# CS 4780/5780 Final Project:

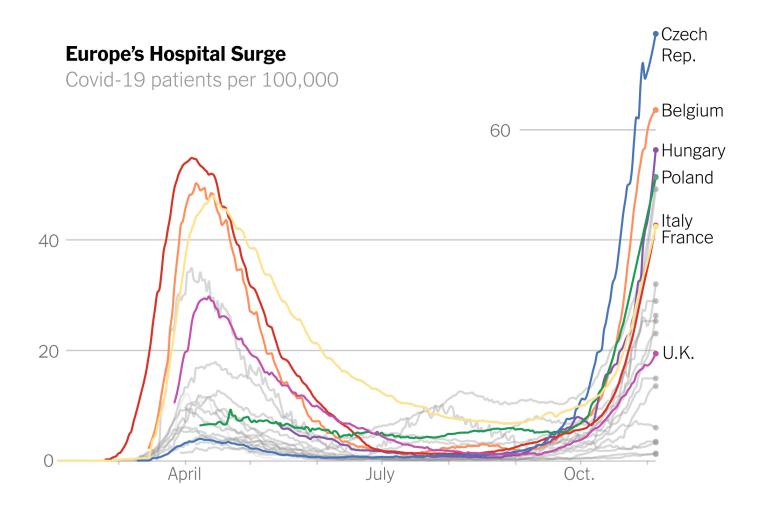
### **COVID-19 Hospitalizations Prediction for EU Countries**

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#### Introduction:

The final project is about conducting a real-world machine learning project on your own, with everything that is involved. Unlike in the programming projects 1-5, where we gave you all the scaffolding and you just filled in the blanks, you now start from scratch. The programming project provide templates for how to do this, and the most recent video lectures summarize some of the tricks you will need (e.g. feature normalization, feature construction). So, this final project brings realism to how you will use machine learning in the real world.

The task you will work on is predicting hospitalizations due to COVID-19. Although hospitalizations are directly related to COVID-19 cases, the different populations, timelines and reactionary measures of different EU countries result in different trends in hospitalization numbers. In this project you will bring the power of machine learning to make predictions for the country-level hospitalizations using COVID-19 age group case data and also previous hospitalization data. There will be two tasks, one will be a basic problem that will require you to use methods learned in class. The second task will be more difficult and will require some additional intuition and insight. Please read the project description PDF file carefully and follow the instructions there. Also make sure you write your code and answers to all the questions in this Jupyter Notebook



#### Part 1: Basics

#### 1.1 Import:

Please import necessary packages to use. Note that learning and using packages are recommended but not required for this project. Some official tutorial for suggested packages includes:

https://scikit-learn.org/stable/tutorial/basic/tutorial.html (https://scikit-learn.org/stable/tutorial/basic/tutorial.html)

https://pytorch.org/tutorials/ (https://pytorch.org/tutorials/)

https://pandas.pydata.org/pandas-docs/stable/user\_guide/10min.html (https://pandas.pydata.org/pandas-docs/stable/user\_guide/10min.html)

```
In [1]: import os
    import pandas as pd
    import numpy as np

import tensorflow as tf
    from sklearn.model_selection import train_test_split
    import matplotlib.pyplot as plt
    from sklearn.preprocessing import StandardScaler

from numpy import mean
    from numpy import std
    from sklearn.datasets import make_classification
    from sklearn.model_selection import cross_val_score
    from sklearn.model_selection import RepeatedStratifiedKFold
    from sklearn.ensemble import AdaBoostClassifier

print(tf.__version__)
#%matplotlib widget
```

2.2.0

## 1.2 Accuracy and Mean Squared Error:

To measure your performance in the Kaggle Competition, we are using accuracy and mean squared error (MSE). As a recap, accuracy is the percent of labels you predict correctly and MSE is the average squared difference between the estimated values and the actual value. To measure this, you can use library functions from sklearn. A simple example is shown below.

```
In [2]: from sklearn.metrics import accuracy_score
    y_pred = [3, 2, 1, 0, 1, 2, 3]
    y_true = [0, 1, 2, 3, 1, 2, 3]
    accuracy_score(y_true, y_pred)

Out[2]: 0.42857142857142855

In [3]: from sklearn.metrics import mean_squared_error
    mean_squared_error(y_true, y_pred)

Out[3]: 2.857142857142857
```

### **Part 2: Baseline Solution**

Note that your code should be commented well and in part 2.4 you can refer to your comments.

#### 2.1 Preprocessing and Feature Extraction:

Given the training dataset and graph information, you need to correctly preprocess the dataset (e.g. feature normalization). Think of what modifications can be done to the data to make it more easily interpretable.

```
In [4]: def load and preprocess data(data path, predict path):
            def common preprocess(data, epoch):
                data = data.rename(columns={'Daily hospital occupancy': 'daily
        _hospital occupancy'})
                # Defining the date encoding as the number of days elapsed sin
        ce a given epoch (choice of epoch doesn't matter)
                data['date'] = pd.to datetime(data['date'])
                data['date encoding'] = (data['date']-epoch).dt.days
                # Drop the date and year week column
                data = data.drop(['date'], axis=1)
                data = data.drop(['year week'], axis=1)
                return data
            # Load the features and t values for the data with known target va
        lues
            data = pd.read csv(data path)
            epoch = pd.to datetime(data['date']).min() # Choose an epoch
            # Preprocess the data
            df = common preprocess(data, epoch)
            # Load the data on which the predictions are to be made
            predict data = pd.read_csv(predict_path)
            index = predict data['country'] + ' ' + predict data['date'] # St
        ore the index for making the csv for submission to kaggle
            # Process the data in the same way as the training data
            predict df = common preprocess(predict data, epoch)
            return index, df, predict df
```

## 2.2 Use At Least Two Training Algorithms from class:

You need to use at least two training algorithms from class. You can use your code from previous projects or any packages you imported in part 1.1.

## **Neural Network**

```
index, df, pdf = load and preprocess data('train baseline.csv', 'test
In [5]:
        baseline no label.csv')
        # Define the categorical and numerical columns for tensorflow
        CATEGORICAL COLUMNS = df.columns[0:1].to numpy().astype('object').toli
        NUMERIC COLUMNS = df.columns[1:].to numpy().tolist()
        NUMERIC COLUMNS.remove('next week increase decrease')
        # Normalize the numerical columns
        scaler = StandardScaler()
        df[NUMERIC COLUMNS] = scaler.fit transform(df[NUMERIC COLUMNS]) # Lear
        n the mean and std and nomalize
        pdf[NUMERIC COLUMNS] = scaler.transform(pdf[NUMERIC COLUMNS]) # Use th
        e learned mean and std to normalize the prediction dataset
        # Generate the final data frame and the labels
        data = df[CATEGORICAL COLUMNS + NUMERIC COLUMNS]
        pdata = pdf[CATEGORICAL COLUMNS + NUMERIC COLUMNS]
        y = df['next week increase decrease']
In [6]: # Split the data into training and validation sets. Using a fixed rand
        om seed for consistency across models
        seed = 42
        train ratio = 0.7
        x train, x val, y train, y val = train test split(data, y, test size =
        1 - train ratio, random state = seed)
In [7]: # Tensorflow takes a tensorflow dataset for it's models
        def create tf df(df, labels, shuffle = True, batch size = 32):
            ds = tf.data.Dataset.from tensor slices((dict(df), labels))
            if shuffle:
                ds = ds.shuffle(buffer size = len(df))
            ds = ds.batch(batch size)
            return ds
        def create pdf(df, batch size = 1):
            ds = tf.data.Dataset.from tensor slices(dict(pdf))
            ds = ds.batch(batch size)
            return ds
        batch size = 40
        # Define the tensorflow datasets
        train df = create tf df(x train, y train, shuffle = False, batch size
        = batch size)
        val df = create tf df(x val, y val, shuffle = False, batch size = batc
        h size)
        pdf df = create pdf(pdf)
```

```
In [8]: feature columns = []
        # Define the feature columns for creating a tensorflow.keras features
        for feature name in CATEGORICAL COLUMNS:
            vocabulary = data[feature name].unique()
            feature columns.append(tf.feature column.indicator column(tf.featu
        re column.categorical column with vocabulary list(feature name, vocabu
        lary)))
        for feature name in NUMERIC COLUMNS:
            feature columns.append(tf.feature column.numeric column(feature na
        me, dtype = tf.float64))
        feature layer = tf.keras.layers.DenseFeatures(feature columns)
        # Define the learning rate for the optimizer
        lr = 0.001
        # Create a neural network with l1 l2 regularization using tf.keras.Seq
        uential
        model = tf.keras.Sequential([
            feature layer,
            tf.keras.layers.Dense(20, activation = 'relu', kernel regularizer
        = tf.keras.regularizers.l1 l2(l1=0, l2=0.01)),
            tf.keras.layers.Dense(20, activation = 'relu', kernel regularizer
        = tf.keras.regularizers.l1 l2(l1=0, l2=0.01)),
            tf.keras.layers.Dense(1, activation='sigmoid')
        1)
        # Define the optimizer for learning the weights of the define model
        optimizer = tf.optimizers.RMSprop(learning rate = lr)
        # Compile the tensorflow model with a mean squared error loss
        model.compile(loss = 'binary crossentropy',
                      optimizer = optimizer,
                      metrics=['accuracy'])
```

In [9]: # Fit the model on the training set and check against the validation s
 et
 history = model.fit(train\_df, validation\_data = val\_df, epochs = 200)

Epoch 1/200

WARNING:tensorflow:Layer dense\_features is casting an input tensor from dtype float64 to the layer's dtype of float32, which is new behavior in TensorFlow 2. The layer has dtype float32 because it's dtype defaults to floatx.

