500
ss: 1070.1973
Epoch 761/1500
ss: 1050.9384
Epoch 762/1500
ss: 1039.3785
Epoch 763/1500
ss: 1029.8741
Epoch 764/1500
ss: 1012.9581
Epoch 765/1500
ss: 999.8828
Epoch 766/1500
ss: 986.2584
Epoch 767/1500
ss: 971.9382
Epoch 768/1500
ss: 964.9323
Epoch 769/1500
ss: 949.7658
Epoch 770/1500
ss: 939.2900
Epoch 771/1500
ss: 932.8599
Epoch 772/1500
ss: 914.6155
Epoch 773/1500
ss: 906.1774
Epoch 774/1500
ss: 890.8035
Epoch 775/1500
ss: 885.1550
Epoch 776/1500
ss: 866.8500
Epoch 777/1500
ss: 865.8677
Epoch 778/1500
ss: 872.1406
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Epoch 779/1500
ss: 836.4861
Epoch 780/1500
ss: 827.6636
Epoch 781/1500
ss: 818.4136
Epoch 782/1500
ss: 819.1367
Epoch 783/1500
ss: 795.5718
Epoch 784/1500
ss: 811.4606
Epoch 785/1500
ss: 778.2332
Epoch 786/1500
ss: 769.8933
Epoch 787/1500
ss: 760.9573
Epoch 788/1500
ss: 759.9105
Epoch 789/1500
ss: 747.3027
Epoch 790/1500
ss: 744.0184
Epoch 791/1500
ss: 729.7725
Epoch 792/1500
ss: 727.7063
Epoch 793/1500
ss: 718.8132
Epoch 794/1500
ss: 708.6901
Epoch 795/1500
ss: 695.3455
Epoch 796/1500
ss: 685.3481
Epoch 797/1500
ss: 704.6281
Epoch 798/1500
ss: 677.0488
Epoch 799/1500
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```
ss: 663.5269
Epoch 800/1500
ss: 653.2641
Epoch 801/1500
ss: 671.9653
Epoch 802/1500
ss: 647.2721
Epoch 803/1500
ss: 630.7172
Epoch 804/1500
ss: 644.7053
Epoch 805/1500
ss: 619.6370
Epoch 806/1500
s: 611.4095
Epoch 807/1500
s: 601.9921
Epoch 808/1500
s: 594.2128
Epoch 809/1500
s: 593.4567
Epoch 810/1500
s: 580.6008
Epoch 811/1500
s: 573.9990
Epoch 812/1500
s: 568.1807
Epoch 813/1500
s: 560.1547
Epoch 814/1500
s: 561.9605
Epoch 815/1500
s: 549.2431
Epoch 816/1500
s: 542.6794
Epoch 817/1500
s: 555.2408
Epoch 818/1500
s: 534.5261
Epoch 819/1500
```

```
s: 520.6180
Epoch 820/1500
s: 524.9151
Epoch 821/1500
s: 509.8562
Epoch 822/1500
s: 503.0722
Epoch 823/1500
s: 495.6976
Epoch 824/1500
s: 486.7249
Epoch 825/1500
s: 481.1329
Epoch 826/1500
s: 478.0005
Epoch 827/1500
s: 478.0031
Epoch 828/1500
s: 470.0927
Epoch 829/1500
s: 456.8111
Epoch 830/1500
s: 453.1703
Epoch 831/1500
s: 446.9253
Epoch 832/1500
s: 440.5645
Epoch 833/1500
s: 430.8253
Epoch 834/1500
s: 426.0840
Epoch 835/1500
s: 424.3719
Epoch 836/1500
s: 416.2242
Epoch 837/1500
s: 407.4433
Epoch 838/1500
s: 414.0014
Epoch 839/1500
s: 398.9286
```

```
Epoch 840/1500
s: 397.5898
Epoch 841/1500
s: 422.8642
Epoch 842/1500
s: 393.6112
Epoch 843/1500
s: 379.3535
Epoch 844/1500
s: 388.8484
Epoch 845/1500
s: 380.8739
Epoch 846/1500
s: 372.1624
Epoch 847/1500
s: 358.7762
Epoch 848/1500
s: 358.6885
Epoch 849/1500
s: 354.7855
Epoch 850/1500
s: 368.9277
Epoch 851/1500
s: 348.3692
Epoch 852/1500
s: 337.7976
Epoch 853/1500
s: 336.0176
Epoch 854/1500
s: 330.5723
Epoch 855/1500
s: 328.1134
Epoch 856/1500
s: 322.1211
Epoch 857/1500
s: 315.6735
Epoch 858/1500
s: 311.1927
Epoch 859/1500
s: 307.6552
Epoch 860/1500
```

```
s: 308.1846
Epoch 861/1500
s: 297.9290
Epoch 862/1500
s: 294.0180
Epoch 863/1500
s: 290.2913
Epoch 864/1500
s: 311.9988
Epoch 865/1500
s: 283.5429
Epoch 866/1500
s: 282.6792
Epoch 867/1500
s: 291.2315
Epoch 868/1500
s: 282.4135
Epoch 869/1500
s: 283.4562
Epoch 870/1500
s: 267.5169
Epoch 871/1500
s: 261.2150
Epoch 872/1500
s: 256.6948
Epoch 873/1500
s: 260.8912
Epoch 874/1500
s: 250.6620
Epoch 875/1500
s: 251.5062
Epoch 876/1500
s: 246.2324
Epoch 877/1500
s: 241.3181
Epoch 878/1500
s: 240.9621
Epoch 879/1500
s: 240.6773
Epoch 880/1500
```

```
s: 234.5037
Epoch 881/1500
s: 229.2457
Epoch 882/1500
s: 233.4877
Epoch 883/1500
s: 227.3667
Epoch 884/1500
s: 242.4557
Epoch 885/1500
s: 228.5848
Epoch 886/1500
s: 219.9381
Epoch 887/1500
s: 212.8636
Epoch 888/1500
s: 224.3081
Epoch 889/1500
s: 210.1923
Epoch 890/1500
s: 209.6279
Epoch 891/1500
s: 209.1414
Epoch 892/1500
s: 202.1313
Epoch 893/1500
s: 217.3840
Epoch 894/1500
s: 200.1058
Epoch 895/1500
s: 202.7283
Epoch 896/1500
s: 189.4615
Epoch 897/1500
s: 197.4876
Epoch 898/1500
s: 210.3005
Epoch 899/1500
s: 183.2907
Epoch 900/1500
14/14 [=============== ] - 1s 36ms/step - loss: 474.3203 - val_los
s: 194.7685
```

```
Epoch 901/1500
s: 177.9774
Epoch 902/1500
s: 178.3417
Epoch 903/1500
s: 181.0752
Epoch 904/1500
s: 168.9247
Epoch 905/1500
s: 170.7478
Epoch 906/1500
s: 166.0403
Epoch 907/1500
s: 175.0452
Epoch 908/1500
s: 169.0978
Epoch 909/1500
s: 163.7158
Epoch 910/1500
s: 159.8914
Epoch 911/1500
s: 156.2380
Epoch 912/1500
s: 164.2376
Epoch 913/1500
s: 159.2352
Epoch 914/1500
s: 161.0018
Epoch 915/1500
s: 152.6458
Epoch 916/1500
s: 151.4906
Epoch 917/1500
s: 147.0482
Epoch 918/1500
s: 142.4565
Epoch 919/1500
s: 142.0402
Epoch 920/1500
s: 140.1232
Epoch 921/1500
```

```
s: 142.6967
Epoch 922/1500
s: 139.3017
Epoch 923/1500
s: 134.6647
Epoch 924/1500
s: 140.6369
Epoch 925/1500
s: 129.9232
Epoch 926/1500
s: 131.0594
Epoch 927/1500
s: 135.1978
Epoch 928/1500
s: 135.8529
Epoch 929/1500
s: 124.8315
Epoch 930/1500
s: 128.3893
Epoch 931/1500
s: 121.3035
Epoch 932/1500
s: 121.1778
Epoch 933/1500
s: 121.8307
Epoch 934/1500
s: 121.2243
Epoch 935/1500
s: 116.5599
Epoch 936/1500
s: 116.5877
Epoch 937/1500
s: 113.9002
Epoch 938/1500
s: 117.5722
Epoch 939/1500
s: 117.2456
Epoch 940/1500
s: 109.3231
Epoch 941/1500
```

```
s: 114.0532
Epoch 942/1500
s: 109.4203
Epoch 943/1500
s: 106.1217
Epoch 944/1500
s: 105.7722
Epoch 945/1500
s: 106.3105
Epoch 946/1500
s: 105.5106
Epoch 947/1500
s: 103.9118
Epoch 948/1500
s: 105.7879
Epoch 949/1500
s: 111.3458
Epoch 950/1500
s: 97.8886
Epoch 951/1500
s: 95.9039
Epoch 952/1500
s: 94.5464
Epoch 953/1500
s: 102.6272
Epoch 954/1500
s: 98.3588
Epoch 955/1500
s: 92.4357
Epoch 956/1500
s: 91.6906
Epoch 957/1500
s: 95.9243
Epoch 958/1500
s: 90.2486
Epoch 959/1500
s: 97.3058
Epoch 960/1500
s: 108.6062
Epoch 961/1500
s: 92.2448
```

```
Epoch 962/1500
s: 90.4459
Epoch 963/1500
s: 85.6553
Epoch 964/1500
s: 88.7810
Epoch 965/1500
s: 85.7271
Epoch 966/1500
s: 88.7033
Epoch 967/1500
s: 82.9973
Epoch 968/1500
s: 93.6771
Epoch 969/1500
s: 86.5934
Epoch 970/1500
s: 116.4903
Epoch 971/1500
s: 79.2942
Epoch 972/1500
s: 90.0888
Epoch 973/1500
s: 78.7562
Epoch 974/1500
s: 84.9941
Epoch 975/1500
s: 78.0028
Epoch 976/1500
s: 80.5779
Epoch 977/1500
s: 76.3197
Epoch 978/1500
s: 74.9431
Epoch 979/1500
s: 84.6603
Epoch 980/1500
s: 78.8515
Epoch 981/1500
s: 71.9722
Epoch 982/1500
```

```
s: 73.6108
Epoch 983/1500
s: 74.4368
Epoch 984/1500
s: 70.4000
Epoch 985/1500
s: 68.8430
Epoch 986/1500
s: 69.9002
Epoch 987/1500
s: 79.8208
Epoch 988/1500
s: 67.8954
Epoch 989/1500
s: 68.3856
Epoch 990/1500
s: 96.0238
Epoch 991/1500
s: 66.6163
Epoch 992/1500
s: 70.2916
Epoch 993/1500
s: 72.7489
Epoch 994/1500
s: 65.2760
Epoch 995/1500
s: 106.1634
Epoch 996/1500
s: 69.1979
Epoch 997/1500
s: 67.0543
Epoch 998/1500
s: 64.9235
Epoch 999/1500
s: 61.7508
Epoch 1000/1500
s: 69.0986
Epoch 1001/1500
s: 65.3786
Epoch 1002/1500
```

```
s: 63.5797
Epoch 1003/1500
s: 76.5664
Epoch 1004/1500
s: 59.4647
Epoch 1005/1500
s: 57.5056
Epoch 1006/1500
s: 68.7991
Epoch 1007/1500
s: 62.2289
Epoch 1008/1500
s: 72.7804
Epoch 1009/1500
s: 60.3063
Epoch 1010/1500
s: 66.5485
Epoch 1011/1500
s: 58.3029
Epoch 1012/1500
s: 58.4036
Epoch 1013/1500
s: 59.0463
Epoch 1014/1500
s: 61.9217
Epoch 1015/1500
s: 75.8410
Epoch 1016/1500
s: 63.1151
Epoch 1017/1500
s: 63.7660
Epoch 1018/1500
s: 61.8500
Epoch 1019/1500
s: 55.4068
Epoch 1020/1500
s: 54.5089
Epoch 1021/1500
s: 57.1422
Epoch 1022/1500
s: 68.4879
```

```
Epoch 1023/1500
s: 59.9247
Epoch 1024/1500
s: 53.9026
Epoch 1025/1500
s: 63.8537
Epoch 1026/1500
s: 54.7501
Epoch 1027/1500
s: 52.8663
Epoch 1028/1500
s: 53.5372
Epoch 1029/1500
s: 51.8654
Epoch 1030/1500
s: 55.5913
Epoch 1031/1500
s: 48.8831
Epoch 1032/1500
s: 52.0478
Epoch 1033/1500
s: 60.7268
Epoch 1034/1500
s: 45.4838
Epoch 1035/1500
s: 67.4163
Epoch 1036/1500
s: 69.6369
Epoch 1037/1500
s: 49.2200
Epoch 1038/1500
s: 71.9295
Epoch 1039/1500
s: 61.0769
Epoch 1040/1500
s: 58.1007
Epoch 1041/1500
s: 48.4187
Epoch 1042/1500
s: 57.5625
Epoch 1043/1500
```

```
s: 85.3490
Epoch 1044/1500
s: 60.3061
Epoch 1045/1500
s: 51.0314
Epoch 1046/1500
s: 50.0794
Epoch 1047/1500
s: 50.5145
Epoch 1048/1500
s: 49.2483
Epoch 1049/1500
s: 49.8604
Epoch 1050/1500
s: 51.4867
Epoch 1051/1500
s: 65.8817
Epoch 1052/1500
s: 48.9339
Epoch 1053/1500
s: 62.7242
Epoch 1054/1500
s: 45.9670
Epoch 1055/1500
s: 49.1418
Epoch 1056/1500
s: 50.9708
Epoch 1057/1500
s: 46.1960
Epoch 1058/1500
s: 91.8006
Epoch 1059/1500
s: 46.1468
Epoch 1060/1500
s: 42.0387
Epoch 1061/1500
s: 43.4203
Epoch 1062/1500
s: 53.7880
Epoch 1063/1500
```

```
s: 60.8415
Epoch 1064/1500
s: 51.7633
Epoch 1065/1500
s: 39.3139
Epoch 1066/1500
s: 110.6340
Epoch 1067/1500
s: 38.8686
Epoch 1068/1500
s: 68.2275
Epoch 1069/1500
s: 45.6102
Epoch 1070/1500
s: 37.4440
Epoch 1071/1500
s: 73.6303
Epoch 1072/1500
s: 36.7879
Epoch 1073/1500
s: 71.3838
Epoch 1074/1500
s: 36.8928
Epoch 1075/1500
s: 75.6616
Epoch 1076/1500
s: 66.5499
Epoch 1077/1500
s: 43.1478
Epoch 1078/1500
s: 45.7648
Epoch 1079/1500
s: 43.8722
Epoch 1080/1500
s: 53.1655
Epoch 1081/1500
s: 40.3551
Epoch 1082/1500
s: 38.1329
Epoch 1083/1500
s: 34.3985
```

```
Epoch 1084/1500
s: 73.8854
Epoch 1085/1500
s: 36.6732
Epoch 1086/1500
s: 43.4137
Epoch 1087/1500
s: 52.6132
Epoch 1088/1500
14/14 [==============] - 1s 36ms/step - loss: 224.3673 - val_los
s: 34.1074
Epoch 1089/1500
s: 33.3282
Epoch 1090/1500
s: 52.3940
Epoch 1091/1500
s: 46.5963
Epoch 1092/1500
s: 36.1658
Epoch 1093/1500
s: 52.8672
Epoch 1094/1500
s: 61.0223
Epoch 1095/1500
s: 35.0152
Epoch 1096/1500
s: 36.9616
Epoch 1097/1500
s: 51.6770
Epoch 1098/1500
s: 37.1481
Epoch 1099/1500
s: 32.3742
Epoch 1100/1500
s: 41.5942
Epoch 1101/1500
s: 50.5010
Epoch 1102/1500
s: 36.1521
Epoch 1103/1500
s: 48.0252
Epoch 1104/1500
```