If you intended to run this layer in float32, you can safely ignore th is warning. If in doubt, this warning is likely only an issue if you a re porting a TensorFlow 1.X model to TensorFlow 2.

To change all layers to have dtype float64 by default, call `tf.keras. backend.set\_floatx('float64')`. To change just this layer, pass dtype ='float64' to the layer constructor. If you are the author of this lay er, you can disable autocasting by passing autocast=False to the base Layer constructor.

```
accuracy: 0.5740 - val loss: 0.9238 - val accuracy: 0.5928
Epoch 2/200
accuracy: 0.6171 - val loss: 0.8126 - val accuracy: 0.6212
Epoch 3/200
accuracy: 0.6278 - val loss: 0.7439 - val accuracy: 0.6229
Epoch 4/200
accuracy: 0.6375 - val loss: 0.7032 - val accuracy: 0.6463
Epoch 5/200
accuracy: 0.6701 - val loss: 0.6781 - val accuracy: 0.6923
Epoch 6/200
accuracy: 0.6967 - val loss: 0.6617 - val accuracy: 0.7023
Epoch 7/200
accuracy: 0.7085 - val loss: 0.6495 - val accuracy: 0.7090
Epoch 8/200
accuracy: 0.7164 - val loss: 0.6402 - val accuracy: 0.7224
Epoch 9/200
accuracy: 0.7178 - val loss: 0.6327 - val accuracy: 0.7274
Epoch 10/200
accuracy: 0.7193 - val loss: 0.6264 - val accuracy: 0.7299
Epoch 11/200
accuracy: 0.7243 - val loss: 0.6208 - val accuracy: 0.7341
Epoch 12/200
accuracy: 0.7250 - val loss: 0.6154 - val accuracy: 0.7400
Epoch 13/200
accuracy: 0.7275 - val loss: 0.6103 - val_accuracy: 0.7425
Epoch 14/200
accuracy: 0.7307 - val loss: 0.6058 - val accuracy: 0.7441
```

```
Epoch 15/200
accuracy: 0.7336 - val loss: 0.6012 - val accuracy: 0.7458
Epoch 16/200
accuracy: 0.7347 - val loss: 0.5963 - val accuracy: 0.7458
Epoch 17/200
accuracy: 0.7368 - val loss: 0.5916 - val accuracy: 0.7517
Epoch 18/200
accuracy: 0.7397 - val_loss: 0.5872 - val_accuracy: 0.7517
Epoch 19/200
accuracy: 0.7404 - val loss: 0.5827 - val accuracy: 0.7517
Epoch 20/200
accuracy: 0.7422 - val loss: 0.5784 - val accuracy: 0.7584
Epoch 21/200
70/70 [============== ] - 0s 6ms/step - loss: 0.5759 -
accuracy: 0.7426 - val loss: 0.5743 - val accuracy: 0.7600
Epoch 22/200
accuracy: 0.7451 - val_loss: 0.5705 - val_accuracy: 0.7609
Epoch 23/200
accuracy: 0.7465 - val loss: 0.5668 - val accuracy: 0.7642
Epoch 24/200
accuracy: 0.7526 - val loss: 0.5631 - val accuracy: 0.7676
Epoch 25/200
accuracy: 0.7558 - val loss: 0.5597 - val accuracy: 0.7701
Epoch 26/200
accuracy: 0.7558 - val loss: 0.5565 - val accuracy: 0.7726
Epoch 27/200
70/70 [============= ] - 1s 8ms/step - loss: 0.5546 -
accuracy: 0.7598 - val loss: 0.5534 - val accuracy: 0.7751
Epoch 28/200
accuracy: 0.7623 - val loss: 0.5507 - val accuracy: 0.7742
Epoch 29/200
accuracy: 0.7630 - val loss: 0.5481 - val accuracy: 0.7751
Epoch 30/200
accuracy: 0.7648 - val loss: 0.5456 - val accuracy: 0.7759
Epoch 31/200
accuracy: 0.7662 - val loss: 0.5434 - val accuracy: 0.7759
Epoch 32/200
accuracy: 0.7662 - val loss: 0.5413 - val accuracy: 0.7784
Epoch 33/200
accuracy: 0.7687 - val loss: 0.5393 - val accuracy: 0.7809
```

```
Epoch 34/200
accuracy: 0.7712 - val loss: 0.5373 - val accuracy: 0.7818
Epoch 35/200
accuracy: 0.7738 - val loss: 0.5355 - val accuracy: 0.7843
Epoch 36/200
accuracy: 0.7770 - val loss: 0.5338 - val accuracy: 0.7851
Epoch 37/200
accuracy: 0.7784 - val_loss: 0.5320 - val_accuracy: 0.7885
Epoch 38/200
accuracy: 0.7806 - val loss: 0.5304 - val accuracy: 0.7901
Epoch 39/200
accuracy: 0.7813 - val loss: 0.5288 - val accuracy: 0.7910
Epoch 40/200
70/70 [============== ] - 1s 11ms/step - loss: 0.5273 -
accuracy: 0.7834 - val loss: 0.5271 - val accuracy: 0.7918
Epoch 41/200
accuracy: 0.7842 - val_loss: 0.5256 - val_accuracy: 0.7935
Epoch 42/200
accuracy: 0.7874 - val loss: 0.5241 - val accuracy: 0.7943
Epoch 43/200
accuracy: 0.7888 - val loss: 0.5227 - val accuracy: 0.7960
Epoch 44/200
accuracy: 0.7910 - val loss: 0.5212 - val accuracy: 0.7993
Epoch 45/200
accuracy: 0.7924 - val loss: 0.5197 - val accuracy: 0.8027
Epoch 46/200
accuracy: 0.7935 - val loss: 0.5185 - val accuracy: 0.8052
Epoch 47/200
accuracy: 0.7946 - val loss: 0.5173 - val accuracy: 0.8069
Epoch 48/200
accuracy: 0.7942 - val loss: 0.5155 - val accuracy: 0.8085
Epoch 49/200
accuracy: 0.7942 - val loss: 0.5142 - val accuracy: 0.8085
Epoch 50/200
accuracy: 0.7956 - val loss: 0.5131 - val accuracy: 0.8085
Epoch 51/200
accuracy: 0.7974 - val loss: 0.5119 - val accuracy: 0.8119
Epoch 52/200
accuracy: 0.7985 - val loss: 0.5109 - val accuracy: 0.8119
```

```
Epoch 53/200
accuracy: 0.7989 - val loss: 0.5098 - val accuracy: 0.8119
Epoch 54/200
accuracy: 0.8003 - val loss: 0.5088 - val accuracy: 0.8127
Epoch 55/200
accuracy: 0.7999 - val loss: 0.5079 - val accuracy: 0.8127
Epoch 56/200
accuracy: 0.8010 - val_loss: 0.5071 - val_accuracy: 0.8127
Epoch 57/200
accuracy: 0.8021 - val loss: 0.5061 - val accuracy: 0.8127
Epoch 58/200
accuracy: 0.8014 - val loss: 0.5052 - val accuracy: 0.8144
Epoch 59/200
70/70 [============== ] - 0s 6ms/step - loss: 0.5051 -
accuracy: 0.8010 - val loss: 0.5043 - val accuracy: 0.8144
Epoch 60/200
accuracy: 0.8014 - val_loss: 0.5034 - val_accuracy: 0.8135
Epoch 61/200
accuracy: 0.8017 - val loss: 0.5025 - val accuracy: 0.8127
Epoch 62/200
accuracy: 0.8024 - val loss: 0.5016 - val accuracy: 0.8144
Epoch 63/200
accuracy: 0.8028 - val loss: 0.5009 - val accuracy: 0.8144
Epoch 64/200
accuracy: 0.8039 - val loss: 0.5002 - val accuracy: 0.8169
Epoch 65/200
accuracy: 0.8046 - val loss: 0.4995 - val accuracy: 0.8169
Epoch 66/200
accuracy: 0.8053 - val loss: 0.4988 - val accuracy: 0.8169
Epoch 67/200
accuracy: 0.8053 - val loss: 0.4982 - val accuracy: 0.8169
Epoch 68/200
accuracy: 0.8064 - val loss: 0.4976 - val accuracy: 0.8186
Epoch 69/200
accuracy: 0.8067 - val loss: 0.4970 - val accuracy: 0.8177
Epoch 70/200
accuracy: 0.8071 - val loss: 0.4963 - val accuracy: 0.8186
Epoch 71/200
accuracy: 0.8067 - val loss: 0.4958 - val accuracy: 0.8186
```

```
Epoch 72/200
accuracy: 0.8071 - val loss: 0.4953 - val accuracy: 0.8177
Epoch 73/200
accuracy: 0.8075 - val loss: 0.4947 - val accuracy: 0.8177
Epoch 74/200
accuracy: 0.8078 - val loss: 0.4942 - val accuracy: 0.8169
Epoch 75/200
accuracy: 0.8082 - val_loss: 0.4936 - val_accuracy: 0.8177
Epoch 76/200
accuracy: 0.8093 - val loss: 0.4930 - val accuracy: 0.8177
Epoch 77/200
accuracy: 0.8096 - val loss: 0.4924 - val accuracy: 0.8177
Epoch 78/200
accuracy: 0.8093 - val loss: 0.4920 - val accuracy: 0.8177
Epoch 79/200
accuracy: 0.8107 - val_loss: 0.4919 - val_accuracy: 0.8152
Epoch 80/200
accuracy: 0.8103 - val loss: 0.4915 - val accuracy: 0.8152
Epoch 81/200
accuracy: 0.8118 - val loss: 0.4905 - val accuracy: 0.8169
Epoch 82/200
accuracy: 0.8107 - val loss: 0.4902 - val accuracy: 0.8177
Epoch 83/200
accuracy: 0.8114 - val loss: 0.4903 - val accuracy: 0.8144
Epoch 84/200
accuracy: 0.8107 - val loss: 0.4895 - val accuracy: 0.8169
Epoch 85/200
accuracy: 0.8110 - val loss: 0.4892 - val accuracy: 0.8152
Epoch 86/200
accuracy: 0.8103 - val loss: 0.4892 - val accuracy: 0.8152
Epoch 87/200
accuracy: 0.8096 - val loss: 0.4883 - val accuracy: 0.8161
Epoch 88/200
accuracy: 0.8100 - val loss: 0.4885 - val_accuracy: 0.8119
Epoch 89/200
accuracy: 0.8096 - val loss: 0.4874 - val accuracy: 0.8144
Epoch 90/200
accuracy: 0.8103 - val loss: 0.4869 - val accuracy: 0.8152
```

```
Epoch 91/200
accuracy: 0.8103 - val loss: 0.4868 - val accuracy: 0.8135
Epoch 92/200
accuracy: 0.8096 - val loss: 0.4859 - val accuracy: 0.8161
Epoch 93/200
accuracy: 0.8100 - val loss: 0.4859 - val accuracy: 0.8161
Epoch 94/200
accuracy: 0.8107 - val_loss: 0.4850 - val_accuracy: 0.8161
Epoch 95/200
accuracy: 0.8107 - val loss: 0.4845 - val accuracy: 0.8186
Epoch 96/200
accuracy: 0.8096 - val loss: 0.4838 - val accuracy: 0.8186
Epoch 97/200
accuracy: 0.8114 - val loss: 0.4833 - val accuracy: 0.8169
Epoch 98/200
accuracy: 0.8103 - val_loss: 0.4832 - val_accuracy: 0.8152
Epoch 99/200
accuracy: 0.8100 - val loss: 0.4825 - val accuracy: 0.8186
Epoch 100/200
accuracy: 0.8110 - val loss: 0.4821 - val accuracy: 0.8186
Epoch 101/200
accuracy: 0.8114 - val loss: 0.4817 - val accuracy: 0.8186
Epoch 102/200
accuracy: 0.8110 - val loss: 0.4813 - val accuracy: 0.8186
Epoch 103/200
accuracy: 0.8121 - val loss: 0.4809 - val accuracy: 0.8186
Epoch 104/200
accuracy: 0.8114 - val loss: 0.4804 - val accuracy: 0.8186
Epoch 105/200
accuracy: 0.8114 - val loss: 0.4799 - val accuracy: 0.8177
Epoch 106/200
accuracy: 0.8114 - val loss: 0.4797 - val accuracy: 0.8177
Epoch 107/200
accuracy: 0.8114 - val loss: 0.4791 - val accuracy: 0.8186
Epoch 108/200
accuracy: 0.8114 - val loss: 0.4786 - val accuracy: 0.8194
Epoch 109/200
accuracy: 0.8121 - val loss: 0.4781 - val accuracy: 0.8202
```

```
Epoch 110/200
accuracy: 0.8118 - val loss: 0.4778 - val accuracy: 0.8211
Epoch 111/200
accuracy: 0.8125 - val loss: 0.4775 - val accuracy: 0.8211
Epoch 112/200
accuracy: 0.8118 - val loss: 0.4771 - val accuracy: 0.8219
Epoch 113/200
accuracy: 0.8110 - val_loss: 0.4768 - val_accuracy: 0.8227
Epoch 114/200
accuracy: 0.8121 - val loss: 0.4764 - val accuracy: 0.8227
Epoch 115/200
accuracy: 0.8125 - val loss: 0.4761 - val accuracy: 0.8236
Epoch 116/200
accuracy: 0.8128 - val loss: 0.4762 - val accuracy: 0.8227
Epoch 117/200
accuracy: 0.8132 - val_loss: 0.4752 - val_accuracy: 0.8244
Epoch 118/200
accuracy: 0.8136 - val loss: 0.4747 - val accuracy: 0.8253
Epoch 119/200
accuracy: 0.8136 - val loss: 0.4745 - val accuracy: 0.8253
Epoch 120/200
accuracy: 0.8136 - val loss: 0.4741 - val accuracy: 0.8269
Epoch 121/200
accuracy: 0.8150 - val loss: 0.4739 - val accuracy: 0.8269
Epoch 122/200
accuracy: 0.8139 - val loss: 0.4735 - val accuracy: 0.8286
Epoch 123/200
accuracy: 0.8136 - val loss: 0.4732 - val accuracy: 0.8286
Epoch 124/200
accuracy: 0.8143 - val loss: 0.4729 - val accuracy: 0.8286
Epoch 125/200
accuracy: 0.8150 - val loss: 0.4728 - val accuracy: 0.8286
Epoch 126/200
accuracy: 0.8157 - val loss: 0.4723 - val accuracy: 0.8294
Epoch 127/200
accuracy: 0.8153 - val loss: 0.4724 - val accuracy: 0.8303
Epoch 128/200
accuracy: 0.8157 - val loss: 0.4716 - val accuracy: 0.8303
```

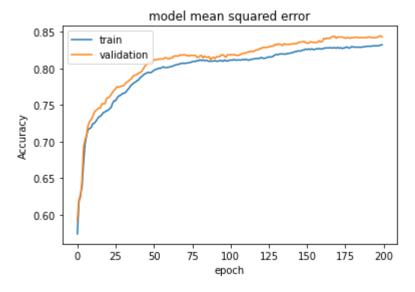
```
Epoch 129/200
accuracy: 0.8168 - val loss: 0.4713 - val accuracy: 0.8303
Epoch 130/200
accuracy: 0.8186 - val loss: 0.4711 - val accuracy: 0.8328
Epoch 131/200
accuracy: 0.8189 - val loss: 0.4709 - val accuracy: 0.8319
Epoch 132/200
accuracy: 0.8186 - val_loss: 0.4706 - val_accuracy: 0.8336
Epoch 133/200
accuracy: 0.8196 - val loss: 0.4705 - val accuracy: 0.8328
Epoch 134/200
accuracy: 0.8196 - val loss: 0.4702 - val accuracy: 0.8328
Epoch 135/200
accuracy: 0.8196 - val loss: 0.4703 - val accuracy: 0.8311
Epoch 136/200
accuracy: 0.8196 - val_loss: 0.4695 - val_accuracy: 0.8336
Epoch 137/200
accuracy: 0.8193 - val loss: 0.4694 - val accuracy: 0.8328
Epoch 138/200
accuracy: 0.8204 - val loss: 0.4692 - val accuracy: 0.8328
Epoch 139/200
accuracy: 0.8204 - val loss: 0.4689 - val accuracy: 0.8328
Epoch 140/200
accuracy: 0.8207 - val loss: 0.4688 - val accuracy: 0.8328
Epoch 141/200
accuracy: 0.8214 - val loss: 0.4686 - val accuracy: 0.8336
Epoch 142/200
accuracy: 0.8218 - val loss: 0.4683 - val accuracy: 0.8336
Epoch 143/200
accuracy: 0.8229 - val loss: 0.4681 - val accuracy: 0.8336
Epoch 144/200
accuracy: 0.8229 - val loss: 0.4678 - val accuracy: 0.8336
Epoch 145/200
accuracy: 0.8240 - val loss: 0.4676 - val accuracy: 0.8353
Epoch 146/200
accuracy: 0.8236 - val loss: 0.4673 - val accuracy: 0.8353
Epoch 147/200
70/70 [============ ] - 1s 9ms/step - loss: 0.4629 -
accuracy: 0.8240 - val loss: 0.4670 - val accuracy: 0.8361
```

```
Epoch 148/200
accuracy: 0.8250 - val loss: 0.4668 - val accuracy: 0.8361
Epoch 149/200
accuracy: 0.8250 - val loss: 0.4667 - val accuracy: 0.8370
Epoch 150/200
accuracy: 0.8265 - val loss: 0.4665 - val accuracy: 0.8353
Epoch 151/200
accuracy: 0.8257 - val_loss: 0.4665 - val_accuracy: 0.8344
Epoch 152/200
accuracy: 0.8265 - val loss: 0.4659 - val accuracy: 0.8344
Epoch 153/200
accuracy: 0.8257 - val loss: 0.4659 - val accuracy: 0.8361
Epoch 154/200
accuracy: 0.8268 - val loss: 0.4656 - val accuracy: 0.8361
Epoch 155/200
accuracy: 0.8257 - val_loss: 0.4655 - val_accuracy: 0.8353
Epoch 156/200
accuracy: 0.8257 - val loss: 0.4653 - val accuracy: 0.8353
Epoch 157/200
accuracy: 0.8268 - val loss: 0.4651 - val accuracy: 0.8353
Epoch 158/200
accuracy: 0.8265 - val loss: 0.4649 - val accuracy: 0.8361
Epoch 159/200
accuracy: 0.8272 - val loss: 0.4646 - val accuracy: 0.8378
Epoch 160/200
accuracy: 0.8265 - val loss: 0.4643 - val accuracy: 0.8361
Epoch 161/200
accuracy: 0.8265 - val loss: 0.4646 - val accuracy: 0.8370
Epoch 162/200
accuracy: 0.8275 - val loss: 0.4640 - val accuracy: 0.8411
Epoch 163/200
accuracy: 0.8279 - val loss: 0.4638 - val accuracy: 0.8403
Epoch 164/200
accuracy: 0.8279 - val loss: 0.4637 - val_accuracy: 0.8411
Epoch 165/200
accuracy: 0.8279 - val loss: 0.4636 - val accuracy: 0.8411
Epoch 166/200
accuracy: 0.8283 - val loss: 0.4633 - val accuracy: 0.8411
```

```
Epoch 167/200
accuracy: 0.8279 - val loss: 0.4631 - val accuracy: 0.8428
Epoch 168/200
accuracy: 0.8279 - val loss: 0.4628 - val accuracy: 0.8436
Epoch 169/200
accuracy: 0.8283 - val loss: 0.4627 - val accuracy: 0.8436
Epoch 170/200
accuracy: 0.8275 - val_loss: 0.4625 - val_accuracy: 0.8411
Epoch 171/200
accuracy: 0.8286 - val loss: 0.4621 - val accuracy: 0.8428
Epoch 172/200
accuracy: 0.8275 - val loss: 0.4619 - val accuracy: 0.8428
Epoch 173/200
accuracy: 0.8283 - val loss: 0.4617 - val accuracy: 0.8428
Epoch 174/200
accuracy: 0.8272 - val_loss: 0.4617 - val_accuracy: 0.8428
Epoch 175/200
accuracy: 0.8279 - val loss: 0.4612 - val accuracy: 0.8420
Epoch 176/200
accuracy: 0.8283 - val loss: 0.4615 - val accuracy: 0.8411
Epoch 177/200
accuracy: 0.8293 - val loss: 0.4611 - val accuracy: 0.8420
Epoch 178/200
accuracy: 0.8279 - val loss: 0.4609 - val accuracy: 0.8420
Epoch 179/200
accuracy: 0.8279 - val loss: 0.4606 - val accuracy: 0.8411
Epoch 180/200
accuracy: 0.8297 - val loss: 0.4606 - val accuracy: 0.8420
Epoch 181/200
accuracy: 0.8293 - val loss: 0.4602 - val accuracy: 0.8420
Epoch 182/200
accuracy: 0.8290 - val loss: 0.4601 - val accuracy: 0.8420
Epoch 183/200
accuracy: 0.8290 - val loss: 0.4602 - val_accuracy: 0.8428
Epoch 184/200
accuracy: 0.8290 - val loss: 0.4602 - val accuracy: 0.8420
Epoch 185/200
70/70 [============= ] - 1s 8ms/step - loss: 0.4535 -
accuracy: 0.8290 - val loss: 0.4597 - val accuracy: 0.8420
```

```
Epoch 186/200
accuracy: 0.8286 - val loss: 0.4599 - val accuracy: 0.8420
Epoch 187/200
accuracy: 0.8293 - val loss: 0.4597 - val accuracy: 0.8420
Epoch 188/200
accuracy: 0.8293 - val loss: 0.4597 - val accuracy: 0.8420
Epoch 189/200
accuracy: 0.8297 - val loss: 0.4594 - val accuracy: 0.8420
Epoch 190/200
accuracy: 0.8300 - val loss: 0.4592 - val accuracy: 0.8420
Epoch 191/200
accuracy: 0.8304 - val loss: 0.4589 - val accuracy: 0.8428
Epoch 192/200
accuracy: 0.8300 - val loss: 0.4589 - val accuracy: 0.8428
Epoch 193/200
accuracy: 0.8304 - val loss: 0.4590 - val accuracy: 0.8420
Epoch 194/200
accuracy: 0.8308 - val loss: 0.4585 - val accuracy: 0.8420
Epoch 195/200
accuracy: 0.8308 - val loss: 0.4585 - val accuracy: 0.8420
Epoch 196/200
accuracy: 0.8308 - val loss: 0.4582 - val accuracy: 0.8420
Epoch 197/200
accuracy: 0.8308 - val loss: 0.4581 - val accuracy: 0.8428
Epoch 198/200
70/70 [============= ] - 1s 8ms/step - loss: 0.4507 -
accuracy: 0.8311 - val loss: 0.4576 - val accuracy: 0.8436
Epoch 199/200
accuracy: 0.8318 - val loss: 0.4577 - val accuracy: 0.8445
Epoch 200/200
accuracy: 0.8322 - val loss: 0.4579 - val accuracy: 0.8428
```

```
In [10]: # Plot the mse error over time
    plt.figure()
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('model mean squared error')
    plt.ylabel('Accuracy')
    plt.xlabel('epoch')
    plt.legend(['train', 'validation'], loc='upper left')
    plt.show()
```



```
In [11]: # Make the prediction on the prediction dataset and write them to a cs
v file
pred = model.predict(pdf_df)
pred = np.where(pred > 0.5, 1, 0)
submit = {'country_id': index, 'next_week_increase_decrease':pred.asty
pe(int).flatten()}
sdf = pd.DataFrame(data = submit)
sdf.to_csv('submit_baseline_neural.csv',index = False)
```