```
s: 42.3669
Epoch 1105/1500
s: 72.4989
Epoch 1106/1500
s: 39.1000
Epoch 1107/1500
s: 54.7356
Epoch 1108/1500
s: 30.5537
Epoch 1109/1500
s: 34.3514
Epoch 1110/1500
s: 31.1502
Epoch 1111/1500
s: 48.0718
Epoch 1112/1500
s: 44.1638
Epoch 1113/1500
s: 38.4154
Epoch 1114/1500
s: 38.3844
Epoch 1115/1500
s: 42.5854
Epoch 1116/1500
s: 43.6070
Epoch 1117/1500
s: 40.5410
Epoch 1118/1500
s: 45.3732
Epoch 1119/1500
s: 41.8527
Epoch 1120/1500
s: 30.8164
Epoch 1121/1500
s: 31.6929
Epoch 1122/1500
s: 36.1832
Epoch 1123/1500
s: 30.1090
Epoch 1124/1500
```

```
s: 33.3451
Epoch 1125/1500
s: 46.8708
Epoch 1126/1500
s: 44.9195
Epoch 1127/1500
s: 31.9432
Epoch 1128/1500
s: 40.8892
Epoch 1129/1500
s: 29.6892
Epoch 1130/1500
s: 34.6996
Epoch 1131/1500
s: 31.0875
Epoch 1132/1500
s: 50.2515
Epoch 1133/1500
s: 29.1675
Epoch 1134/1500
s: 39.2335
Epoch 1135/1500
s: 31.3594
Epoch 1136/1500
s: 35.0565
Epoch 1137/1500
s: 40.3467
Epoch 1138/1500
s: 29.3599
Epoch 1139/1500
s: 39.6856
Epoch 1140/1500
s: 43.8601
Epoch 1141/1500
s: 29.4021
Epoch 1142/1500
s: 30.4151
Epoch 1143/1500
s: 23.8387
Epoch 1144/1500
```

```
Epoch 1145/1500
s: 37.6782
Epoch 1146/1500
s: 33.6138
Epoch 1147/1500
s: 32.0993
Epoch 1148/1500
s: 27.3172
Epoch 1149/1500
s: 25.5015
Epoch 1150/1500
s: 46.8774
Epoch 1151/1500
s: 33.9440
Epoch 1152/1500
s: 28.4055
Epoch 1153/1500
s: 30.2598
Epoch 1154/1500
s: 27.3973
Epoch 1155/1500
s: 30.2590
Epoch 1156/1500
s: 99.9756
Epoch 1157/1500
s: 36.3781
Epoch 1158/1500
s: 27.2735
Epoch 1159/1500
s: 31.4819
Epoch 1160/1500
s: 27.9713
Epoch 1161/1500
s: 50.5280
Epoch 1162/1500
s: 55.3485
Epoch 1163/1500
s: 35.2686
Epoch 1164/1500
s: 42.0739
Epoch 1165/1500
```

```
s: 50.5160
Epoch 1166/1500
s: 38.9824
Epoch 1167/1500
s: 72.5888
Epoch 1168/1500
s: 31.5999
Epoch 1169/1500
s: 38.0888
Epoch 1170/1500
s: 30.0284
Epoch 1171/1500
s: 28.6419
Epoch 1172/1500
s: 37.0229
Epoch 1173/1500
s: 37.8325
Epoch 1174/1500
s: 53.8643
Epoch 1175/1500
s: 25.8945
Epoch 1176/1500
s: 33.5971
Epoch 1177/1500
s: 30.6289
Epoch 1178/1500
s: 46.7903
Epoch 1179/1500
s: 24.6140
Epoch 1180/1500
s: 55.7604
Epoch 1181/1500
s: 31.0644
Epoch 1182/1500
s: 41.4272
Epoch 1183/1500
s: 47.7887
Epoch 1184/1500
s: 52.5216
Epoch 1185/1500
```

```
s: 36.5185
Epoch 1186/1500
s: 34.1333
Epoch 1187/1500
s: 28.2395
Epoch 1188/1500
s: 45.7617
Epoch 1189/1500
s: 36.8734
Epoch 1190/1500
s: 28.8742
Epoch 1191/1500
s: 47.1340
Epoch 1192/1500
s: 27.1851
Epoch 1193/1500
s: 36.3214
Epoch 1194/1500
s: 33.0449
Epoch 1195/1500
s: 31.3011
Epoch 1196/1500
s: 27.1309
Epoch 1197/1500
s: 40.3410
Epoch 1198/1500
s: 25.9719
Epoch 1199/1500
s: 28.6703
Epoch 1200/1500
s: 42.4938
Epoch 1201/1500
s: 34.7886
Epoch 1202/1500
s: 27.4012
Epoch 1203/1500
s: 39.2801
Epoch 1204/1500
s: 25.3141
Epoch 1205/1500
s: 39.1117
```

```
Epoch 1206/1500
s: 39.6505
Epoch 1207/1500
s: 44.9611
Epoch 1208/1500
s: 38.2137
Epoch 1209/1500
s: 26.2604
Epoch 1210/1500
s: 25.6871
Epoch 1211/1500
s: 33.8878
Epoch 1212/1500
s: 25.4491
Epoch 1213/1500
s: 28.3667
Epoch 1214/1500
s: 27.2990
Epoch 1215/1500
s: 35.0599
Epoch 1216/1500
s: 28.6515
Epoch 1217/1500
s: 28.4185
Epoch 1218/1500
s: 33.0166
Epoch 1219/1500
s: 26.3706
Epoch 1220/1500
s: 36.7813
Epoch 1221/1500
s: 41.0783
Epoch 1222/1500
s: 61.4059
Epoch 1223/1500
s: 43.2138
Epoch 1224/1500
s: 57.9660
Epoch 1225/1500
s: 30.9931
Epoch 1226/1500
```

```
s: 47.8955
Epoch 1227/1500
s: 24.5865
Epoch 1228/1500
s: 32.5388
Epoch 1229/1500
s: 34.9064
Epoch 1230/1500
s: 35.2399
Epoch 1231/1500
s: 26.1506
Epoch 1232/1500
s: 28.9129
Epoch 1233/1500
s: 52.7850
Epoch 1234/1500
s: 34.2844
Epoch 1235/1500
s: 33.2182
Epoch 1236/1500
s: 23.6291
Epoch 1237/1500
s: 28.2876
Epoch 1238/1500
s: 29.8252
Epoch 1239/1500
s: 25.1212
Epoch 1240/1500
s: 30.8981
Epoch 1241/1500
s: 58.8118
Epoch 1242/1500
s: 26.9564
Epoch 1243/1500
s: 42.6245
Epoch 1244/1500
s: 25.4228
Epoch 1245/1500
s: 51.1725
Epoch 1246/1500
```

```
s: 39.7566
Epoch 1247/1500
s: 25.6394
Epoch 1248/1500
s: 30.5341
Epoch 1249/1500
s: 36.3342
Epoch 1250/1500
s: 26.8935
Epoch 1251/1500
s: 37.0609
Epoch 1252/1500
s: 25.8240
Epoch 1253/1500
s: 50.4254
Epoch 1254/1500
s: 31.5877
Epoch 1255/1500
s: 36.4431
Epoch 1256/1500
s: 27.5435
Epoch 1257/1500
s: 31.0309
Epoch 1258/1500
s: 43.9657
Epoch 1259/1500
s: 25.9118
Epoch 1260/1500
s: 26.2133
Epoch 1261/1500
s: 30.1354
Epoch 1262/1500
s: 23.1058
Epoch 1263/1500
s: 30.1235
Epoch 1264/1500
s: 66.3341
Epoch 1265/1500
s: 27.8981
Epoch 1266/1500
s: 50.9905
```

```
Epoch 1267/1500
s: 49.2626
Epoch 1268/1500
s: 28.2446
Epoch 1269/1500
s: 24.0475
Epoch 1270/1500
s: 26.4475
Epoch 1271/1500
s: 36.4884
Epoch 1272/1500
s: 32.2686
Epoch 1273/1500
s: 23.6432
Epoch 1274/1500
s: 35.9215
Epoch 1275/1500
s: 25.0428
Epoch 1276/1500
s: 52.5956
Epoch 1277/1500
s: 27.1420
Epoch 1278/1500
s: 28.7893
Epoch 1279/1500
s: 45.4899
Epoch 1280/1500
s: 27.7967
Epoch 1281/1500
s: 32.6936
Epoch 1282/1500
s: 61.8542
Epoch 1283/1500
s: 27.6503
Epoch 1284/1500
s: 29.4813
Epoch 1285/1500
s: 23.4975
Epoch 1286/1500
s: 40.0479
Epoch 1287/1500
```

```
s: 26.5941
Epoch 1288/1500
s: 45.5843
Epoch 1289/1500
s: 33.9990
Epoch 1290/1500
s: 26.9823
Epoch 1291/1500
s: 28.8676
Epoch 1292/1500
s: 44.6732
Epoch 1293/1500
s: 22.3622
Epoch 1294/1500
s: 23.1376
Epoch 1295/1500
s: 40.4292
Epoch 1296/1500
s: 22.6905
Epoch 1297/1500
s: 24.7396
Epoch 1298/1500
s: 52.3560
Epoch 1299/1500
s: 22.7488
Epoch 1300/1500
s: 33.2555
Epoch 1301/1500
s: 35.3320
Epoch 1302/1500
s: 25.1394
Epoch 1303/1500
s: 42.5740
Epoch 1304/1500
s: 32.1403
Epoch 1305/1500
s: 30.8113
Epoch 1306/1500
s: 30.0472
Epoch 1307/1500
```

```
s: 28.1442
Epoch 1308/1500
s: 44.2236
Epoch 1309/1500
s: 22.2466
Epoch 1310/1500
s: 28.0491
Epoch 1311/1500
s: 28.2103
Epoch 1312/1500
s: 23.6985
Epoch 1313/1500
s: 29.2585
Epoch 1314/1500
s: 27.6666
Epoch 1315/1500
s: 78.3179
Epoch 1316/1500
s: 34.0898
Epoch 1317/1500
s: 46.2348
Epoch 1318/1500
s: 66.5638
Epoch 1319/1500
s: 22.6568
Epoch 1320/1500
s: 36.5320
Epoch 1321/1500
s: 30.5972
Epoch 1322/1500
s: 43.0288
Epoch 1323/1500
s: 29.0214
Epoch 1324/1500
s: 65.8721
Epoch 1325/1500
s: 55.9608
Epoch 1326/1500
s: 32.6172
Epoch 1327/1500
s: 36.5456
```

```
Epoch 1328/1500
s: 25.1231
Epoch 1329/1500
s: 24.6838
Epoch 1330/1500
s: 35.0907
Epoch 1331/1500
s: 29.5460
Epoch 1332/1500
s: 30.4866
Epoch 1333/1500
s: 25.4954
Epoch 1334/1500
s: 32.9571
Epoch 1335/1500
s: 33.6957
Epoch 1336/1500
s: 29.9634
Epoch 1337/1500
s: 23.2910
Epoch 1338/1500
s: 49.6469
Epoch 1339/1500
s: 38.3891
Epoch 1340/1500
s: 27.6139
Epoch 1341/1500
s: 28.3782
Epoch 1342/1500
s: 28.4796
Epoch 1343/1500
s: 24.1933
Epoch 1344/1500
s: 25.2110
Epoch 1345/1500
s: 41.7000
Epoch 1346/1500
s: 27.1734
Epoch 1347/1500
s: 35.5417
Epoch 1348/1500
```

```
s: 39.1885
Epoch 1349/1500
s: 33.8644
Epoch 1350/1500
s: 26.5480
Epoch 1351/1500
s: 23.9776
Epoch 1352/1500
s: 38.5912
Epoch 1353/1500
s: 33.3500
Epoch 1354/1500
s: 28.7016
Epoch 1355/1500
s: 38.5283
Epoch 1356/1500
s: 28.5014
Epoch 1357/1500
s: 23.3716
Epoch 1358/1500
s: 24.6575
Epoch 1359/1500
s: 24.4639
Epoch 1360/1500
s: 31.4822
Epoch 1361/1500
s: 48.2807
Epoch 1362/1500
s: 54.8763
Epoch 1363/1500
s: 29.9726
Epoch 1364/1500
s: 32.0910
Epoch 1365/1500
s: 29.1461
Epoch 1366/1500
s: 49.9905
Epoch 1367/1500
s: 34.2042
Epoch 1368/1500
```

```
s: 45.2494
Epoch 1369/1500
s: 34.9299
Epoch 1370/1500
s: 40.7042
Epoch 1371/1500
s: 37.3632
Epoch 1372/1500
s: 35.5125
Epoch 1373/1500
s: 39.1906
Epoch 1374/1500
s: 27.9239
Epoch 1375/1500
s: 23.5697
Epoch 1376/1500
s: 25.5784
Epoch 1377/1500
s: 25.7546
Epoch 1378/1500
s: 28.0763
Epoch 1379/1500
s: 49.8051
Epoch 1380/1500
s: 34.9085
Epoch 1381/1500
s: 35.4654
Epoch 1382/1500
s: 40.1719
Epoch 1383/1500
s: 25.7772
Epoch 1384/1500
s: 38.7856
Epoch 1385/1500
s: 23.0303
Epoch 1386/1500
s: 33.8217
Epoch 1387/1500
s: 39.0498
Epoch 1388/1500
s: 48.7019
```

```
Epoch 1389/1500
s: 32.3197
Epoch 1390/1500
s: 25.5214
Epoch 1391/1500
s: 25.3100
Epoch 1392/1500
s: 74.4420
Epoch 1393/1500
s: 42.9979
Epoch 1394/1500
s: 45.6726
Epoch 1395/1500
s: 28.3642
Epoch 1396/1500
s: 32.5924
Epoch 1397/1500
s: 32.3378
Epoch 1398/1500
s: 23.2800
Epoch 1399/1500
s: 38.1826
Epoch 1400/1500
s: 27.3225
Epoch 1401/1500
s: 28.3923
Epoch 1402/1500
s: 22.8127
Epoch 1403/1500
s: 23.1457
Epoch 1404/1500
s: 36.8044
Epoch 1405/1500
s: 31.8075
Epoch 1406/1500
s: 27.0005
Epoch 1407/1500
s: 39.0864
Epoch 1408/1500
s: 24.0089
Epoch 1409/1500
```