## **Adaboost**

```
index, df, pdf = load and preprocess data('train baseline.csv', 'test
In [12]:
         baseline no label.csv')
         # Encode the country column with one-hot encoding
         def one_hot encoding(df):
             encoded columns = pd.get dummies(df['country'])
             df = df.join(encoded columns).drop('country', axis=1)
             return df
         df = one_hot_encoding(df)
         pdf = one hot encoding(pdf)
         # Normalize the numerical columns
         NUMERICAL FEATURES = ['daily hospital occupancy', 'under 15 cases', '15-
         24_cases','25-49_cases','50-64_cases','65-79_cases','over_80_cases',
         'date_encoding']
         scaler = StandardScaler()
         df[NUMERIC COLUMNS] = scaler.fit transform(df[NUMERIC COLUMNS]) # Lear
         n the mean and std and nomalize
         pdf[NUMERIC COLUMNS] = scaler.transform(pdf[NUMERIC COLUMNS]) # Use th
         e learned mean and std to normalize the prediction dataset
         v = df['next week increase decrease']
         df = df.drop(['next week increase decrease'], axis = 1)
         feature names = [f'{i}' for i in df.columns]
         #final features = feature names[0:29]
         X = df.iloc[:,:].values
         v = v.values
```

```
In [13]: # compare the number of repeats for repeated k-fold cross-validation
         from scipy.stats import sem
         from matplotlib import pyplot
         def evaluate model(X, y, repeats):
                 # prepare the cross-validation procedure
             cv = RepeatedStratifiedKFold(n splits=10, n repeats=repeats, rando
         m state=1)
             # create model
             model = AdaBoostClassifier(n estimators =15, random state = 0, learn
         ing rate = 1)
             #evaluate model
             scores = cross val score(model, X, y, scoring='accuracy', cv=cv, n
         _jobs=-1)
             return scores
         # create dataset
         #X, y = make classification(n samples=1000, n features=20, n informati
         ve=15, n redundant=5, random state=1)
         # configurations to test
         repeats = range(1,16)
         results = list()
         for r in repeats:
                 # evaluate using a given number of repeats
                 scores = evaluate model(X, y, r)
                 # summarize
                 print('>%d mean=%.4f se=%.3f' % (r, mean(scores), std(scores
         ))))
                 # store
                 results.append(scores)
         # plot the results
         pyplot.boxplot(results, labels=[str(r) for r in repeats], showmeans=Tr
         ue)
         pyplot.show()
```

```
>1 mean=0.7548 se=0.019

>2 mean=0.7522 se=0.019

>3 mean=0.7509 se=0.017

>4 mean=0.7541 se=0.019

>5 mean=0.7530 se=0.022

>6 mean=0.7536 se=0.021

>7 mean=0.7547 se=0.021

>8 mean=0.7547 se=0.021

>9 mean=0.7544 se=0.021

>10 mean=0.7544 se=0.021

>11 mean=0.7544 se=0.021

>12 mean=0.7547 se=0.021

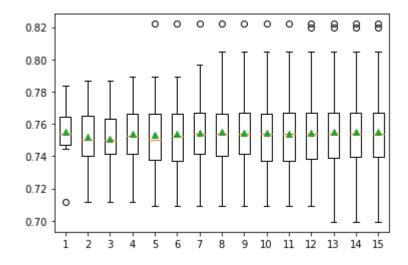
>13 mean=0.7549 se=0.021

>14 mean=0.7550 se=0.021

>15 mean=0.7550 se=0.021
```