```
s: 26.9658
Epoch 1410/1500
s: 24.7942
Epoch 1411/1500
s: 24.8832
Epoch 1412/1500
s: 29.2752
Epoch 1413/1500
s: 27.3999
Epoch 1414/1500
s: 33.3324
Epoch 1415/1500
s: 23.8700
Epoch 1416/1500
s: 23.9837
Epoch 1417/1500
s: 30.8778
Epoch 1418/1500
s: 26.9533
Epoch 1419/1500
s: 24.4741
Epoch 1420/1500
s: 35.7493
Epoch 1421/1500
s: 51.0428
Epoch 1422/1500
s: 24.4889
Epoch 1423/1500
s: 28.8691
Epoch 1424/1500
s: 24.2327
Epoch 1425/1500
s: 26.3570
Epoch 1426/1500
s: 33.5667
Epoch 1427/1500
s: 22.7790
Epoch 1428/1500
s: 23.6868
Epoch 1429/1500
```

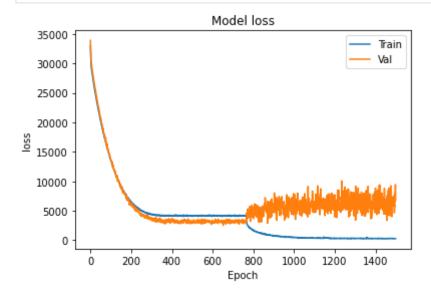
```
s: 29.2730
Epoch 1430/1500
s: 30.0093
Epoch 1431/1500
s: 25.0059
Epoch 1432/1500
s: 24.6502
Epoch 1433/1500
s: 30.0853
Epoch 1434/1500
s: 29.3449
Epoch 1435/1500
s: 34.6411
Epoch 1436/1500
s: 24.4026
Epoch 1437/1500
s: 29.5813
Epoch 1438/1500
s: 26.5354
Epoch 1439/1500
s: 27.1321
Epoch 1440/1500
s: 33.6620
Epoch 1441/1500
s: 28.6381
Epoch 1442/1500
s: 26.3071
Epoch 1443/1500
s: 24.6127
Epoch 1444/1500
s: 25.0941
Epoch 1445/1500
s: 37.5436
Epoch 1446/1500
s: 26.6625
Epoch 1447/1500
s: 27.9438
Epoch 1448/1500
s: 22.9870
Epoch 1449/1500
s: 23.1430
```

```
Epoch 1450/1500
s: 29.1476
Epoch 1451/1500
s: 28.6124
Epoch 1452/1500
s: 26.8868
Epoch 1453/1500
s: 49.5206
Epoch 1454/1500
s: 29.8954
Epoch 1455/1500
s: 34.6645
Epoch 1456/1500
s: 31.0265
Epoch 1457/1500
s: 40.4057
Epoch 1458/1500
s: 26.6073
Epoch 1459/1500
s: 27.7594
Epoch 1460/1500
s: 26.8951
Epoch 1461/1500
s: 28.8376
Epoch 1462/1500
s: 83.7577
Epoch 1463/1500
s: 29.7263
Epoch 1464/1500
s: 25.6072
Epoch 1465/1500
s: 26.8007
Epoch 1466/1500
s: 30.2162
Epoch 1467/1500
s: 25.0581
Epoch 1468/1500
s: 27.0871
Epoch 1469/1500
s: 34.3807
Epoch 1470/1500
```

```
s: 27.6133
Epoch 1471/1500
s: 26.9090
Epoch 1472/1500
s: 31.2138
Epoch 1473/1500
s: 24.7630
Epoch 1474/1500
s: 24.7116
Epoch 1475/1500
s: 30.4697
Epoch 1476/1500
s: 24.5269
Epoch 1477/1500
s: 35.3079
Epoch 1478/1500
s: 23.1550
Epoch 1479/1500
s: 21.7266
Epoch 1480/1500
s: 27.8749
Epoch 1481/1500
s: 23.7468
Epoch 1482/1500
s: 23.4081
Epoch 1483/1500
s: 63.9323
Epoch 1484/1500
s: 22.4398
Epoch 1485/1500
s: 25.8858
Epoch 1486/1500
s: 32.4771
Epoch 1487/1500
s: 28.6520
Epoch 1488/1500
s: 28.6150
Epoch 1489/1500
s: 22.9852
Epoch 1490/1500
```

```
s: 23.7803
     Epoch 1491/1500
     s: 31.8610
     Epoch 1492/1500
     s: 25.3716
     Epoch 1493/1500
     s: 26.7372
     Epoch 1494/1500
                   14/14 [========
     s: 22.6986
     Epoch 1495/1500
     s: 24.8382
     Epoch 1496/1500
     s: 27.4761
     Epoch 1497/1500
     s: 28.1025
     Epoch 1498/1500
     s: 30.3197
     Epoch 1499/1500
     s: 32.3442
     Epoch 1500/1500
     CPU times: user 16min 31s, sys: 33 s, total: 17min 4s
     Wall time: 13min 26s
In [62]:
      print(history.history["loss"][-1])
     189.47265625
In [63]:
      print('Training MSE for Model 1', model.evaluate(X train, y train, verbose=0))
     Training MSE for Model 1 24.01258659362793
In [83]:
     model.predict(X_train) - y_train.values
Out[83]: array([[
            2.95023071, -143.86976929,
                              1.78023071, \ldots, -144.99976929,
           19.62023071, 4.95023071],
         [ 147.15701782,
                    0.33701782, 145.98701782, ..., -0.79298218,
          163.82701782, 149.15701782],
                             3.27254028, ..., -143.50745972,
           4.44254028, -142.37745972,
           21.11254028,
                    6.44254028],
         . . . ,
         [ 143.92276489,
                   -2.89723511, 142.75276489, ..., -4.02723511,
          160.59276489, 145.92276489],
         [-14.04496277, -160.86496277, -15.21496277, ..., -161.99496277,
            2.62503723, -12.04496277],
           0.6628772 , -146.1571228 , -0.5071228 , ..., -147.2871228 ,
           17.3328772 ,
                    2.6628772 ]])
In [64]:
```

```
#save for the best model
    model.save('models/Group3_RNN_model.h5')
In []: loss_plot(history)
```



Comment on Model #1 Training Output

- The training and validation losses start at a high value of approximately 35000
- There is a drastic decrease in the first 200 epochs
- The gap between training and validation loss remains steady until about 800 epochs
- The final training loss achieved is approximately 189

```
In [85]:
          y_test=np.array(y_test)
          y pred = model.predict(X test, verbose = 0)
In [87]:
          y pred[:20]
         array([[130.02972],
Out[87]:
                [147.80804],
                [114.17725],
                [188.1433
                [111.11356],
                [114.54795],
                [116.98694],
                [152.87953],
                [116.82906],
                [160.26447],
                [172.04114],
                [248.34659],
                [176.55379],
                [154.58133],
                [190.42662],
                [285.1028
                [233.29152],
                [333.38208],
```

```
[120.063614],
                 [195.56525 ]], dtype=float32)
In [88]:
          #calculate test loss/mse
          mean_squared_error(y_pred, y_test)
         21.196446387090102
Out[88]:
In [ ]:
          score = model.evaluate(X_test, y_test, verbose=False)
          print('Metric Names', model.metrics names)
          print('Test Score:', score)
In [90]:
          score = model.evaluate(X_train, y_train, verbose=False)
          print('Metric Names', model.metrics_names)
          print('Training Score:', score)
         Metric Names ['loss']
         Training Score: 24.01258659362793
In [99]:
          result_array=pd.DataFrame({'y_test':y_test, 'y_predicted':y_pred.ravel(),'Date':
In [101...
          #result_array = result_array.sort_values(by=['Date'])
          result_array=result_array.reset_index(drop=True, inplace=False)
          result array
Out [101...
               y_test y_predicted
                                       Date
            0 132.85 130.029724 2015-07-21
            1 144.49 147.808044 2017-06-28
            2 116.44
                      114.177254 2015-09-25
               191.81
                      188.143295 2019-06-10
            4
               108.91
                       111.113564 2016-04-08
          372 112.02
                       110.918327 2015-12-17
          373 205.53
                      215.097290 2019-08-02
          374 148.82 149.203873 2017-07-17
          375 273.61
                      281.391571 2020-04-22
          376 284.82 287.908386 2019-12-26
         377 rows × 3 columns
In [103...
          result array['Date'] =pd.to datetime(result array.Date)
In [104...
          result array=result array.sort values(by='Date')
          result array
```

Out[104		y_test	y_predicted	Date
	45	125.72	124.952179	2015-07-15
3	357	127.74	126.632896	2015-07-16
	0	132.85	130.029724	2015-07-21
1	128	125.32	126.351768	2015-07-24
2	241	123.38	124.806816	2015-07-28
	•••			
	49	319.25	326.039917	2020-05-29
	34	344.72	347.023743	2020-06-12
	76	351.46	345.197784	2020-06-16
2	236	365.00	348.616974	2020-06-24
2	232	353.25	348.882324	2020-06-29

377 rows × 3 columns

Comments about y_true/y_pred dataframe

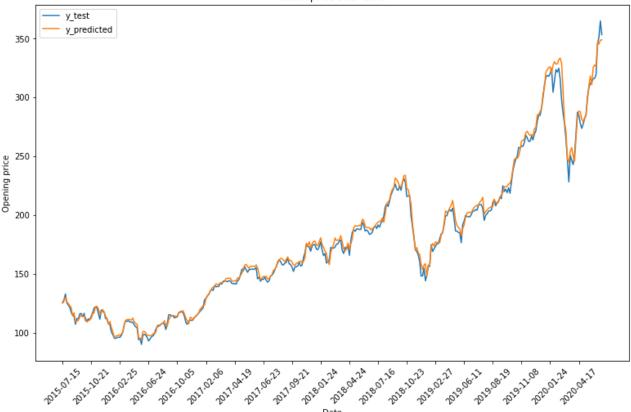
The model has a good output. The predicted values of y and close to the true values. From the 10 values shown above, the largest value of |y_pred - y_true| is 12, although most have a difference of less than 5.

```
In [105...
    result_array=result_array.reset_index(drop=True, inplace=False)

In [106...
    result_array.iloc[0:,0:2].plot.line(figsize=(13,8))
    plt.xticks(np.arange(0, 377, step=20), result_array["Date"].dt.date.iloc[lambda plt.xlabel('Date')
    plt.ylabel('Opening price')
    plt.title('Stock price over time')
Out[106...

Text(0.5, 1.0, 'Stock price over time')
```

Stock price over time



Comments about Stock Price over time plot

The plots of y_test(y_true) and y_pred mostly overlap. The largest gaps in both plots occurs sometime in 2020. This could be due to the Coronavirus pandemic.

Model #2

```
In [108...
          model 1 = tf.keras.models.Sequential([
              # Shape [batch, time, features] => [batch, time, 1stm units]
              tf.keras.layers.GRU(75, return sequences=True, input shape=(12,1)),
              tf.keras.layers.Dropout(0.2),
              tf.keras.layers.GRU(30, return sequences=True),
              tf.keras.layers.Dropout(0.2),
              tf.keras.layers.GRU(30),
              tf.keras.layers.Dropout(0.2),
              # Shape => [batch, time, features]
              tf.keras.layers.Dense(units=1)
          ])
In [109...
          model_1.compile(optimizer='adam', loss='mean_squared_error')
          monitor = EarlyStopping(monitor='val loss', min delta=1e-3, patience=5, verbose=
In [110...
          model 1.summary()
         Model: "sequential 2"
```

```
Output Shape
                                                          Param #
Layer (type)
                                                          17550
gru_3 (GRU)
                               (None, 12, 75)
dropout_6 (Dropout)
                               (None, 12, 75)
gru_4 (GRU)
                               (None, 12, 30)
                                                          9630
dropout_7 (Dropout)
                               (None, 12, 30)
                                                          0
                                                          5580
gru_5 (GRU)
                               (None, 30)
dropout 8 (Dropout)
                               (None, 30)
                                                          0
dense_2 (Dense)
                                                          31
                               (None, 1)
Total params: 32,791
Trainable params: 32,791
Non-trainable params: 0
```

```
In [111...
```

```
%%time
history = model_1.fit(X_train,y_train,validation_split=0.05,epochs=1500,batch_si
```

```
Epoch 1/1500
loss: 33685.1328
Epoch 2/1500
oss: 32045.0938
Epoch 3/1500
oss: 31518.3359
Epoch 4/1500
oss: 31242.7559
Epoch 5/1500
oss: 31045.9004
Epoch 6/1500
oss: 30867.7832
Epoch 7/1500
oss: 30699.9551
Epoch 8/1500
oss: 30536.5566
Epoch 9/1500
oss: 30372.2676
Epoch 10/1500
oss: 30215.9609
Epoch 11/1500
oss: 30061.7578
Epoch 12/1500
oss: 29908.4434
```

```
Epoch 13/1500
oss: 29759.2168
Epoch 14/1500
oss: 29612.5918
Epoch 15/1500
oss: 29466.7422
Epoch 16/1500
oss: 29322.0059
Epoch 17/1500
oss: 29176.6426
Epoch 18/1500
oss: 29032.7930
Epoch 19/1500
oss: 28889.2246
Epoch 20/1500
oss: 28744.5605
Epoch 21/1500
oss: 28603.0059
Epoch 22/1500
oss: 28463.1250
Epoch 23/1500
oss: 28325.1738
Epoch 24/1500
oss: 28187.0059
Epoch 25/1500
oss: 28048.6270
Epoch 26/1500
oss: 27913.5449
Epoch 27/1500
oss: 27778.8105
Epoch 28/1500
oss: 27644.9805
Epoch 29/1500
oss: 27509.2520
Epoch 30/1500
oss: 27373.9980
Epoch 31/1500
oss: 27240.8691
Epoch 32/1500
oss: 27106.6797
Epoch 33/1500
```

```
oss: 26976.4883
Epoch 34/1500
oss: 26845.3750
Epoch 35/1500
oss: 26714.9980
Epoch 36/1500
oss: 26583.9375
Epoch 37/1500
oss: 26454.6758
Epoch 38/1500
oss: 26324.9688
Epoch 39/1500
oss: 26196.6621
Epoch 40/1500
oss: 26071.0859
Epoch 41/1500
oss: 25945.2793
Epoch 42/1500
oss: 25819.2949
Epoch 43/1500
oss: 25694.0176
Epoch 44/1500
oss: 25566.8691
Epoch 45/1500
oss: 25444.5508
Epoch 46/1500
oss: 25321.0879
Epoch 47/1500
oss: 25197.8145
Epoch 48/1500
oss: 25076.1816
Epoch 49/1500
oss: 24956.1016
Epoch 50/1500
oss: 24834.4316
Epoch 51/1500
oss: 24712.7559
Epoch 52/1500
oss: 24592.9805
Epoch 53/1500
```

```
oss: 24469.9668
Epoch 54/1500
oss: 24350.4707
Epoch 55/1500
oss: 24230.3301
Epoch 56/1500
oss: 24111.6680
Epoch 57/1500
oss: 23995.5820
Epoch 58/1500
oss: 23881.7441
Epoch 59/1500
oss: 23765.9375
Epoch 60/1500
oss: 23648.8672
Epoch 61/1500
oss: 23529.6016
Epoch 62/1500
oss: 23411.4492
Epoch 63/1500
oss: 23297.2363
Epoch 64/1500
oss: 23182.4004
Epoch 65/1500
oss: 23068.2930
Epoch 66/1500
oss: 22952.5703
Epoch 67/1500
oss: 22836.0488
Epoch 68/1500
oss: 22722.6797
Epoch 69/1500
oss: 22610.9121
Epoch 70/1500
oss: 22499.9824
Epoch 71/1500
oss: 22390.1289
Epoch 72/1500
oss: 22279.0137
Epoch 73/1500
oss: 22168.5762
```