/home/hsharsh/anaconda3/envs/mlenv/lib/python3.8/site-packages/numpy/c ore/\_asarray.py:83: VisibleDeprecationWarning: Creating an ndarray fro m ragged nested sequences (which is a list-or-tuple of lists-or-tuples -or ndarrays with different lengths or shapes) is deprecated. If you m eant to do this, you must specify 'dtype=object' when creating the nda rray

return array(a, dtype, copy=False, order=order)



```
In [14]: # Define the model
    model = AdaBoostClassifier(n_estimators =15,random_state = 0,learning_
    rate = 1.0)
    model.fit(X,y)

print(f'Training accuracy: {model.score(X,y)}')

# evaluate the model
    cv = RepeatedStratifiedKFold(n_splits=20, n_repeats=3, random_state=1)
    n_scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_j
    obs=-1, error_score='raise')
# report performance
    print(f'Validataion Accuracy: {mean(n_scores)}) ({std(n_scores)})')
```

Training accuracy: 0.7708908406524467 Validataion Accuracy: 0.7502286432160805 (0.026210752403874882)

```
In [15]: pred = model.predict(pdf)
    submit = {'country_id': index, 'next_week_increase_decrease':pred.asty
    pe(int).flatten()}
    sdf = pd.DataFrame(data = submit)
    sdf.to_csv('submit_baseline_adaboost.csv',index = False)
```

#### 2.4 Explanation in Words:

You need to answer the following questions in the markdown cell after this cell:

- 2.4.1 How did you preprocess the dataset and features, and how did you formulate the learning problem (or problems)?
- 2.4.2 Which two learning methods from class did you choose and why did you made the choices?
- 2.4.3 How did you do the model selection?
- 2.4.4 Does the test performance reach a given baseline 70% performance? (Please include a screenshot of Kaggle Submission)

#### 2.4.1 Features

The most important thing getting a good model for us was choosing which features we wanted to use and in what way we wanted to tweak them to allow for better learning. We will describe what we did with each feature one by one:

- Country: Country should be an important feature because the rates at which the daily hospital occupancy
  changes majorly depends on how well a country did to keep COVID in check. Since, this was the only
  categorical feature, we decided to use one-hot encoding for this.
- Date: The number of COVID cases and hence next week's hospitalization numbers definitely have a
  temporal component to them, therefore, the date was certainly an important feature. To encode the date we
  decided to count the number of days elapsed till the current date since a fixed date. To choose this fixed
  date we found the earliest date in the training set and used that as an epoch. Note that the choice of this
  epoch doesn't really affect the final results because in the end we normalize all the numerical features.
- year-week: We decided to drop the feature year-week because it does a very similar job to Date and after
  converting the categorical feature into a week encoding we will end up with something very close to the Date
  encoding we described before.
- **Daily Hospital Occupancy**: Daily Hospital occupancy will certainly affect the hospital occupancy in the next week, so we decided to keep the feature.
- under\_15\_cases, over\_80\_cases, x-y\_cases: We decided to keep all the features of this form because it
  is possible that one age group is most susceptible to being hospitalized or spread COVID more than others.
  Thus, knowing the current number should allow the model to predict next week's hospitalization numbers
  better.

Finally, we normalized all the numerical features (everything except the country one-hot encoding) with sklearn.preprocessing.StandardScaler.

# 2.4.2 Two Learning Models

The two learning models are shown below:

- **Neural Networks**: Neural networks were chosen for this learning problem as neural networks are extremely flexible as well as can be generally used for mapping of inputs to their outputs.
- Adaboost Regressor: One main reason why we decided to apply Adaboost was because when we tried decision tree regressor here we realized that the number of features in this dataset are quite large and one decision tree might result in ambiguity as their are many features to look at. (e.g. if we add new number of cases into the test data, which was not recognized earlier by the tree). So ensemble methods were the ideal next step as they take in multiple weakclassifier models to result in a stronger prediction classifier. The following configurations of the adaboost regressor were utilized: n\_estimators: Number of weak learners to train in each iteration. Since the number of features were 25. We decided to set the task to around 15 finally based on the stratified kfold cross validation result, as well as the result based on the public leadership board submitted to kaggle. learning\_rate: It contributes to the weights of weak learners. This was set to 1 as the default value.

### 2.4.3 Model Selection

- Neural Networks: For the deep neural net; the dataset; which is the train\_baseline was split into a train and validation set. The train and validation set was split in a ratio of 70:30. The final model, or the configuration of the neural network was selected based on the overall performance we noticed on the validation accuracy. The validation accuracy was model by the loss curves in comparision to the loss curves of the training set. If the validation accuracy and train accuracy had a hude difference we would often classify the model as overfit. Else the best model selected was the one with highest validation accuracy. Thus the final model chosen for the neural network was one with two hidden layers of 20 nodes each, where the 'ReLu' activation function was applied. The model also had sigmoid function applied at its output(since this is a classification task), and the loss funtion used here was "binary cross entropy" as this is classification task, and the optimizer used was the RMS prop. The neural network got an accuracy of 71.853.
- Adaboost Regressor: For the Adaboost model; the model parameters, that is the n\_estimator where finalized by running a stratifiedKfold cross validation. This can be directly imported from sklearn package. What this basically does is repeat the kfold cross validation n times. This helps to reduce the noisey estimate of the dataset, and that is why this was used. The kfold cross validation was run on various configurations of the Adaboost Regressor, and the n\_estimator that performed best on kfold cross validation was used as the final model. In our case the n\_estimator at 15 resulted in the best accuracy on the validation set as well as the kaggle test set, and hence 15 estimators were used. Any model greater than 15 resulted in overfitting as the training accuracy increased but the testing accuracy decreased. For the kfolds the best repeat was chosen to be three, as shown in the graph below and a standard default value of 10 was used for the kfold spilt. We chose 3 for repeats in the stratified kfold as that gave the lowest standard error in comparision to the remaining number of repeats.