```
Epoch 74/1500
oss: 22058.1738
Epoch 75/1500
oss: 21948.3145
Epoch 76/1500
oss: 21839.5293
Epoch 77/1500
oss: 21731.7832
Epoch 78/1500
oss: 21621.9805
Epoch 79/1500
oss: 21513.8242
Epoch 80/1500
oss: 21407.0137
Epoch 81/1500
oss: 21299.8145
Epoch 82/1500
oss: 21190.8984
Epoch 83/1500
oss: 21084.0371
Epoch 84/1500
oss: 20978.9941
Epoch 85/1500
oss: 20872.1641
Epoch 86/1500
oss: 20767.6543
Epoch 87/1500
oss: 20664.7891
Epoch 88/1500
oss: 20561.8887
Epoch 89/1500
oss: 20460.0312
Epoch 90/1500
oss: 20358.9395
Epoch 91/1500
oss: 20259.3164
Epoch 92/1500
oss: 20159.3184
Epoch 93/1500
oss: 20055.4512
Epoch 94/1500
```

```
oss: 19956.4922
Epoch 95/1500
oss: 19857.2988
Epoch 96/1500
oss: 19759.1133
Epoch 97/1500
oss: 19658.3535
Epoch 98/1500
oss: 19557.4297
Epoch 99/1500
oss: 19459.4004
Epoch 100/1500
oss: 19363.1699
Epoch 101/1500
oss: 19264.1719
Epoch 102/1500
oss: 19165.4258
Epoch 103/1500
oss: 19068.0859
Epoch 104/1500
oss: 18972.1582
Epoch 105/1500
oss: 18874.8730
Epoch 106/1500
oss: 18780.1875
Epoch 107/1500
oss: 18684.5059
Epoch 108/1500
oss: 18591.6738
Epoch 109/1500
oss: 18496.1113
Epoch 110/1500
oss: 18402.1875
Epoch 111/1500
oss: 18308.6113
Epoch 112/1500
oss: 18212.4199
Epoch 113/1500
oss: 18118.8828
Epoch 114/1500
```

```
oss: 18026.4355
Epoch 115/1500
oss: 17935.8320
Epoch 116/1500
oss: 17844.9238
Epoch 117/1500
oss: 17750.8828
Epoch 118/1500
oss: 17659.3457
Epoch 119/1500
oss: 17569.8926
Epoch 120/1500
oss: 17481.6387
Epoch 121/1500
oss: 17390.0547
Epoch 122/1500
oss: 17299.6797
Epoch 123/1500
oss: 17209.4883
Epoch 124/1500
oss: 17120.5137
Epoch 125/1500
oss: 17032.2676
Epoch 126/1500
oss: 16942.2891
Epoch 127/1500
oss: 16857.0332
Epoch 128/1500
oss: 16771.9551
Epoch 129/1500
oss: 16683.4375
Epoch 130/1500
oss: 16595.4434
Epoch 131/1500
oss: 16509.6016
Epoch 132/1500
oss: 16423.3457
Epoch 133/1500
oss: 16338.0146
Epoch 134/1500
oss: 16251.3271
```

```
Epoch 135/1500
oss: 16167.3008
Epoch 136/1500
oss: 16084.1904
Epoch 137/1500
oss: 16001.7803
Epoch 138/1500
oss: 15918.1465
Epoch 139/1500
oss: 15834.8125
Epoch 140/1500
oss: 15752.8945
Epoch 141/1500
oss: 15670.5039
Epoch 142/1500
oss: 15590.7461
Epoch 143/1500
oss: 15512.1338
Epoch 144/1500
oss: 15432.8008
Epoch 145/1500
oss: 15353.6592
Epoch 146/1500
oss: 15273.8154
Epoch 147/1500
oss: 15191.7383
Epoch 148/1500
oss: 15111.3369
Epoch 149/1500
oss: 15032.1064
Epoch 150/1500
oss: 14952.5156
Epoch 151/1500
oss: 14870.9814
Epoch 152/1500
oss: 14792.2588
Epoch 153/1500
oss: 14715.0840
Epoch 154/1500
oss: 14639.3604
Epoch 155/1500
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oss: 14563.1631
Epoch 156/1500
oss: 14487.9814
Epoch 157/1500
oss: 14412.4189
Epoch 158/1500
oss: 14337.1562
Epoch 159/1500
oss: 14261.1006
Epoch 160/1500
oss: 14184.8135
Epoch 161/1500
oss: 14106.0195
Epoch 162/1500
oss: 14029.7129
Epoch 163/1500
oss: 13954.6807
Epoch 164/1500
oss: 13880.8428
Epoch 165/1500
oss: 13803.0615
Epoch 166/1500
oss: 13731.2100
Epoch 167/1500
oss: 13660.1504
Epoch 168/1500
oss: 13587.7930
Epoch 169/1500
oss: 13514.5352
Epoch 170/1500
oss: 13441.8633
Epoch 171/1500
oss: 13371.0596
Epoch 172/1500
oss: 13298.7646
Epoch 173/1500
oss: 13225.8779
Epoch 174/1500
oss: 13152.6055
Epoch 175/1500
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oss: 13079.2344
Epoch 176/1500
oss: 13006.6836
Epoch 177/1500
oss: 12936.4492
Epoch 178/1500
oss: 12867.4902
Epoch 179/1500
oss: 12795.5752
Epoch 180/1500
oss: 12726.1162
Epoch 181/1500
oss: 12657.0654
Epoch 182/1500
oss: 12588.9375
Epoch 183/1500
oss: 12522.0029
Epoch 184/1500
oss: 12451.0967
Epoch 185/1500
oss: 12384.9033
Epoch 186/1500
oss: 12317.8398
Epoch 187/1500
oss: 12252.3662
Epoch 188/1500
oss: 12187.0811
Epoch 189/1500
oss: 12121.3311
Epoch 190/1500
oss: 12051.8867
Epoch 191/1500
oss: 11985.2568
Epoch 192/1500
oss: 11917.0215
Epoch 193/1500
oss: 11851.2080
Epoch 194/1500
oss: 11785.8711
Epoch 195/1500
oss: 11720.3789
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Epoch 196/1500
14/14 [=============================== ] - 0s 32ms/step - loss: 11614.6709 - val 1
oss: 11656.1162
Epoch 197/1500
oss: 11588.4189
Epoch 198/1500
oss: 11523.7471
Epoch 199/1500
oss: 11461.1260
Epoch 200/1500
oss: 11401.2041
Epoch 201/1500
oss: 11338.3506
Epoch 202/1500
oss: 11276.3213
Epoch 203/1500
oss: 11215.3525
Epoch 204/1500
oss: 11155.8184
Epoch 205/1500
oss: 11095.8975
Epoch 206/1500
oss: 11036.8672
Epoch 207/1500
oss: 10977.2012
Epoch 208/1500
oss: 10919.5195
Epoch 209/1500
oss: 10856.8477
Epoch 210/1500
oss: 10794.2979
Epoch 211/1500
oss: 10735.5635
Epoch 212/1500
oss: 10675.9648
Epoch 213/1500
oss: 10618.0811
Epoch 214/1500
oss: 10558.0322
Epoch 215/1500
oss: 10500.2510
Epoch 216/1500
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oss: 10441.3867
Epoch 217/1500
oss: 10382.8320
Epoch 218/1500
oss: 10324.8115
Epoch 219/1500
oss: 10269.2881
Epoch 220/1500
oss: 10213.9180
Epoch 221/1500
oss: 10158.4814
Epoch 222/1500
oss: 10102.8350
Epoch 223/1500
oss: 10047.0820
Epoch 224/1500
oss: 9991.3477
Epoch 225/1500
oss: 9937.0615
Epoch 226/1500
oss: 9881.0967
Epoch 227/1500
ss: 9826.5342
Epoch 228/1500
ss: 9774.7773
Epoch 229/1500
ss: 9721.1611
Epoch 230/1500
ss: 9668.7773
Epoch 231/1500
ss: 9616.9053
Epoch 232/1500
ss: 9564.4131
Epoch 233/1500
ss: 9510.9873
Epoch 234/1500
ss: 9460.0186
Epoch 235/1500
ss: 9408.7891
Epoch 236/1500
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ss: 9357.1553
Epoch 237/1500
ss: 9305.7646
Epoch 238/1500
ss: 9256.4424
Epoch 239/1500
ss: 9205.9072
Epoch 240/1500
ss: 9155.4883
Epoch 241/1500
ss: 9104.4023
Epoch 242/1500
ss: 9054.2783
Epoch 243/1500
ss: 9003.9941
Epoch 244/1500
ss: 8955.1738
Epoch 245/1500
ss: 8905.9043
Epoch 246/1500
ss: 8857.2637
Epoch 247/1500
ss: 8810.5479
Epoch 248/1500
ss: 8763.4951
Epoch 249/1500
ss: 8716.0938
Epoch 250/1500
ss: 8667.4189
Epoch 251/1500
ss: 8618.4648
Epoch 252/1500
ss: 8569.4844
Epoch 253/1500
ss: 8521.8643
Epoch 254/1500
ss: 8473.2305
Epoch 255/1500
ss: 8421.8770
Epoch 256/1500
ss: 8374.6865
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Epoch 257/1500
ss: 8328.2109
Epoch 258/1500
ss: 8280.8555
Epoch 259/1500
ss: 8233.0713
Epoch 260/1500
ss: 8186.3721
Epoch 261/1500
ss: 8141.9453
Epoch 262/1500
ss: 8098.5527
Epoch 263/1500
ss: 8054.8066
Epoch 264/1500
ss: 8010.3970
Epoch 265/1500
ss: 7968.2891
Epoch 266/1500
ss: 7923.2217
Epoch 267/1500
ss: 7880.3643
Epoch 268/1500
ss: 7838.3545
Epoch 269/1500
ss: 7795.3496
Epoch 270/1500
ss: 7752.2749
Epoch 271/1500
ss: 7711.6641
Epoch 272/1500
ss: 7671.8062
Epoch 273/1500
ss: 7631.0293
Epoch 274/1500
ss: 7586.7808
Epoch 275/1500
ss: 7544.8501
Epoch 276/1500
ss: 7500.8667
Epoch 277/1500
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ss: 7457.4375
Epoch 278/1500
ss: 7415.5854
Epoch 279/1500
ss: 7374.6333
Epoch 280/1500
ss: 7334.9199
Epoch 281/1500
ss: 7295.5435
Epoch 282/1500
ss: 7257.4536
Epoch 283/1500
ss: 7217.9873
Epoch 284/1500
ss: 7180.4985
Epoch 285/1500
14/14 [==============] - 0s 32ms/step - loss: 7440.4746 - val_lo
ss: 7144.1221
Epoch 286/1500
ss: 7105.6699
Epoch 287/1500
ss: 7066.5542
Epoch 288/1500
ss: 7027.7974
Epoch 289/1500
ss: 6987.8262
Epoch 290/1500
ss: 6950.6982
Epoch 291/1500
ss: 6915.2173
Epoch 292/1500
ss: 6878.7812
Epoch 293/1500
ss: 6842.4683
Epoch 294/1500
ss: 6807.2651
Epoch 295/1500
ss: 6770.7998
Epoch 296/1500
ss: 6735.7886
Epoch 297/1500
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ss: 6699.4077
Epoch 298/1500
ss: 6662.6255
Epoch 299/1500
ss: 6628.0156
Epoch 300/1500
ss: 6590.9785
Epoch 301/1500
ss: 6555.1235
Epoch 302/1500
ss: 6521.1392
Epoch 303/1500
ss: 6486.3096
Epoch 304/1500
ss: 6451.0518
Epoch 305/1500
ss: 6418.1831
Epoch 306/1500
ss: 6384.2856
Epoch 307/1500
ss: 6352.2051
Epoch 308/1500
ss: 6318.1230
Epoch 309/1500
ss: 6282.9707
Epoch 310/1500
ss: 6248.9526
Epoch 311/1500
ss: 6217.0469
Epoch 312/1500
ss: 6183.0908
Epoch 313/1500
ss: 6151.8750
Epoch 314/1500
ss: 6120.1499
Epoch 315/1500
ss: 6089.2090
Epoch 316/1500
ss: 6056.3667
Epoch 317/1500
ss: 6026.1675
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Epoch 318/1500
ss: 5994.8418
Epoch 319/1500
ss: 5965.0142
Epoch 320/1500
ss: 5936.1362
Epoch 321/1500
ss: 5905.7559
Epoch 322/1500
ss: 5875.5630
Epoch 323/1500
ss: 5846.1387
Epoch 324/1500
ss: 5814.1875
Epoch 325/1500
ss: 5784.7759
Epoch 326/1500
ss: 5755.0425
Epoch 327/1500
ss: 5726.5298
Epoch 328/1500
ss: 5700.3730
Epoch 329/1500
ss: 5673.5908
Epoch 330/1500
ss: 5646.7676
Epoch 331/1500
ss: 5619.4658
Epoch 332/1500
ss: 5593.1362
Epoch 333/1500
ss: 5565.5176
Epoch 334/1500
ss: 5536.2769
Epoch 335/1500
ss: 5508.1440
Epoch 336/1500
ss: 5481.4053
Epoch 337/1500
ss: 5455.4082
Epoch 338/1500
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ss: 5429.4849
Epoch 339/1500
ss: 5402.2026
Epoch 340/1500
ss: 5377.2949
Epoch 341/1500
ss: 5350.7451
Epoch 342/1500
ss: 5325.3569
Epoch 343/1500
ss: 5298.1987
Epoch 344/1500
ss: 5271.8159
Epoch 345/1500
ss: 5246.7974
Epoch 346/1500
ss: 5222.0630
Epoch 347/1500
ss: 5195.5063
Epoch 348/1500
ss: 5167.6348
Epoch 349/1500
ss: 5142.5942
Epoch 350/1500
ss: 5118.6289
Epoch 351/1500
ss: 5096.3389
Epoch 352/1500
ss: 5072.3921
Epoch 353/1500
ss: 5049.3037
Epoch 354/1500
ss: 5026.6313
Epoch 355/1500
ss: 5004.6411
Epoch 356/1500
ss: 4983.4336
Epoch 357/1500
ss: 4960.5112
Epoch 358/1500
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ss: 4937.6851
Epoch 359/1500
ss: 4913.5366
Epoch 360/1500
ss: 4890.7720
Epoch 361/1500
ss: 4868.4165
Epoch 362/1500
ss: 4846.4888
Epoch 363/1500
ss: 4825.6636
Epoch 364/1500
ss: 4803.5410
Epoch 365/1500
ss: 4782.9438
Epoch 366/1500
ss: 4762.8062
Epoch 367/1500
ss: 4742.4590
Epoch 368/1500
ss: 4721.2222
Epoch 369/1500
ss: 4699.4458
Epoch 370/1500
ss: 4676.9697
Epoch 371/1500
ss: 4657.5444
Epoch 372/1500
ss: 4637.3145
Epoch 373/1500
ss: 4617.8481
Epoch 374/1500
ss: 4598.8340
Epoch 375/1500
ss: 4580.6797
Epoch 376/1500
ss: 4561.0767
Epoch 377/1500
ss: 4542.2505
Epoch 378/1500
ss: 4523.1787
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Epoch 379/1500
ss: 4504.0054
Epoch 380/1500
ss: 4486.8340
Epoch 381/1500
ss: 4468.8135
Epoch 382/1500
ss: 4448.7417
Epoch 383/1500
ss: 4431.1426
Epoch 384/1500
ss: 4413.0425
Epoch 385/1500
ss: 4394.2085
Epoch 386/1500
ss: 4375.6450
Epoch 387/1500
ss: 4355.3833
Epoch 388/1500
ss: 4337.8901
Epoch 389/1500
ss: 4323.1968
Epoch 390/1500
ss: 4304.9590
Epoch 391/1500
ss: 4286.0952
Epoch 392/1500
ss: 4268.7295
Epoch 393/1500
ss: 4252.6113
Epoch 394/1500
ss: 4236.5137
Epoch 395/1500
ss: 4220.8574
Epoch 396/1500
ss: 4205.6177
Epoch 397/1500
ss: 4190.5791
Epoch 398/1500
ss: 4175.3364
Epoch 399/1500
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ss: 4161.1309
Epoch 400/1500
ss: 4145.9985
Epoch 401/1500
ss: 4127.9639
Epoch 402/1500
ss: 4114.6812
Epoch 403/1500
ss: 4100.1235
Epoch 404/1500
ss: 4084.9475
Epoch 405/1500
ss: 4070.2576
Epoch 406/1500
ss: 4052.5237
Epoch 407/1500
ss: 4038.7922
Epoch 408/1500
ss: 4025.4065
Epoch 409/1500
ss: 4011.4258
Epoch 410/1500
ss: 3996.9326
Epoch 411/1500
ss: 3981.3318
Epoch 412/1500
ss: 3966.4937
Epoch 413/1500
ss: 3953.7354
Epoch 414/1500
14/14 [===============] - 0s 32ms/step - loss: 4851.3564 - val_lo
ss: 3941.2734
Epoch 415/1500
ss: 3928.5632
Epoch 416/1500
ss: 3915.9619
Epoch 417/1500
ss: 3903.8679
Epoch 418/1500
ss: 3891.2351
Epoch 419/1500
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ss: 3879.7073
Epoch 420/1500
ss: 3864.3826
Epoch 421/1500
ss: 3852.6912
Epoch 422/1500
ss: 3841.1836
Epoch 423/1500
ss: 3829.8674
Epoch 424/1500
ss: 3819.9495
Epoch 425/1500
ss: 3807.8962
Epoch 426/1500
ss: 3796.0015
Epoch 427/1500
ss: 3785.1165
Epoch 428/1500
ss: 3772.4111
Epoch 429/1500
ss: 3760.7024
Epoch 430/1500
ss: 3748.7329
Epoch 431/1500
ss: 3736.8445
Epoch 432/1500
ss: 3725.3486
Epoch 433/1500
ss: 3714.8057
Epoch 434/1500
ss: 3704.8103
Epoch 435/1500
ss: 3695.4421
Epoch 436/1500
ss: 3685.8835
Epoch 437/1500
ss: 3678.1096
Epoch 438/1500
ss: 3668.9392
Epoch 439/1500
ss: 3658.5935
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Epoch 440/1500
ss: 3651.0444
Epoch 441/1500
ss: 3642.4709
Epoch 442/1500
ss: 3632.3010
Epoch 443/1500
ss: 3622.8459
Epoch 444/1500
ss: 3613.8884
Epoch 445/1500
ss: 3605.5710
Epoch 446/1500
ss: 3597.0227
Epoch 447/1500
ss: 3587.5237
Epoch 448/1500
ss: 3579.0610
Epoch 449/1500
ss: 3571.3999
Epoch 450/1500
ss: 3563.5359
Epoch 451/1500
ss: 3553.4258
Epoch 452/1500
ss: 3543.4924
Epoch 453/1500
ss: 3536.4216
Epoch 454/1500
ss: 3529.5913
Epoch 455/1500
ss: 3520.5920
Epoch 456/1500
ss: 3512.9294
Epoch 457/1500
ss: 3506.3596
Epoch 458/1500
ss: 3499.7507
Epoch 459/1500
ss: 3492.4556
Epoch 460/1500
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ss: 3485.9414
Epoch 461/1500
ss: 3479.0205
Epoch 462/1500
ss: 3470.0662
Epoch 463/1500
ss: 3462.2642
Epoch 464/1500
ss: 3453.6538
Epoch 465/1500
ss: 3446.4507
Epoch 466/1500
ss: 3440.3342
Epoch 467/1500
ss: 3433.2322
Epoch 468/1500
14/14 [=============] - Os 35ms/step - loss: 4415.9399 - val_lo
ss: 3423.6924
Epoch 469/1500
ss: 3415.6365
Epoch 470/1500
ss: 3408.5149
Epoch 471/1500
ss: 3403.3931
Epoch 472/1500
ss: 3397.6799
Epoch 473/1500
ss: 3392.3069
Epoch 474/1500
14/14 [=============================] - 0s 33ms/step - loss: 4406.2715 - val lo
ss: 3386.0820
Epoch 475/1500
ss: 3379.2803
Epoch 476/1500
ss: 3372.9104
Epoch 477/1500
ss: 3367.0649
Epoch 478/1500
ss: 3360.4783
Epoch 479/1500
ss: 3355.3477
Epoch 480/1500
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ss: 3349.4958
Epoch 481/1500
ss: 3344.9517
Epoch 482/1500
ss: 3339.6782
Epoch 483/1500
ss: 3334.7815
Epoch 484/1500
ss: 3328.8945
Epoch 485/1500
ss: 3324.2202
Epoch 486/1500
ss: 3319.4600
Epoch 487/1500
ss: 3315.5439
Epoch 488/1500
ss: 3309.9268
Epoch 489/1500
ss: 3304.8022
Epoch 490/1500
ss: 3299.8376
Epoch 491/1500
ss: 3294.6443
Epoch 492/1500
ss: 3289.8811
Epoch 493/1500
ss: 3287.2195
Epoch 494/1500
ss: 3283.8960
Epoch 495/1500
ss: 3280.1787
Epoch 496/1500
ss: 3276.2039
Epoch 497/1500
ss: 3271.9607
Epoch 498/1500
ss: 3269.2542
Epoch 499/1500
ss: 3264.3337
Epoch 500/1500
ss: 3260.3850
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Epoch 501/1500
ss: 3257.1460
Epoch 502/1500
ss: 3252.9900
Epoch 503/1500
ss: 3249.6040
Epoch 504/1500
ss: 3246.3479
Epoch 505/1500
ss: 3242.6631
Epoch 506/1500
ss: 3238.5276
Epoch 507/1500
ss: 3233.0049
Epoch 508/1500
ss: 3229.8752
Epoch 509/1500
ss: 3226.5283
Epoch 510/1500
ss: 3224.7053
Epoch 511/1500
ss: 3222.2627
Epoch 512/1500
ss: 3218.8999
Epoch 513/1500
ss: 3214.8337
Epoch 514/1500
ss: 3210.7268
Epoch 515/1500
ss: 3205.2849
Epoch 516/1500
ss: 3201.6194
Epoch 517/1500
ss: 3198.7014
Epoch 518/1500
ss: 3195.2727
Epoch 519/1500
ss: 3191.7141
Epoch 520/1500
ss: 3188.6150
Epoch 521/1500
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ss: 3185.6321
Epoch 522/1500
ss: 3183.3279
Epoch 523/1500
ss: 3181.6633
Epoch 524/1500
ss: 3179.2227
Epoch 525/1500
ss: 3177.3005
Epoch 526/1500
ss: 3175.4080
Epoch 527/1500
ss: 3173.7190
Epoch 528/1500
ss: 3171.6501
Epoch 529/1500
ss: 3168.9456
Epoch 530/1500
ss: 3165.9424
Epoch 531/1500
ss: 3164.2148
Epoch 532/1500
ss: 3161.2905
Epoch 533/1500
ss: 3158.1814
Epoch 534/1500
ss: 3155.9600
Epoch 535/1500
ss: 3152.8899
Epoch 536/1500
14/14 [==============================] - 0s 34ms/step - loss: 4230.7261 - val_lo
ss: 3149.6951
Epoch 537/1500
ss: 3148.4392
Epoch 538/1500
ss: 3145.9358
Epoch 539/1500
ss: 3143.9460
Epoch 540/1500
ss: 3142.4485
Epoch 541/1500
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ss: 3140.6045
Epoch 542/1500
ss: 3138.4658
Epoch 543/1500
ss: 3136.7659
Epoch 544/1500
ss: 3133.9485
Epoch 545/1500
ss: 3132.5588
Epoch 546/1500
ss: 3131.1157
Epoch 547/1500
ss: 3128.9312
Epoch 548/1500
ss: 3126.3274
Epoch 549/1500
ss: 3124.6931
Epoch 550/1500
ss: 3122.2166
Epoch 551/1500
ss: 3119.6611
Epoch 552/1500
ss: 3118.4412
Epoch 553/1500
ss: 3118.0146
Epoch 554/1500
ss: 3116.6182
Epoch 555/1500
ss: 3115.4177
Epoch 556/1500
ss: 3114.5967
Epoch 557/1500
ss: 3112.6704
Epoch 558/1500
ss: 3109.5266
Epoch 559/1500
ss: 3105.3914
Epoch 560/1500
ss: 3103.6421
Epoch 561/1500
ss: 3102.1877
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Epoch 562/1500
ss: 3101.5693
Epoch 563/1500
ss: 3100.4468
Epoch 564/1500
ss: 3099.8240
Epoch 565/1500
ss: 3098.5427
Epoch 566/1500
ss: 3095.7576
Epoch 567/1500
ss: 3094.4517
Epoch 568/1500
ss: 3092.4084
Epoch 569/1500
ss: 3091.8054
Epoch 570/1500
ss: 3090.7148
Epoch 571/1500
ss: 3089.8369
Epoch 572/1500
ss: 3087.7788
Epoch 573/1500
ss: 3086.6548
Epoch 574/1500
ss: 3085.0330
Epoch 575/1500
ss: 3084.1787
Epoch 576/1500
ss: 3083.3435
Epoch 577/1500
ss: 3082.2297
Epoch 578/1500
ss: 3081.9104
Epoch 579/1500
ss: 3081.1460
Epoch 580/1500
ss: 3080.4084
Epoch 581/1500
ss: 3080.8281
Epoch 582/1500
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ss: 3080.3298
Epoch 583/1500
ss: 3077.6797
Epoch 584/1500
ss: 3076.4092
Epoch 585/1500
ss: 3076.5181
Epoch 586/1500
ss: 3073.7983
Epoch 587/1500
ss: 3070.9507
Epoch 588/1500
ss: 3069.3538
Epoch 589/1500
ss: 3068.9578
Epoch 590/1500
ss: 3068.0530
Epoch 591/1500
ss: 3068.1326
Epoch 592/1500
ss: 3067.9524
Epoch 593/1500
ss: 3066.6350
Epoch 594/1500
ss: 3066.3188
Epoch 595/1500
ss: 3065.9194
Epoch 596/1500
ss: 3064.4915
Epoch 597/1500
ss: 3064.0530
Epoch 598/1500
ss: 3064.7444
Epoch 599/1500
ss: 3064.5750
Epoch 600/1500
ss: 3063.8977
Epoch 601/1500
ss: 3063.4944
Epoch 602/1500
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ss: 3062.9443
Epoch 603/1500
ss: 3061.9509
Epoch 604/1500
ss: 3061.1592
Epoch 605/1500
ss: 3061.1235
Epoch 606/1500
ss: 3059.2322
Epoch 607/1500
ss: 3058.0557
Epoch 608/1500
ss: 3058.3962
Epoch 609/1500
ss: 3058.5640
Epoch 610/1500
ss: 3058.5740
Epoch 611/1500
ss: 3057.2649
Epoch 612/1500
ss: 3057.0923
Epoch 613/1500
ss: 3056.5095
Epoch 614/1500
ss: 3057.0266
Epoch 615/1500
ss: 3056.6741
Epoch 616/1500
ss: 3057.5393
Epoch 617/1500
ss: 3056.6001
Epoch 618/1500
ss: 3056.2217
Epoch 619/1500
ss: 3055.8430
Epoch 620/1500
ss: 3054.7869
Epoch 621/1500
ss: 3054.5393
Epoch 622/1500
ss: 3053.8474
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Epoch 623/1500
ss: 3053.2664
Epoch 624/1500
ss: 3052.2256
Epoch 625/1500
ss: 3051.2109
Epoch 626/1500
ss: 3051.6030
Epoch 627/1500
14/14 [=============] - Os 35ms/step - loss: 4138.7456 - val_lo
ss: 3051.7366
Epoch 628/1500
ss: 3052.0022
Epoch 629/1500
ss: 3052.6663
Epoch 630/1500
ss: 3052.1814
Epoch 631/1500
ss: 3052.6140
Epoch 632/1500
ss: 3050.2615
Epoch 633/1500
ss: 3049.9470
Epoch 634/1500
ss: 3049.3408
Epoch 635/1500
ss: 3049.9670
Epoch 636/1500
ss: 3051.2080
Epoch 637/1500
ss: 3050.9773
Epoch 638/1500
ss: 3049.9456
Epoch 639/1500
ss: 3050.1196
Epoch 640/1500
ss: 3051.2471
Epoch 641/1500
ss: 3050.3962
Epoch 642/1500
ss: 3050.2061
Epoch 643/1500
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ss: 3050.3469
Epoch 644/1500
ss: 3050.8630
Epoch 645/1500
ss: 3049.4460
Epoch 646/1500
ss: 3048.7773
Epoch 647/1500
ss: 3048.0459
Epoch 648/1500
ss: 3048.8157
Epoch 649/1500
ss: 3050.2227
Epoch 650/1500
ss: 3050.4033
Epoch 651/1500
ss: 3051.6538
Epoch 652/1500
ss: 3051.7712
Epoch 653/1500
ss: 3051.2725
Epoch 654/1500
ss: 3049.6553
Epoch 655/1500
ss: 3047.9155
Epoch 656/1500
ss: 3047.9587
Epoch 657/1500
ss: 3048.5881
Epoch 658/1500
ss: 3048.6150
Epoch 659/1500
ss: 3048.0842
Epoch 660/1500
ss: 3047.9377
Epoch 661/1500
ss: 3048.4539
Epoch 662/1500
ss: 3047.7556
Epoch 663/1500
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ss: 3047.0476
Epoch 664/1500
ss: 3047.3032
Epoch 665/1500
ss: 3046.4985
Epoch 666/1500
ss: 3046.0376
Epoch 667/1500
ss: 3045.7932
Epoch 668/1500
ss: 3046.7600
Epoch 669/1500
ss: 3047.3647
Epoch 670/1500
ss: 3048.2642
Epoch 671/1500
ss: 3048.5979
Epoch 672/1500
ss: 3047.8718
Epoch 673/1500
ss: 3048.5461
Epoch 674/1500
ss: 3048.1780
Epoch 675/1500
ss: 3048.1912
Epoch 676/1500
ss: 3049.3298
Epoch 677/1500
ss: 3049.0198
Epoch 678/1500
ss: 3048.0056
Epoch 679/1500
ss: 3046.6218
Epoch 680/1500
ss: 3045.4124
Epoch 681/1500
ss: 3044.9517
Epoch 682/1500
ss: 3044.0618
Epoch 683/1500
ss: 3044.1780
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Epoch 684/1500
ss: 3044.1272
Epoch 685/1500
ss: 3043.1038
Epoch 686/1500
ss: 3041.5664
Epoch 687/1500
ss: 3042.2827
Epoch 688/1500
ss: 3041.3735
Epoch 689/1500
ss: 3041.4893
Epoch 690/1500
ss: 3041.8992
Epoch 691/1500
ss: 3042.1765
Epoch 692/1500
ss: 3042.4829
Epoch 693/1500
ss: 3043.0103
Epoch 694/1500
ss: 3042.9163
Epoch 695/1500
ss: 3041.9900
Epoch 696/1500
ss: 3040.8625
Epoch 697/1500
ss: 3041.0928
Epoch 698/1500
ss: 3041.8975
Epoch 699/1500
ss: 3042.0967
Epoch 700/1500
ss: 3040.9382
Epoch 701/1500
ss: 3039.5884
Epoch 702/1500
ss: 3038.5447
Epoch 703/1500
ss: 3039.0156
Epoch 704/1500
```

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ss: 3039.1189
Epoch 705/1500
ss: 3040.3572
Epoch 706/1500
ss: 3040.7788
Epoch 707/1500
ss: 3040.0742
Epoch 708/1500
ss: 3040.1882
Epoch 709/1500
ss: 3040.9353
Epoch 710/1500
ss: 3041.2322
Epoch 711/1500
ss: 3041.7671
Epoch 712/1500
ss: 3041.9893
Epoch 713/1500
ss: 3042.3557
Epoch 714/1500
ss: 3042.2146
Epoch 715/1500
ss: 3042.8313
Epoch 716/1500
ss: 3041.8118
Epoch 717/1500
ss: 3042.4412
Epoch 718/1500
ss: 3041.4658
Epoch 719/1500
14/14 [===============] - 0s 33ms/step - loss: 4113.8228 - val_lo
ss: 3040.4189
Epoch 720/1500
ss: 3040.5046
Epoch 721/1500
ss: 3038.8389
Epoch 722/1500
ss: 3038.9124
Epoch 723/1500
ss: 3039.2698
Epoch 724/1500
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ss: 3038.7681
Epoch 725/1500
ss: 3038.2561
Epoch 726/1500
ss: 3038.6890
Epoch 727/1500
ss: 3038.5432
Epoch 728/1500
ss: 3039.2041
Epoch 729/1500
ss: 3040.1914
Epoch 730/1500
ss: 3041.6538
Epoch 731/1500
ss: 3039.9338
Epoch 732/1500
ss: 3038.9883
Epoch 733/1500
ss: 3038.2483
Epoch 734/1500
ss: 3038.7437
Epoch 735/1500
ss: 3038.9236
Epoch 736/1500
ss: 3038.7407
Epoch 737/1500
ss: 3037.5798
Epoch 738/1500
ss: 3037.6838
Epoch 739/1500
ss: 3037.4023
Epoch 740/1500
ss: 3037.0759
Epoch 741/1500
ss: 3038.2209
Epoch 742/1500
ss: 3037.2283
Epoch 743/1500
ss: 3035.9080
Epoch 744/1500
ss: 3036.4382
```