## 2.4.4 Baseline Performance Screenshot

**NEURALNETWORKS** - ACCURACY\_BASELINE

submit\_baseline\_neural.csv
10 hours ago by Harsh
add submission details

0.72027



#### ADABOOSTREGRESSOR- ACCURACY BASELINE

Name submit\_baseline\_adaboost.csv

Submitted just now

Wait time 1 seconds

Execution time 0 seconds Score 0.70279

Complete

## **Part 3: Creative Solution**

#### 3.1 Open-ended Code:

You may follow the steps in part 2 again but making innovative changes like creating/using new features, using new training algorithms, etc. Make sure you explain everything clearly in part 3.2. Note that reaching the 150k MSE creative baseline is only a small portion of this part. Any creative ideas will receive most points as long as they are reasonable and clearly explained.

```
In [16]: def load and preprocess data(data path, t data path, predict path, t p
         redict path, t values = 0):
             def common preprocess(data, t data, epoch):
                 for i in range(1,t values+1):
                     data['value t-'+str(i)] = data['Daily hospital occupancy']
         - t data['value t-'+str(i)]
                                              # Use increase in hospitalization
         numbers instead of using t values directly
                 data = data.rename(columns={'Daily hospital occupancy': 'daily
         hospital occupancy'})
                 # Defining the date encoding as the number of days elapsed sin
         ce a given epoch (choice of epoch doesn't matter)
                 data['date'] = pd.to datetime(data['date'])
                 print(epoch)
                 data['date encoding'] = (data['date']-epoch).dt.days
                 # Drop the date and year week column
                 data = data.drop(['date'], axis=1)
                 data = data.drop(['year week'], axis=1)
                 return data
             # Load the features and t values for the data with known target va
         lues
             data = pd.read csv(data path)
             t data = pd.read csv(t data path)
             epoch = pd.to_datetime(data['date']).min() # Choose an epoch
             # Preprocess the data
             df = common preprocess(data, t data, epoch)
             # Load the data on which the predictions are to be made
             predict data = pd.read csv(predict path)
             index = predict data['country'] + ' ' + predict data['date'] # St
         ore the index for making the csv for submission to kaggle
             t predict data = pd.read csv(t predict path)
             # Process the data in the same way as the training data
             predict df = common preprocess(predict data, t predict data, epoch
         )
             return index, df, predict df
```

```
In [17]: | t values = 7
         index, df, pdf = load and preprocess data('train creative.csv', 'train
         _creative_t_values.csv',    'test_creative_no_label.csv',    'test_creative_
         t_values.csv', t_values)
         # Define the categorical and numerical columns for tensorflow
         CATEGORICAL COLUMNS = df.columns[0:1].to numpy().astype('object').toli
         st()
         NUMERIC COLUMNS = df.columns[1:].to numpy().tolist()
         NUMERIC_COLUMNS.remove('next_week_hospitalizations')
         # Normalize the numerical columns
         scaler = StandardScaler()
         df[NUMERIC COLUMNS] = scaler.fit transform(df[NUMERIC COLUMNS]) # Lear
         n the mean and std and nomalize
         pdf[NUMERIC COLUMNS] = scaler.transform(pdf[NUMERIC COLUMNS]) # Use th
         e learned mean and std to normalize the prediction dataset
         # Generate the final data frame and the labels
         data = df[CATEGORICAL COLUMNS + NUMERIC COLUMNS]
         pdata = pdf[CATEGORICAL COLUMNS + NUMERIC COLUMNS]
         y = df['next_week hospitalizations']
```

2020-02-12 00:00:00 2020-02-12 00:00:00

```
In [18]: # Split the data into training and validation sets. Using a fixed rand
  om_seed for consistency across models

seed = 42

train_ratio = 0.7

x_train, x_val, y_train, y_val = train_test_split(data, y, test_size =
  1 - train_ratio, random_state = seed)
```

```
In [19]: # Tensorflow takes a tensorflow dataset for it's models
         def create tf df(df, labels, shuffle = True, batch size = 32):
             ds = tf.data.Dataset.from_tensor_slices((dict(df), labels))
             if shuffle:
                 ds = ds.shuffle(buffer_size = len(df))
             ds = ds.batch(batch size)
             return ds
         def create_pdf(df, batch_size = 1):
             ds = tf.data.Dataset.from_tensor_slices(dict(pdf))
             ds = ds.batch(batch size)
             return ds
         batch size = 40
         # Define the tensorflow datasets
         train_df = create_tf_df(x_train, y_train, shuffle = False, batch_size
         = batch size)
         val_df = create_tf_df(x_val, y_val, shuffle = False, batch_size = batc
         h size)
         pdf df = create pdf(pdf)
```

```
In [20]: feature columns = []
         # Define the feature columns for creating a tensorflow.keras features
         for feature name in CATEGORICAL COLUMNS:
             vocabulary = data[feature name].unique()
             feature columns.append(tf.feature column.indicator column(tf.featu
         re column.categorical column with vocabulary list(feature name, vocabu
         lary)))
         for feature name in NUMERIC COLUMNS:
             feature columns.append(tf.feature column.numeric column(feature na
         me, dtype = tf.float64))
         feature layer = tf.keras.layers.DenseFeatures(feature columns)
         # Define a learning rate schedule for the optimizer
         initial lr = 0.001
         # lr schedule = tf.keras.optimizers.schedules.ExponentialDecay(
               initial lr,
         #
               decay steps = 100000,
               decay rate = 0.96,
               staircase = True)
         # Create a neural network with l1 l2 regularization using tf.keras.Seq
         uential
         model = tf.keras.Sequential([
             feature layer,
             tf.keras.layers.Dense(20, activation = 'relu', kernel regularizer
         = tf.keras.regularizers.l1_l2(l1=0.2, l2=0.01)),
             tf.keras.layers.Dense(20, activation = 'relu', kernel regularizer
         = tf.keras.regularizers.l1_l2(l1=0.2, l2=0.01)),
             tf.keras.layers.Dense(20, activation = 'relu', kernel regularizer
         = tf.keras.regularizers.l1 l2(l1=0.2, l2=0.01)),
             tf.keras.layers.Dense(1)
         ])
         # Define the optimizer for learning the weights of the define model
         optimizer = tf.optimizers.RMSprop(learning rate = initial lr)
         # Compile the tensorflow model with a mean squared error loss
         model.compile(loss = 'mse',
                       optimizer = optimizer,
                       metrics=['mse'])
```

In [21]: # Fit the model on the training set and check against the validation s
et
history = model.fit(train\_df, validation\_data = val\_df, epochs = 1500)

Epoch 1/1500

WARNING:tensorflow:Layer dense\_features\_1 is casting an input tensor f rom dtype float64 to the layer's dtype of float32, which is new behavi or in TensorFlow 2. The layer has dtype float32 because it's dtype de faults to floatx.

If you intended to run this layer in float32, you can safely ignore th is warning. If in doubt, this warning is likely only an issue if you a re porting a TensorFlow 1.X model to TensorFlow 2.

To change all layers to have dtype float64 by default, call `tf.keras. backend.set\_floatx('float64')`. To change just this layer, pass dtype ='float64' to the layer constructor. If you are the author of this lay er, you can disable autocasting by passing autocast=False to the base Layer constructor.

```
0000 - mse: 41434212.0000 - val loss: 38948392.0000 - val mse: 3894834
4.0000
Epoch 2/1500
0000 - mse: 41378932.0000 - val loss: 38845880.0000 - val mse: 3884583
6.0000
Epoch 3/1500
0000 - mse: 41157556.0000 - val loss: 38504532.0000 - val mse: 3850446
8.0000
Epoch 4/1500
0000 - mse: 40567896.0000 - val loss: 37719932.0000 - val mse: 3771987
6.0000
Epoch 5/1500
0000 - mse: 39337376.0000 - val loss: 36212508.0000 - val mse: 3621244
0.0000
Epoch 6/1500
0000 - mse: 37135232.0000 - val loss: 33703272.0000 - val mse: 3370320
4.0000
Epoch 7/1500
0000 - mse: 33653332.0000 - val loss: 29977070.0000 - val mse: 2997698
6.0000
Epoch 8/1500
0000 - mse: 28764262.0000 - val loss: 25060424.0000 - val mse: 2506033
8.0000
Epoch 9/1500
0000 - mse: 22690508.0000 - val loss: 19335870.0000 - val mse: 1933577
0.0000
Epoch 10/1500
- mse: 16427592.000 - 1s 7ms/step - loss: 16240570.0000 - mse: 1624046
8.0000 - val loss: 13803723.0000 - val mse: 13803614.0000
Epoch 11/1500
```

```
0000 - mse: 10990863.0000 - val loss: 9997829.0000 - val mse: 9997713.
0000
Epoch 12/1500
000 - mse: 8361987.5000 - val loss: 8465506.0000 - val mse: 8465387.00
Epoch 13/1500
000 - mse: 7352270.0000 - val loss: 7532733.0000 - val mse: 7532615.00
00
Epoch 14/1500
000 - mse: 6585991.5000 - val loss: 6689995.5000 - val mse: 6689875.50
00
Epoch 15/1500
000 - mse: 5879274.0000 - val loss: 5936408.0000 - val mse: 5936287.00
Epoch 16/1500
000 - mse: 5245110.0000 - val loss: 5294216.5000 - val mse: 5294096.50
00
Epoch 17/1500
000 - mse: 4688118.5000 - val loss: 4761369.5000 - val mse: 4761248.00
00
Epoch 18/1500
000 - mse: 4206740.0000 - val loss: 4314621.0000 - val mse: 4314499.00
00
Epoch 19/1500
70/70 [============================] - 1s 9ms/step - loss: 3782889.5
000 - mse: 3782766.5000 - val loss: 3924845.5000 - val mse: 3924722.75
00
Epoch 20/1500
7500 - mse: 3402321.7500 - val loss: 3572698.5000 - val mse: 3572574.0
000
Epoch 21/1500
500 - mse: 3056953.5000 - val_loss: 3249785.0000 - val_mse: 3249661.50
00
Epoch 22/1500
70/70 [============================] - 1s 10ms/step - loss: 2743254.
5000 - mse: 2743131.2500 - val loss: 2952328.2500 - val mse: 2952203.7
500
Epoch 23/1500
500 - mse: 2459765.0000 - val loss: 2677356.2500 - val mse: 2677231.75
00
Epoch 24/1500
2500 - mse: 2204785.0000 - val_loss: 2423822.5000 - val_mse: 2423697.2
500
Epoch 25/1500
3750 - mse: 1977645.3750 - val loss: 2190470.7500 - val mse: 2190344.2
```

```
500
Epoch 26/1500
750 - mse: 1777930.2500 - val loss: 1976028.8750 - val mse: 1975901.75
00
Epoch 27/1500
500 - mse: 1603088.8750 - val loss: 1786271.6250 - val mse: 1786143.37
50
Epoch 28/1500
750 - mse: 1453575.0000 - val_loss: 1618650.3750 - val_mse: 1618521.87
Epoch 29/1500
70/70 [============================] - 0s 2ms/step - loss: 1326378.0
000 - mse: 1326249.0000 - val loss: 1469669.0000 - val mse: 1469539.50
00
Epoch 30/1500
500 - mse: 1218327.8750 - val loss: 1338601.2500 - val_mse: 1338471.37
50
Epoch 31/1500
250 - mse: 1127140.5000 - val_loss: 1225101.0000 - val mse: 1224970.75
00
Epoch 32/1500
250 - mse: 1049719.0000 - val loss: 1124422.3750 - val mse: 1124291.87
Epoch 33/1500
70/70 [===========================] - 0s 2ms/step - loss: 982668.68
75 - mse: 982537.8125 - val loss: 1034978.6875 - val mse: 1034847.8750
Epoch 34/1500
75 - mse: 923462.1250 - val loss: 954337.9375 - val mse: 954206.6875
Epoch 35/1500
50 - mse: 872165.9375 - val_loss: 882307.3750 - val_mse: 882176.0625
Epoch 36/1500
50 - mse: 826782.0000 - val_loss: 817713.7500 - val_mse: 817582.3750
Epoch 37/1500
75 - mse: 786151.3125 - val loss: 759521.1875 - val mse: 759389.5625
Epoch 38/1500
70/70 [============================] - 0s 2ms/step - loss: 750233.75
00 - mse: 750102.2500 - val_loss: 707906.3750 - val_mse: 707774.8750
Epoch 39/1500
50 - mse: 718214.6875 - val_loss: 662354.8125 - val_mse: 662223.1875
Epoch 40/1500
00 - mse: 689669.6875 - val_loss: 621915.3750 - val_mse: 621783.5625
Epoch 41/1500
25 - mse: 663978.4375 - val loss: 586258.3750 - val mse: 586126.5000
Epoch 42/1500
```