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Epoch 745/1500
ss: 3036.0315
Epoch 746/1500
ss: 3036.0195
Epoch 747/1500
ss: 3035.6956
Epoch 748/1500
ss: 3035.5986
Epoch 749/1500
14/14 [==============] - Os 34ms/step - loss: 4374.8184 - val_lo
ss: 3036.5732
Epoch 750/1500
ss: 3036.5959
Epoch 751/1500
ss: 3035.6865
Epoch 752/1500
ss: 3033.9922
Epoch 753/1500
ss: 3033.5039
Epoch 754/1500
ss: 3033.4578
Epoch 755/1500
ss: 3031.8142
Epoch 756/1500
ss: 3031.3831
Epoch 757/1500
ss: 3032.0054
Epoch 758/1500
ss: 3032.3970
Epoch 759/1500
ss: 3033.8618
Epoch 760/1500
ss: 3033.5803
Epoch 761/1500
ss: 3033.6616
Epoch 762/1500
ss: 3034.1689
Epoch 763/1500
ss: 3035.5422
Epoch 764/1500
ss: 3035.7607
Epoch 765/1500
```

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ss: 3036.2119
Epoch 766/1500
ss: 3036.8420
Epoch 767/1500
ss: 3037.2205
Epoch 768/1500
ss: 3036.6196
Epoch 769/1500
ss: 3035.9016
Epoch 770/1500
ss: 3035.2439
Epoch 771/1500
ss: 3035.0510
Epoch 772/1500
ss: 3036.5171
Epoch 773/1500
ss: 3034.9978
Epoch 774/1500
ss: 3034.2656
Epoch 775/1500
ss: 3034.4390
Epoch 776/1500
ss: 3033.1638
Epoch 777/1500
ss: 3032.8225
Epoch 778/1500
ss: 3032.2563
Epoch 779/1500
ss: 3031.0447
Epoch 780/1500
ss: 3029.4109
Epoch 781/1500
ss: 3029.0237
Epoch 782/1500
ss: 3029.4924
Epoch 783/1500
ss: 3029.6140
Epoch 784/1500
ss: 3029.9312
Epoch 785/1500
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ss: 3030.0420
Epoch 786/1500
ss: 3028.6116
Epoch 787/1500
ss: 3028.5781
Epoch 788/1500
ss: 3028.7219
Epoch 789/1500
ss: 3029.2649
Epoch 790/1500
ss: 3029.2705
Epoch 791/1500
ss: 3029.7092
Epoch 792/1500
ss: 3029.6951
Epoch 793/1500
ss: 3029.3101
Epoch 794/1500
ss: 3028.1929
Epoch 795/1500
ss: 3027.4648
Epoch 796/1500
ss: 3027.7100
Epoch 797/1500
ss: 3028.8892
Epoch 798/1500
ss: 3030.3245
Epoch 799/1500
ss: 3031.5337
Epoch 800/1500
ss: 3033.1560
Epoch 801/1500
ss: 3031.4624
Epoch 802/1500
ss: 3031.3040
Epoch 803/1500
ss: 3031.3796
Epoch 804/1500
ss: 3032.7585
Epoch 805/1500
ss: 3034.7939
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Epoch 806/1500
ss: 3035.6318
Epoch 807/1500
ss: 3036.8608
Epoch 808/1500
ss: 3037.6370
Epoch 809/1500
ss: 3039.5361
Epoch 810/1500
ss: 3039.7983
Epoch 811/1500
ss: 3040.2031
Epoch 812/1500
ss: 3041.0234
Epoch 813/1500
ss: 3038.7600
Epoch 814/1500
ss: 3038.7009
Epoch 815/1500
ss: 3039.0046
Epoch 816/1500
ss: 3038.1423
Epoch 817/1500
ss: 3038.7412
Epoch 818/1500
ss: 3040.2737
Epoch 819/1500
ss: 3039.7952
Epoch 820/1500
ss: 3040.7297
Epoch 821/1500
ss: 3039.7463
Epoch 822/1500
ss: 3039.4663
Epoch 823/1500
ss: 3038.5959
Epoch 824/1500
ss: 3037.9993
Epoch 825/1500
ss: 3036.8203
Epoch 826/1500
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ss: 3037.1814
Epoch 827/1500
ss: 3035.7429
Epoch 828/1500
ss: 3034.9702
Epoch 829/1500
ss: 3035.1345
Epoch 830/1500
ss: 3035.7615
Epoch 831/1500
ss: 3037.0789
Epoch 832/1500
ss: 3036.2581
Epoch 833/1500
ss: 3037.0393
Epoch 834/1500
ss: 3037.2983
Epoch 835/1500
ss: 3036.4673
Epoch 836/1500
ss: 3036.6062
Epoch 837/1500
ss: 3036.6570
Epoch 838/1500
ss: 3036.2952
Epoch 839/1500
ss: 3035.7256
Epoch 840/1500
ss: 3034.8188
Epoch 841/1500
14/14 [=============================] - 1s 36ms/step - loss: 4273.3472 - val_lo
ss: 3035.4404
Epoch 842/1500
ss: 3036.2432
Epoch 843/1500
ss: 3037.1448
Epoch 844/1500
ss: 3038.4922
Epoch 845/1500
ss: 3039.1978
Epoch 846/1500
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ss: 3038.5388
Epoch 847/1500
ss: 3039.3892
Epoch 848/1500
ss: 3039.9790
Epoch 849/1500
ss: 3040.0742
Epoch 850/1500
ss: 3039.3704
Epoch 851/1500
ss: 3039.4375
Epoch 852/1500
ss: 3038.8303
Epoch 853/1500
ss: 3038.8967
Epoch 854/1500
ss: 3038.1016
Epoch 855/1500
ss: 3037.6384
Epoch 856/1500
ss: 3038.3352
Epoch 857/1500
ss: 3038.7385
Epoch 858/1500
ss: 3038.9993
Epoch 859/1500
ss: 3037.8271
Epoch 860/1500
ss: 3037.4592
Epoch 861/1500
ss: 3038.5076
Epoch 862/1500
ss: 3037.9390
Epoch 863/1500
ss: 3038.3008
Epoch 864/1500
ss: 3038.0007
Epoch 865/1500
ss: 3038.3240
Epoch 866/1500
ss: 3038.2915
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Epoch 867/1500
ss: 3036.7463
Epoch 868/1500
ss: 3036.6560
Epoch 869/1500
ss: 3037.3772
Epoch 870/1500
ss: 3038.4729
Epoch 871/1500
14/14 [=============] - Os 35ms/step - loss: 4322.4043 - val_lo
ss: 3039.1143
Epoch 872/1500
ss: 3037.7983
Epoch 873/1500
ss: 3038.4880
Epoch 874/1500
ss: 3038.3843
Epoch 875/1500
ss: 3038.4297
Epoch 876/1500
ss: 3037.2976
Epoch 877/1500
ss: 3037.6877
Epoch 878/1500
ss: 3038.5627
Epoch 879/1500
ss: 3036.6594
Epoch 880/1500
ss: 3036.0237
Epoch 881/1500
ss: 3034.8447
Epoch 882/1500
ss: 3034.4268
Epoch 883/1500
ss: 3034.4150
Epoch 884/1500
ss: 3034.3018
Epoch 885/1500
ss: 3035.1208
Epoch 886/1500
ss: 3036.1604
Epoch 887/1500
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ss: 3037.6201
Epoch 888/1500
ss: 3038.3289
Epoch 889/1500
ss: 3038.0298
Epoch 890/1500
ss: 3039.1147
Epoch 891/1500
ss: 3040.5234
Epoch 892/1500
ss: 3041.0547
Epoch 893/1500
ss: 3042.2361
Epoch 894/1500
ss: 3042.3962
Epoch 895/1500
ss: 3042.7046
Epoch 896/1500
ss: 3043.9468
Epoch 897/1500
ss: 3043.7476
Epoch 898/1500
ss: 3043.5510
Epoch 899/1500
ss: 3044.0142
Epoch 900/1500
ss: 3042.9404
Epoch 901/1500
ss: 3043.0505
Epoch 902/1500
ss: 3042.2732
Epoch 903/1500
ss: 3043.6248
Epoch 904/1500
ss: 3043.4944
Epoch 905/1500
ss: 3044.3811
Epoch 906/1500
ss: 3043.6423
Epoch 907/1500
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ss: 3041.9163
Epoch 908/1500
ss: 3042.3687
Epoch 909/1500
ss: 3043.7727
Epoch 910/1500
ss: 3043.3267
Epoch 911/1500
ss: 3043.5732
Epoch 912/1500
ss: 3042.7593
Epoch 913/1500
ss: 3043.5647
Epoch 914/1500
ss: 3044.7649
Epoch 915/1500
ss: 3045.3025
Epoch 916/1500
ss: 3045.3062
Epoch 917/1500
ss: 3044.1057
Epoch 918/1500
ss: 3045.4485
Epoch 919/1500
ss: 3045.6572
Epoch 920/1500
ss: 3044.8005
Epoch 921/1500
ss: 3043.8921
Epoch 922/1500
ss: 3043.0859
Epoch 923/1500
ss: 3041.4233
Epoch 924/1500
ss: 3040.4333
Epoch 925/1500
ss: 3040.4624
Epoch 926/1500
ss: 3041.3640
Epoch 927/1500
ss: 3040.0330
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Epoch 928/1500
ss: 3038.6670
Epoch 929/1500
ss: 3038.0376
Epoch 930/1500
ss: 3037.8232
Epoch 931/1500
ss: 3038.3174
Epoch 932/1500
14/14 [=============] - 1s 36ms/step - loss: 4280.4731 - val_lo
ss: 3038.2881
Epoch 933/1500
ss: 3038.4170
Epoch 934/1500
ss: 3036.9978
Epoch 935/1500
ss: 3037.9578
Epoch 936/1500
ss: 3038.2297
Epoch 937/1500
ss: 3037.2695
Epoch 938/1500
ss: 3036.9475
Epoch 939/1500
ss: 3034.9858
Epoch 940/1500
ss: 3033.2034
Epoch 941/1500
ss: 3030.9031
Epoch 942/1500
ss: 3030.4053
Epoch 943/1500
ss: 3030.4978
Epoch 944/1500
ss: 3031.7607
Epoch 945/1500
ss: 3031.3337
Epoch 946/1500
ss: 3028.9294
Epoch 947/1500
ss: 3027.4023
Epoch 948/1500
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ss: 3027.1960
Epoch 949/1500
ss: 3027.4758
Epoch 950/1500
ss: 3027.2419
Epoch 951/1500
ss: 3027.1780
Epoch 952/1500
ss: 3027.3689
Epoch 953/1500
ss: 3026.8828
Epoch 954/1500
ss: 3027.2380
Epoch 955/1500
ss: 3027.0486
Epoch 956/1500
ss: 3026.9351
Epoch 957/1500
ss: 3026.0078
Epoch 958/1500
ss: 3026.4685
Epoch 959/1500
ss: 3025.9631
Epoch 960/1500
ss: 3025.5625
Epoch 961/1500
ss: 3025.8459
Epoch 962/1500
ss: 3091.7288
Epoch 963/1500
ss: 3233.7727
Epoch 964/1500
ss: 2230.6233
Epoch 965/1500
ss: 2152.4900
Epoch 966/1500
ss: 2117.9177
Epoch 967/1500
ss: 2112.5999
Epoch 968/1500
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ss: 2093.9863
Epoch 969/1500
ss: 2080.8994
Epoch 970/1500
ss: 2105.2432
Epoch 971/1500
ss: 1978.4790
Epoch 972/1500
ss: 1983.8906
Epoch 973/1500
ss: 1938.7427
Epoch 974/1500
ss: 1916.0978
Epoch 975/1500
ss: 1891.6050
Epoch 976/1500
ss: 1887.0311
Epoch 977/1500
ss: 1853.3419
Epoch 978/1500
ss: 1830.9336
Epoch 979/1500
ss: 1817.7645
Epoch 980/1500
ss: 1789.1375
Epoch 981/1500
ss: 1768.2234
Epoch 982/1500
ss: 1749.5112
Epoch 983/1500
ss: 1756.7841
Epoch 984/1500
ss: 1725.2036
Epoch 985/1500
ss: 1701.6251
Epoch 986/1500
ss: 1699.4609
Epoch 987/1500
ss: 1669.8237
Epoch 988/1500
ss: 1665.0664
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Epoch 989/1500
ss: 1639.3226
Epoch 990/1500
ss: 1632.0714
Epoch 991/1500
ss: 1610.1851
Epoch 992/1500
ss: 1601.9871
Epoch 993/1500
ss: 1594.9379
Epoch 994/1500
ss: 1586.6997
Epoch 995/1500
ss: 1557.2626
Epoch 996/1500
ss: 1548.6360
Epoch 997/1500
ss: 1538.8032
Epoch 998/1500
ss: 1519.8524
Epoch 999/1500
ss: 1503.8610
Epoch 1000/1500
ss: 1499.7472
Epoch 1001/1500
ss: 1486.3102
Epoch 1002/1500
ss: 1469.3654
Epoch 1003/1500
ss: 1479.5255
Epoch 1004/1500
ss: 1453.4402
Epoch 1005/1500
ss: 1435.0743
Epoch 1006/1500
ss: 1428.6718
Epoch 1007/1500
ss: 1416.1571
Epoch 1008/1500
ss: 1398.4231
Epoch 1009/1500
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ss: 1391.7535
Epoch 1010/1500
ss: 1377.0504
Epoch 1011/1500
ss: 1370.5713
Epoch 1012/1500
ss: 1360.3842
Epoch 1013/1500
ss: 1346.5542
Epoch 1014/1500
ss: 1338.6002
Epoch 1015/1500
ss: 1326.5923
Epoch 1016/1500
ss: 1311.7269
Epoch 1017/1500
ss: 1313.7069
Epoch 1018/1500
ss: 1296.3243
Epoch 1019/1500
ss: 1286.0851
Epoch 1020/1500
ss: 1287.4515
Epoch 1021/1500
ss: 1266.4523
Epoch 1022/1500
ss: 1251.7673
Epoch 1023/1500
ss: 1246.6250
Epoch 1024/1500
ss: 1234.1503
Epoch 1025/1500
ss: 1229.8724
Epoch 1026/1500
ss: 1217.1390
Epoch 1027/1500
ss: 1204.0132
Epoch 1028/1500
ss: 1196.9414
Epoch 1029/1500
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ss: 1190.3501
Epoch 1030/1500
ss: 1190.0977
Epoch 1031/1500
ss: 1169.2589
Epoch 1032/1500
ss: 1164.6984
Epoch 1033/1500
ss: 1159.6335
Epoch 1034/1500
ss: 1150.5140
Epoch 1035/1500
ss: 1138.0110
Epoch 1036/1500
ss: 1125.7684
Epoch 1037/1500
ss: 1117.4469
Epoch 1038/1500
ss: 1117.9545
Epoch 1039/1500
ss: 1102.9489
Epoch 1040/1500
ss: 1111.9922
Epoch 1041/1500
ss: 1088.1731
Epoch 1042/1500
ss: 1079.3564
Epoch 1043/1500
ss: 1075.2645
Epoch 1044/1500
ss: 1067.9302
Epoch 1045/1500
ss: 1056.4487
Epoch 1046/1500
ss: 1044.8070
Epoch 1047/1500
ss: 1054.9058
Epoch 1048/1500
ss: 1032.9847
Epoch 1049/1500
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Epoch 1050/1500
ss: 1016.9228
Epoch 1051/1500
ss: 1030.5187
Epoch 1052/1500
ss: 1026.8845
Epoch 1053/1500
ss: 1006.7726
Epoch 1054/1500
ss: 992.6892
Epoch 1055/1500
ss: 986.5500
Epoch 1056/1500
ss: 978.0893
Epoch 1057/1500
ss: 968.5293
Epoch 1058/1500
ss: 967.4910
Epoch 1059/1500
ss: 956.5000
Epoch 1060/1500
ss: 948.2391
Epoch 1061/1500
ss: 942.9205
Epoch 1062/1500
ss: 945.8121
Epoch 1063/1500
ss: 944.7252
Epoch 1064/1500
ss: 920.8134
Epoch 1065/1500
ss: 915.9766
Epoch 1066/1500
ss: 913.3220
Epoch 1067/1500
ss: 908.4851
Epoch 1068/1500
ss: 899.4842
Epoch 1069/1500
ss: 907.8570
Epoch 1070/1500
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ss: 888.1163
Epoch 1071/1500
ss: 885.2924
Epoch 1072/1500
ss: 875.8871
Epoch 1073/1500
ss: 902.8253
Epoch 1074/1500
ss: 884.4658
Epoch 1075/1500
ss: 856.8017
Epoch 1076/1500
ss: 860.8760
Epoch 1077/1500
ss: 851.9700
Epoch 1078/1500
ss: 856.0649
Epoch 1079/1500
ss: 833.7961
Epoch 1080/1500
ss: 828.9690
Epoch 1081/1500
ss: 823.1113
Epoch 1082/1500
ss: 813.5153
Epoch 1083/1500
ss: 808.2320
Epoch 1084/1500
ss: 806.4432
Epoch 1085/1500
ss: 795.7019
Epoch 1086/1500
ss: 802.3862
Epoch 1087/1500
ss: 789.7150
Epoch 1088/1500
ss: 781.1454
Epoch 1089/1500
ss: 778.6865
Epoch 1090/1500
```

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ss: 775.1373
Epoch 1091/1500
ss: 808.6949
Epoch 1092/1500
ss: 776.3711
Epoch 1093/1500
ss: 778.5518
Epoch 1094/1500
ss: 746.9926
Epoch 1095/1500
ss: 738.4994
Epoch 1096/1500
ss: 739.2676
Epoch 1097/1500
ss: 733.2304
Epoch 1098/1500
ss: 729.2133
Epoch 1099/1500
ss: 720.2366
Epoch 1100/1500
ss: 716.2720
Epoch 1101/1500
ss: 708.5924
Epoch 1102/1500
ss: 705.3914
Epoch 1103/1500
ss: 709.7602
Epoch 1104/1500
ss: 696.8222
Epoch 1105/1500
ss: 699.5782
Epoch 1106/1500
ss: 684.5785
Epoch 1107/1500
ss: 681.4637
Epoch 1108/1500
ss: 676.1191
Epoch 1109/1500
ss: 673.5215
Epoch 1110/1500
ss: 664.3990
```

```
Epoch 1111/1500
ss: 658.7143
Epoch 1112/1500
ss: 659.9025
Epoch 1113/1500
ss: 672.8853
Epoch 1114/1500
ss: 646.4379
Epoch 1115/1500
ss: 647.2205
Epoch 1116/1500
ss: 634.2656
Epoch 1117/1500
ss: 649.0309
Epoch 1118/1500
ss: 647.9315
Epoch 1119/1500
ss: 620.0162
Epoch 1120/1500
ss: 635.2924
Epoch 1121/1500
ss: 620.4293
Epoch 1122/1500
ss: 616.6785
Epoch 1123/1500
ss: 602.6583
Epoch 1124/1500
ss: 597.5057
Epoch 1125/1500
ss: 596.8086
Epoch 1126/1500
ss: 591.8699
Epoch 1127/1500
ss: 594.3398
Epoch 1128/1500
ss: 575.7723
Epoch 1129/1500
14/14 [============== ] - 1s 36ms/step - loss: 1084.9889 - val lo
ss: 572.5671
Epoch 1130/1500
ss: 568.0294
Epoch 1131/1500
```

```
s: 565.0829
Epoch 1132/1500
ss: 557.8310
Epoch 1133/1500
ss: 559.3495
Epoch 1134/1500
ss: 556.7634
Epoch 1135/1500
s: 545.9226
Epoch 1136/1500
s: 545.9244
Epoch 1137/1500
ss: 541.2759
Epoch 1138/1500
ss: 549.4729
Epoch 1139/1500
s: 540.3704
Epoch 1140/1500
ss: 544.4746
Epoch 1141/1500
ss: 526.7607
Epoch 1142/1500
s: 517.4389
Epoch 1143/1500
s: 512.8114
Epoch 1144/1500
s: 521.7548
Epoch 1145/1500
s: 507.8279
Epoch 1146/1500
ss: 529.1803
Epoch 1147/1500
s: 504.1935
Epoch 1148/1500
s: 495.0721
Epoch 1149/1500
ss: 496.8777
Epoch 1150/1500
s: 499.5720
Epoch 1151/1500
```

```
s: 495.6735
Epoch 1152/1500
s: 489.9189
Epoch 1153/1500
s: 485.7437
Epoch 1154/1500
s: 496.4899
Epoch 1155/1500
s: 470.2473
Epoch 1156/1500
s: 467.3199
Epoch 1157/1500
s: 480.7240
Epoch 1158/1500
s: 515.8094
Epoch 1159/1500
s: 458.6089
Epoch 1160/1500
s: 455.8466
Epoch 1161/1500
s: 466.6306
Epoch 1162/1500
s: 475.7117
Epoch 1163/1500
s: 455.9998
Epoch 1164/1500
s: 437.5216
Epoch 1165/1500
s: 431.8158
Epoch 1166/1500
s: 432.4665
Epoch 1167/1500
s: 430.8361
Epoch 1168/1500
s: 422.7309
Epoch 1169/1500
s: 417.3174
Epoch 1170/1500
s: 415.4178
Epoch 1171/1500
s: 428.6257
```

```
Epoch 1172/1500
s: 408.9656
Epoch 1173/1500
s: 408.5845
Epoch 1174/1500
s: 406.8925
Epoch 1175/1500
s: 401.0486
Epoch 1176/1500
s: 399.0193
Epoch 1177/1500
s: 422.9339
Epoch 1178/1500
s: 394.5107
Epoch 1179/1500
s: 389.3272
Epoch 1180/1500
s: 395.0829
Epoch 1181/1500
s: 394.8844
Epoch 1182/1500
s: 391.7783
Epoch 1183/1500
s: 378.1314
Epoch 1184/1500
s: 371.4276
Epoch 1185/1500
s: 372.7520
Epoch 1186/1500
s: 366.6919
Epoch 1187/1500
s: 364.4539
Epoch 1188/1500
s: 362.4190
Epoch 1189/1500
s: 360.8999
Epoch 1190/1500
s: 355.0496
Epoch 1191/1500
s: 364.7861
Epoch 1192/1500
```

```
s: 348.4870
Epoch 1193/1500
s: 345.6607
Epoch 1194/1500
s: 345.5298
Epoch 1195/1500
s: 365.3965
Epoch 1196/1500
s: 348.2456
Epoch 1197/1500
s: 343.1253
Epoch 1198/1500
s: 338.2461
Epoch 1199/1500
s: 334.6542
Epoch 1200/1500
s: 327.8579
Epoch 1201/1500
s: 333.6102
Epoch 1202/1500
s: 332.4110
Epoch 1203/1500
s: 367.2807
Epoch 1204/1500
s: 329.8121
Epoch 1205/1500
s: 324.5834
Epoch 1206/1500
s: 317.8781
Epoch 1207/1500
s: 314.6546
Epoch 1208/1500
s: 311.7462
Epoch 1209/1500
s: 302.2094
Epoch 1210/1500
s: 302.7838
Epoch 1211/1500
s: 310.7887
Epoch 1212/1500
```

```
s: 298.1274
Epoch 1213/1500
s: 293.3153
Epoch 1214/1500
s: 296.9133
Epoch 1215/1500
s: 291.3700
Epoch 1216/1500
s: 285.9859
Epoch 1217/1500
s: 285.0818
Epoch 1218/1500
s: 301.8879
Epoch 1219/1500
s: 278.5745
Epoch 1220/1500
s: 275.5186
Epoch 1221/1500
s: 276.0561
Epoch 1222/1500
s: 271.4576
Epoch 1223/1500
s: 277.2399
Epoch 1224/1500
s: 272.8282
Epoch 1225/1500
s: 265.5157
Epoch 1226/1500
s: 263.4052
Epoch 1227/1500
s: 259.7696
Epoch 1228/1500
s: 259.9866
Epoch 1229/1500
s: 256.7520
Epoch 1230/1500
s: 257.6064
Epoch 1231/1500
s: 258.8557
Epoch 1232/1500
s: 262.8686
```

```
Epoch 1233/1500
s: 249.2136
Epoch 1234/1500
s: 268.3040
Epoch 1235/1500
s: 246.2803
Epoch 1236/1500
s: 248.6685
Epoch 1237/1500
s: 240.5149
Epoch 1238/1500
s: 246.8789
Epoch 1239/1500
s: 253.0725
Epoch 1240/1500
s: 232.4924
Epoch 1241/1500
s: 229.8377
Epoch 1242/1500
s: 227.1881
Epoch 1243/1500
s: 231.4645
Epoch 1244/1500
s: 236.4638
Epoch 1245/1500
s: 223.3297
Epoch 1246/1500
s: 222.1382
Epoch 1247/1500
s: 220.9313
Epoch 1248/1500
s: 225.6677
Epoch 1249/1500
s: 222.3365
Epoch 1250/1500
s: 212.7742
Epoch 1251/1500
s: 221.2507
Epoch 1252/1500
s: 209.9566
Epoch 1253/1500
```

```
s: 204.7749
Epoch 1254/1500
s: 209.0800
Epoch 1255/1500
s: 206.5594
Epoch 1256/1500
s: 200.3004
Epoch 1257/1500
s: 202.4302
Epoch 1258/1500
s: 199.4209
Epoch 1259/1500
s: 194.9560
Epoch 1260/1500
s: 195.7630
Epoch 1261/1500
s: 197.8580
Epoch 1262/1500
s: 193.1758
Epoch 1263/1500
s: 189.1923
Epoch 1264/1500
s: 190.5748
Epoch 1265/1500
s: 190.7015
Epoch 1266/1500
s: 239.6139
Epoch 1267/1500
s: 199.3525
Epoch 1268/1500
s: 195.8590
Epoch 1269/1500
s: 181.9615
Epoch 1270/1500
s: 183.7272
Epoch 1271/1500
s: 177.6272
Epoch 1272/1500
s: 178.4134
Epoch 1273/1500
```

```
s: 177.7191
Epoch 1274/1500
s: 180.4194
Epoch 1275/1500
s: 179.8624
Epoch 1276/1500
s: 174.1776
Epoch 1277/1500
s: 168.6041
Epoch 1278/1500
s: 169.2173
Epoch 1279/1500
s: 180.2611
Epoch 1280/1500
s: 168.2285
Epoch 1281/1500
s: 171.5020
Epoch 1282/1500
s: 168.1962
Epoch 1283/1500
s: 162.5408
Epoch 1284/1500
s: 164.4157
Epoch 1285/1500
s: 170.8651
Epoch 1286/1500
s: 161.2558
Epoch 1287/1500
s: 186.6631
Epoch 1288/1500
s: 154.6430
Epoch 1289/1500
s: 153.6561
Epoch 1290/1500
s: 149.2359
Epoch 1291/1500
s: 153.4867
Epoch 1292/1500
s: 168.9110
Epoch 1293/1500
s: 154.0860
```

```
Epoch 1294/1500
s: 151.4125
Epoch 1295/1500
s: 146.2298
Epoch 1296/1500
s: 156.0872
Epoch 1297/1500
s: 148.6859
Epoch 1298/1500
s: 153.1374
Epoch 1299/1500
s: 139.0395
Epoch 1300/1500
s: 149.8158
Epoch 1301/1500
s: 148.7510
Epoch 1302/1500
s: 151.4075
Epoch 1303/1500
s: 143.8952
Epoch 1304/1500
s: 144.1650
Epoch 1305/1500
s: 141.5716
Epoch 1306/1500
s: 152.7219
Epoch 1307/1500
s: 151.2641
Epoch 1308/1500
s: 136.5009
Epoch 1309/1500
s: 130.4005
Epoch 1310/1500
s: 130.4575
Epoch 1311/1500
s: 126.7459
Epoch 1312/1500
s: 125.1481
Epoch 1313/1500
s: 122.4525
Epoch 1314/1500
```