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00 - mse: 640886.0625 - val_loss: 554803.9375 - val_mse: 554672.1875
Epoch 43/1500
75 - mse: 620405.5625 - val loss: 527562.3750 - val mse: 527430.6875
Epoch 44/1500
50 - mse: 602240.1875 - val loss: 503258.0625 - val mse: 503126.2500
Epoch 45/1500
25 - mse: 585843.5625 - val loss: 481756.8438 - val mse: 481625.0938
Epoch 46/1500
00 - mse: 571367.3750 - val loss: 462540.1875 - val mse: 462408.2812
Epoch 47/1500
00 - mse: 558337.4375 - val loss: 445891.5000 - val mse: 445759.5000
Epoch 48/1500
00 - mse: 546606.4375 - val loss: 431251.9062 - val_mse: 431119.8125
Epoch 49/1500
00 - mse: 536042.8125 - val loss: 419034.7812 - val mse: 418902.6250
Epoch 50/1500
50 - mse: 526881.3750 - val loss: 408165.3125 - val mse: 408033.0938
Epoch 51/1500
75 - mse: 518519.6875 - val loss: 398533.1875 - val mse: 398400.8438
Epoch 52/1500
62 - mse: 510846.3438 - val loss: 390035.5625 - val mse: 389903.1562
Epoch 53/1500
50 - mse: 503885.2812 - val_loss: 382517.6875 - val_mse: 382385.1875
Epoch 54/1500
62 - mse: 497949.0625 - val loss: 375534.7188 - val mse: 375402.0625
Epoch 55/1500
70/70 [============================] - 0s 2ms/step - loss: 492261.75
00 - mse: 492128.9688 - val_loss: 369810.0938 - val_mse: 369677.3438
Epoch 56/1500
12 - mse: 487119.8438 - val loss: 364233.6562 - val mse: 364100.7812
Epoch 57/1500
88 - mse: 482336.5312 - val loss: 359527.5312 - val mse: 359394.5312
Epoch 58/1500
38 - mse: 477972.0938 - val_loss: 355254.7188 - val_mse: 355121.6875
Epoch 59/1500
25 - mse: 473811.4688 - val_loss: 351838.4062 - val_mse: 351705.1875
Epoch 60/1500
75 - mse: 470180.9375 - val loss: 348324.9375 - val mse: 348191.7188
Epoch 61/1500
```

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88 - mse: 466548.1562 - val loss: 345390.2188 - val mse: 345256.8750
Epoch 62/1500
00 - mse: 463237.6562 - val loss: 342735.1562 - val mse: 342601.6250
Epoch 63/1500
62 - mse: 460224.2500 - val loss: 340127.4375 - val mse: 339993.8750
Epoch 64/1500
25 - mse: 457282.0000 - val loss: 337910.1562 - val mse: 337776.4688
Epoch 65/1500
12 - mse: 454780.2812 - val_loss: 335743.7188 - val_mse: 335610.0312
Epoch 66/1500
25 - mse: 452159.8750 - val loss: 333847.3438 - val mse: 333713.4688
Epoch 67/1500
75 - mse: 449638.7188 - val loss: 332080.3750 - val mse: 331946.4688
Epoch 68/1500
70/70 [===========================] - 0s 3ms/step - loss: 447408.25
00 - mse: 447274.2188 - val loss: 330425.0938 - val mse: 330291.0625
Epoch 69/1500
50 - mse: 445019.4375 - val loss: 328900.7500 - val mse: 328766.5938
Epoch 70/1500
50 - mse: 442772.4688 - val loss: 327613.2188 - val mse: 327478.9688
Epoch 71/1500
50 - mse: 440837.1875 - val loss: 326298.6562 - val mse: 326164.2812
Epoch 72/1500
38 - mse: 438812.2188 - val loss: 325139.1875 - val mse: 325004.7500
Epoch 73/1500
38 - mse: 437043.8750 - val loss: 323892.7500 - val mse: 323758.1562
Epoch 74/1500
mse: 414974.312 - 0s 3ms/step - loss: 435339.2500 - mse: 435204.6875 -
val loss: 322832.3125 - val mse: 322697.7188
Epoch 75/1500
12 - mse: 433446.9062 - val loss: 321931.4375 - val mse: 321796.8125
Epoch 76/1500
50 - mse: 431758.1875 - val loss: 320986.9688 - val mse: 320852.2812
Epoch 77/1500
75 - mse: 430119.2500 - val loss: 320014.4375 - val mse: 319879.5312
Epoch 78/1500
75 - mse: 428683.6250 - val loss: 319103.9688 - val mse: 318969.0625
Epoch 79/1500
00 - mse: 427077.8438 - val loss: 318433.5000 - val mse: 318298.4062
```