```
s: 128.5121
Epoch 1315/1500
s: 127.2599
Epoch 1316/1500
s: 124.2781
Epoch 1317/1500
s: 126.1387
Epoch 1318/1500
s: 136.3971
Epoch 1319/1500
s: 119.4764
Epoch 1320/1500
s: 142.2932
Epoch 1321/1500
s: 136.8399
Epoch 1322/1500
s: 115.1019
Epoch 1323/1500
s: 117.7725
Epoch 1324/1500
s: 118.5414
Epoch 1325/1500
s: 118.1922
Epoch 1326/1500
s: 113.6737
Epoch 1327/1500
s: 140.5488
Epoch 1328/1500
s: 117.9853
Epoch 1329/1500
s: 109.7916
Epoch 1330/1500
s: 109.4039
Epoch 1331/1500
s: 116.1843
Epoch 1332/1500
s: 109.5121
Epoch 1333/1500
s: 109.8980
Epoch 1334/1500
```

```
s: 105.2440
Epoch 1335/1500
s: 108.4959
Epoch 1336/1500
s: 113.6896
Epoch 1337/1500
s: 102.9054
Epoch 1338/1500
s: 107.1145
Epoch 1339/1500
s: 103.2172
Epoch 1340/1500
s: 108.5967
Epoch 1341/1500
s: 106.9916
Epoch 1342/1500
s: 101.4912
Epoch 1343/1500
s: 102.5585
Epoch 1344/1500
s: 97.3372
Epoch 1345/1500
s: 115.4193
Epoch 1346/1500
s: 116.9601
Epoch 1347/1500
s: 111.6746
Epoch 1348/1500
s: 99.7268
Epoch 1349/1500
s: 97.0292
Epoch 1350/1500
s: 121.7337
Epoch 1351/1500
s: 97.5877
Epoch 1352/1500
s: 96.1950
Epoch 1353/1500
s: 98.2812
Epoch 1354/1500
```

```
Epoch 1355/1500
s: 94.5193
Epoch 1356/1500
s: 91.1687
Epoch 1357/1500
s: 107.0425
Epoch 1358/1500
s: 92.6798
Epoch 1359/1500
s: 101.5800
Epoch 1360/1500
s: 85.4939
Epoch 1361/1500
s: 85.6952
Epoch 1362/1500
s: 92.2434
Epoch 1363/1500
s: 93.9043
Epoch 1364/1500
s: 83.3065
Epoch 1365/1500
s: 89.9824
Epoch 1366/1500
s: 91.3891
Epoch 1367/1500
s: 85.3969
Epoch 1368/1500
s: 80.4525
Epoch 1369/1500
s: 86.8338
Epoch 1370/1500
s: 81.9796
Epoch 1371/1500
s: 96.8661
Epoch 1372/1500
s: 91.3101
Epoch 1373/1500
s: 91.7900
Epoch 1374/1500
s: 82.9151
Epoch 1375/1500
```

```
s: 82.8345
Epoch 1376/1500
s: 81.3700
Epoch 1377/1500
s: 83.9264
Epoch 1378/1500
s: 88.7955
Epoch 1379/1500
s: 107.3474
Epoch 1380/1500
s: 92.5676
Epoch 1381/1500
s: 77.0926
Epoch 1382/1500
s: 74.6810
Epoch 1383/1500
s: 72.9168
Epoch 1384/1500
s: 73.8850
Epoch 1385/1500
s: 77.2140
Epoch 1386/1500
s: 75.5666
Epoch 1387/1500
s: 70.9032
Epoch 1388/1500
s: 70.5891
Epoch 1389/1500
s: 86.2522
Epoch 1390/1500
s: 70.6082
Epoch 1391/1500
s: 69.4227
Epoch 1392/1500
s: 77.1910
Epoch 1393/1500
s: 69.5723
Epoch 1394/1500
s: 71.8898
Epoch 1395/1500
```

```
s: 78.1914
Epoch 1396/1500
s: 79.0259
Epoch 1397/1500
s: 76.1638
Epoch 1398/1500
s: 67.9361
Epoch 1399/1500
s: 80.9666
Epoch 1400/1500
s: 69.4389
Epoch 1401/1500
s: 66.3944
Epoch 1402/1500
s: 64.5228
Epoch 1403/1500
s: 70.0648
Epoch 1404/1500
s: 63.4741
Epoch 1405/1500
s: 76.3989
Epoch 1406/1500
s: 63.6570
Epoch 1407/1500
s: 84.2048
Epoch 1408/1500
s: 78.8748
Epoch 1409/1500
s: 61.4077
Epoch 1410/1500
s: 63.3928
Epoch 1411/1500
s: 65.2034
Epoch 1412/1500
s: 60.6782
Epoch 1413/1500
s: 62.4335
Epoch 1414/1500
s: 62.4646
Epoch 1415/1500
s: 76.4091
```

```
Epoch 1416/1500
s: 77.1472
Epoch 1417/1500
s: 59.9414
Epoch 1418/1500
s: 66.4592
Epoch 1419/1500
s: 96.0496
Epoch 1420/1500
s: 66.1801
Epoch 1421/1500
s: 59.0907
Epoch 1422/1500
s: 64.6895
Epoch 1423/1500
s: 60.0972
Epoch 1424/1500
s: 61.8637
Epoch 1425/1500
s: 60.9471
Epoch 1426/1500
s: 77.1100
Epoch 1427/1500
s: 67.9126
Epoch 1428/1500
s: 54.4698
Epoch 1429/1500
s: 57.8486
Epoch 1430/1500
s: 60.1262
Epoch 1431/1500
s: 57.6197
Epoch 1432/1500
s: 57.1986
Epoch 1433/1500
s: 58.0763
Epoch 1434/1500
s: 63.9089
Epoch 1435/1500
s: 62.1043
Epoch 1436/1500
```

```
s: 52.5244
Epoch 1437/1500
s: 59.5267
Epoch 1438/1500
s: 54.7459
Epoch 1439/1500
s: 66.3858
Epoch 1440/1500
s: 66.5075
Epoch 1441/1500
s: 54.0060
Epoch 1442/1500
s: 59.3700
Epoch 1443/1500
s: 53.5623
Epoch 1444/1500
s: 68.8143
Epoch 1445/1500
s: 60.3433
Epoch 1446/1500
s: 70.6709
Epoch 1447/1500
s: 54.5617
Epoch 1448/1500
s: 55.2018
Epoch 1449/1500
s: 70.1111
Epoch 1450/1500
s: 51.5231
Epoch 1451/1500
s: 71.9393
Epoch 1452/1500
s: 51.0176
Epoch 1453/1500
s: 46.5316
Epoch 1454/1500
s: 52.9948
Epoch 1455/1500
s: 48.6402
Epoch 1456/1500
```

```
s: 57.5132
Epoch 1457/1500
s: 54.1785
Epoch 1458/1500
s: 48.2553
Epoch 1459/1500
s: 59.8318
Epoch 1460/1500
s: 55.1109
Epoch 1461/1500
s: 52.1949
Epoch 1462/1500
s: 55.8307
Epoch 1463/1500
s: 46.5542
Epoch 1464/1500
s: 49.1246
Epoch 1465/1500
s: 51.4001
Epoch 1466/1500
s: 62.1001
Epoch 1467/1500
s: 51.7986
Epoch 1468/1500
s: 49.2498
Epoch 1469/1500
s: 54.6237
Epoch 1470/1500
s: 43.9362
Epoch 1471/1500
s: 61.4662
Epoch 1472/1500
s: 43.8233
Epoch 1473/1500
s: 51.1491
Epoch 1474/1500
s: 59.2971
Epoch 1475/1500
s: 63.4007
Epoch 1476/1500
s: 42.8293
```

```
Epoch 1477/1500
s: 44.8174
Epoch 1478/1500
s: 44.8349
Epoch 1479/1500
s: 51.6113
Epoch 1480/1500
s: 53.6510
Epoch 1481/1500
s: 46.5286
Epoch 1482/1500
s: 70.7335
Epoch 1483/1500
s: 47.5913
Epoch 1484/1500
s: 55.4387
Epoch 1485/1500
s: 41.7606
Epoch 1486/1500
s: 47.4596
Epoch 1487/1500
s: 49.4629
Epoch 1488/1500
s: 40.5839
Epoch 1489/1500
s: 54.0362
Epoch 1490/1500
s: 51.5501
Epoch 1491/1500
s: 41.1830
Epoch 1492/1500
s: 38.9969
Epoch 1493/1500
s: 64.8349
Epoch 1494/1500
s: 37.4590
Epoch 1495/1500
s: 50.5216
Epoch 1496/1500
s: 46.1722
Epoch 1497/1500
```

```
======== | - 1s 36ms/step - loss: 383.2633 - val los
        s: 38.9415
        Epoch 1498/1500
        s: 36.0181
        Epoch 1499/1500
        14/14 [======
                             s: 44.9635
        Epoch 1500/1500
        14/14 [======
                              ======= ] - 1s 40ms/step - loss: 292.2680 - val los
        s: 42.8146
        CPU times: user 15min 23s, sys: 37.4 s, total: 16min
        Wall time: 12min 26s
In [112...
         print(history.history["loss"][-1])
        292.26800537109375
In [113...
        print('training MSE', model_1.evaluate(X_train, y_train, verbose=0))
        training MSE 89.08911895751953
In [114...
        print(history.history.keys())
        dict_keys(['loss', 'val_loss'])
In [115...
         loss plot(history)
                             Model loss
          35000
                                                Train
                                                Val
          30000
          25000
          20000
         15000
          10000
          5000
            0
                   200
                                              1400
               0
                        400
                             600
                                 800
                                     1000
                                          1200
                               Epoch
```

Comment on Model #2 Training Output

- The training and validation losses start at a high value of approximately 35000
- There is a drastic decrease in the first 200 epochs
- The training and validation losses continue to decrease
- The final training loss achieved is approximately 292

```
In [116...
           y_test=np.array(y_test)
```

```
y pred = model 1.predict(X test, verbose=0)
In [117...
          y_pred[:20]
Out[117... array([[125.660934],
                [144.5896],
                [110.064964],
                [184.48605],
                [107.21594],
                 [113.757805],
                [112.20062],
                 [149.78496],
                [111.87024],
                [156.93988],
                 [168.75972],
                [245.05467],
                [173.32153],
                [151.28717],
                [186.90234],
                [283.3356],
                [228.92291],
                 [302.5869],
                [116.39398],
                 [191.75362 ]], dtype=float32)
In [118...
          #calculate test loss/mse
          mean squared error(y pred, y test)
         52.513931808736615
Out[118...
In [119...
          score = model 1.evaluate(X test, y test, verbose=False)
          print('Metric Names', model_1.metrics_names)
          print('Test Score for Model 2:', score)
         Metric Names ['loss']
         Test Score for Model 2: 52.5139274597168
In [120...
          score = model 1.evaluate(X train, y train, verbose=False)
          print('Metric Names', model 1.metrics names)
          print('Training Score for Model 2:', score)
         Metric Names ['loss']
         Training Score for Model 2: 89.08911895751953
In [121...
          result_array=pd.DataFrame({'y_test':y_test, 'y_predicted':y_pred.ravel(),'Date':
 In [ ]:
          result array=result array.reset index(drop=True, inplace=False)
          result array
In [124...
          result array['Date'] =pd.to datetime(result array.Date)
In [125...
          result array=result array.sort values(by='Date')
```

result_array

Out[125		y_test	y_predicted	Date
	45	125.72	120.705017	2015-07-15
	357	127.74	122.633720	2015-07-16
	0	132.85	125.660934	2015-07-21
	128	125.32	123.803505	2015-07-24
	241	123.38	120.971870	2015-07-28
	•••	•••		
	49	319.25	302.511902	2020-05-29
	34	344.72	302.652496	2020-06-12
	76	351.46	302.647675	2020-06-16
	236	365.00	302.658325	2020-06-24
	232	353.25	302.659149	2020-06-29

377 rows × 3 columns

Comments about y_true/y_pred dataframe

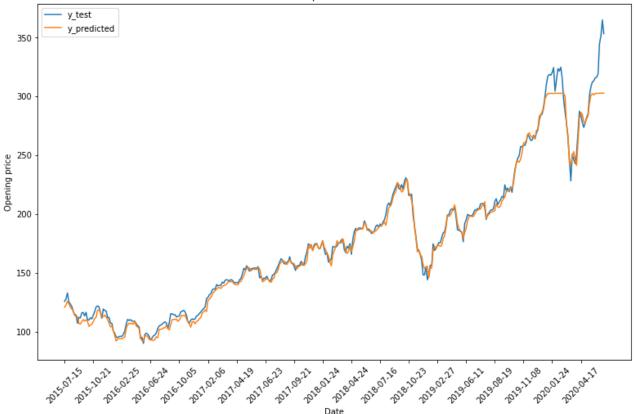
The model has a fairly good output, though not as good as Model #1. The predicted values of y are close to the true values. From the 10 values shown above, there are much larger values of |y_pred - y_true| than model #1. Some datapoints have a difference of over 40.

```
In [126...
    result_array=result_array.reset_index(drop=True, inplace=False)

In [127...
    result_array.iloc[0:,0:2].plot.line(figsize=(13,8))
    plt.xticks(np.arange(0, 377, step=20), result_array["Date"].dt.date.iloc[lambda plt.xlabel('Date')
    plt.ylabel('Opening price')
    plt.title('Stock price over time')

Out[127...
    Text(0.5, 1.0, 'Stock price over time')
```

Stock price over time



Comments about Stock Price over time plot

The plots of y_test(y_true) and y_pred mostly overlap. There is significant variation in the plots in 2019 and 2020. The plot for Model #1 seems to be more accurate.

Final Network Architecture

Model #1 is chosen because it has a better performance.

MODEL 1

LSTM LAYER 1 - 50 units --> Dropout 0.2 --> LSTM LAYER 2 - 50 units --> Dropout 0.2 --> LSTM LAYER 3 - 50 units --> Dropout 0.2 --> Dense Layer - 1 unit

This model uses three LSTM layers. 20 % of the nodes at each layer are unused to avoid overfitting and improve model performance.

Optimizer - Adam

Loss Metric - Mean Squared Error

Activation Function in Dense layer - Linear

Batch Size - 64

Number of Epochs - 1500

The model utilises Early Stopping in order to converge faster and avoid overfitting.

Effect of Adding More Features

After increasing the features to 40 i.e (using data from the latest 10 days) we observed the following:

- The model trained for a longer time with the same number of epochs.
- The model performance was significantly improved. The training loss was approximately 15 using Model #1 as compared to 189 using Model #1 with 12 Features
- The final plot of predicted values against true values in the test set are almost identical.
- External Resources suggest that the prices and volumes are not the best features for stock prediction. Return value is suggested to be a better input.

References

1 "LSTM Optimizer Choice ?" https://deepdatascience.wordpress.com/2016/11/18/which-lstm-optimizer-to-use/

In []:		