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Epoch 80/1500
12 - mse: 425562.8750 - val loss: 317707.6250 - val mse: 317572.5625
Epoch 81/1500
875 - mse: 424139.0312 - val_loss: 316857.5938 - val mse: 316722.4062
Epoch 82/1500
562 - mse: 422676.0625 - val_loss: 316174.9688 - val mse: 316039.7812
Epoch 83/1500
38 - mse: 421276.0938 - val_loss: 315532.6875 - val_mse: 315397.3438
Epoch 84/1500
938 - mse: 419929.2188 - val loss: 314772.0625 - val mse: 314636.6562
Epoch 85/1500
50 - mse: 418706.1250 - val loss: 314009.3438 - val mse: 313873.8750
Epoch 86/1500
062 - mse: 417380.0938 - val loss: 313346.5625 - val mse: 313210.9688
Epoch 87/1500
00 - mse: 416140.9062 - val_loss: 312661.0000 - val_mse: 312525.3438
Epoch 88/1500
88 - mse: 414933.9062 - val loss: 312005.8750 - val mse: 311870.2188
Epoch 89/1500
62 - mse: 413696.0000 - val loss: 311407.3750 - val mse: 311271.5938
Epoch 90/1500
75 - mse: 412659.1562 - val loss: 310681.6875 - val mse: 310545.9062
Epoch 91/1500
12 - mse: 411450.8750 - val loss: 310118.7188 - val mse: 309982.8125
Epoch 92/1500
12 - mse: 410300.5938 - val loss: 309541.8750 - val mse: 309405.8750
Epoch 93/1500
00 - mse: 409154.6875 - val loss: 308998.8750 - val mse: 308862.7812
Epoch 94/1500
50 - mse: 408158.4375 - val loss: 308411.6562 - val mse: 308275.5000
Epoch 95/1500
88 - mse: 407019.9062 - val loss: 307914.5312 - val mse: 307778.3438
Epoch 96/1500
70/70 [============================] - 0s 2ms/step - loss: 406028.25
00 - mse: 405892.0000 - val loss: 307384.0938 - val mse: 307247.7812
Epoch 97/1500
50 - mse: 405042.5312 - val loss: 306755.6562 - val mse: 306619.2500
Epoch 98/1500
00 - mse: 403934.6875 - val loss: 306296.6250 - val mse: 306160.1562
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Epoch 99/1500
62 - mse: 402892.7500 - val loss: 305811.7188 - val mse: 305675.0938
Epoch 100/1500
25 - mse: 401935.5938 - val loss: 305234.6875 - val mse: 305098.0625
Epoch 101/1500
50 - mse: 401043.7500 - val loss: 304718.2500 - val mse: 304581.5625
Epoch 102/1500
00 - mse: 400049.7500 - val_loss: 304288.0000 - val_mse: 304151.1562
Epoch 103/1500
38 - mse: 399159.5000 - val loss: 303807.6250 - val mse: 303670.7188
Epoch 104/1500
25 - mse: 398141.8125 - val loss: 303344.2812 - val mse: 303207.2188
Epoch 105/1500
88 - mse: 397336.8750 - val loss: 302839.3125 - val mse: 302702.1875
Epoch 106/1500
00 - mse: 396472.4375 - val_loss: 302385.7812 - val_mse: 302248.5625
Epoch 107/1500
75 - mse: 395500.8125 - val loss: 301814.7812 - val mse: 301677.5000
Epoch 108/1500
25 - mse: 394692.7500 - val loss: 301223.0938 - val mse: 301085.8438
Epoch 109/1500
25 - mse: 393830.4375 - val loss: 300749.3125 - val mse: 300611.8438
Epoch 110/1500
12 - mse: 392900.8438 - val loss: 300250.8438 - val mse: 300113.3438
Epoch 111/1500
50 - mse: 392056.6250 - val loss: 299768.6875 - val mse: 299631.0938
Epoch 112/1500
75 - mse: 391292.6562 - val loss: 299315.9688 - val mse: 299178.2188
Epoch 113/1500
50 - mse: 390367.5938 - val loss: 298825.7188 - val mse: 298687.9375
Epoch 114/1500
75 - mse: 389564.7500 - val loss: 298347.3125 - val mse: 298209.4375
Epoch 115/1500
38 - mse: 388810.5312 - val loss: 297879.9688 - val mse: 297742.0312
Epoch 116/1500
12 - mse: 387914.2188 - val loss: 297421.2812 - val mse: 297283.1562
Epoch 117/1500
00 - mse: 387181.3750 - val loss: 296957.9062 - val mse: 296819.7812
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Epoch 118/1500
62 - mse: 386365.5312 - val loss: 296525.4375 - val mse: 296387.1250
Epoch 119/1500
75 - mse: 385656.7812 - val loss: 296061.9688 - val mse: 295923.6250
Epoch 120/1500
50 - mse: 384797.8750 - val loss: 295670.0312 - val mse: 295531.6250
Epoch 121/1500
88 - mse: 384096.7812 - val_loss: 295251.2500 - val_mse: 295112.7812
Epoch 122/1500
38 - mse: 383188.2500 - val loss: 294810.5312 - val mse: 294672.0000
Epoch 123/1500
00 - mse: 382450.2188 - val loss: 294299.5625 - val mse: 294160.8750
Epoch 124/1500
88 - mse: 381583.8438 - val loss: 293801.8438 - val mse: 293663.0938
Epoch 125/1500
38 - mse: 380851.0938 - val_loss: 293261.7812 - val_mse: 293122.9062
Epoch 126/1500
75 - mse: 380044.0625 - val loss: 292750.0312 - val mse: 292611.1250
Epoch 127/1500
62 - mse: 379311.4375 - val loss: 292257.4062 - val mse: 292118.3750
Epoch 128/1500
12 - mse: 378446.8125 - val loss: 291736.8750 - val mse: 291597.6875
Epoch 129/1500
12 - mse: 377658.0938 - val loss: 291214.2188 - val mse: 291075.0000
Epoch 130/1500
12 - mse: 376821.0312 - val loss: 290673.8438 - val mse: 290534.5938
Epoch 131/1500
50 - mse: 376085.3438 - val loss: 290151.4375 - val mse: 290011.9688
Epoch 132/1500
62 - mse: 375236.6562 - val loss: 289368.2188 - val mse: 289228.7188
Epoch 133/1500
38 - mse: 373974.5938 - val loss: 288318.0312 - val mse: 288178.3438
Epoch 134/1500
00 - mse: 372402.8125 - val loss: 286808.7500 - val mse: 286669.0000
Epoch 135/1500
62 - mse: 369178.7812 - val loss: 285597.4375 - val mse: 285457.5000
Epoch 136/1500
62 - mse: 365663.4062 - val loss: 283614.7188 - val mse: 283474.5000
```

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Epoch 137/1500
25 - mse: 360455.9062 - val loss: 281265.7500 - val mse: 281125.4688
Epoch 138/1500
12 - mse: 356545.6562 - val loss: 279439.5000 - val mse: 279299.0938
Epoch 139/1500
25 - mse: 353094.8438 - val loss: 278349.5625 - val mse: 278208.9062
Epoch 140/1500
12 - mse: 350753.4062 - val_loss: 277403.4375 - val_mse: 277262.6250
Epoch 141/1500
75 - mse: 349117.0938 - val loss: 276516.0938 - val mse: 276375.0938
Epoch 142/1500
50 - mse: 347196.1562 - val loss: 275910.0625 - val mse: 275768.9375
Epoch 143/1500
62 - mse: 345905.8125 - val loss: 275207.3125 - val mse: 275066.0312
Epoch 144/1500
25 - mse: 344271.0312 - val_loss: 274552.4688 - val_mse: 274410.9688
Epoch 145/1500
00 - mse: 342926.7188 - val loss: 274183.8438 - val mse: 274042.2500
Epoch 146/1500
12 - mse: 341691.8125 - val loss: 273623.6250 - val mse: 273481.8750
Epoch 147/1500
88 - mse: 340213.3438 - val loss: 273017.9688 - val mse: 272876.0000
Epoch 148/1500
38 - mse: 339043.3125 - val loss: 272305.3750 - val mse: 272163.2500
Epoch 149/1500
00 - mse: 337786.0312 - val loss: 271486.2500 - val mse: 271344.0000
Epoch 150/1500
25 - mse: 336782.7188 - val loss: 271041.2500 - val mse: 270898.8750
Epoch 151/1500
62 - mse: 335822.8125 - val loss: 270524.4375 - val mse: 270381.8750
Epoch 152/1500
25 - mse: 334636.0312 - val loss: 269944.2188 - val mse: 269801.4688
Epoch 153/1500
70/70 [============================] - Os 3ms/step - loss: 333552.90
62 - mse: 333410.2500 - val loss: 269366.8750 - val mse: 269224.0000
Epoch 154/1500
00 - mse: 332327.4375 - val loss: 268914.7500 - val mse: 268771.7812
Epoch 155/1500
62 - mse: 331174.0625 - val loss: 268452.0000 - val mse: 268308.8125
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Epoch 156/1500
12 - mse: 329995.4375 - val loss: 268034.4688 - val mse: 267891.0625
Epoch 157/1500
62 - mse: 328945.9688 - val loss: 267798.9375 - val mse: 267655.4375
Epoch 158/1500
25 - mse: 328088.5625 - val loss: 267332.7500 - val mse: 267189.0938
Epoch 159/1500
75 - mse: 326937.0625 - val_loss: 266791.1562 - val_mse: 266647.4062
Epoch 160/1500
88 - mse: 325874.4375 - val loss: 266367.1562 - val mse: 266223.2188
Epoch 161/1500
12 - mse: 324753.4062 - val loss: 266083.7500 - val mse: 265939.7188
Epoch 162/1500
88 - mse: 323826.6250 - val loss: 265830.7500 - val mse: 265686.5938
Epoch 163/1500
38 - mse: 322612.2500 - val_loss: 265469.1250 - val_mse: 265324.7500
Epoch 164/1500
88 - mse: 321514.8750 - val loss: 264936.9375 - val mse: 264792.5312
Epoch 165/1500
62 - mse: 320463.1875 - val loss: 264405.1250 - val mse: 264260.4375
Epoch 166/1500
38 - mse: 319366.2500 - val loss: 263922.7500 - val mse: 263778.0000
Epoch 167/1500
50 - mse: 318411.3438 - val loss: 263643.5312 - val mse: 263498.6562
Epoch 168/1500
62 - mse: 317439.3125 - val loss: 263092.4375 - val mse: 262947.4062
Epoch 169/1500
38 - mse: 316560.0625 - val loss: 262505.5938 - val mse: 262360.4688
Epoch 170/1500
75 - mse: 315713.1562 - val loss: 262144.3750 - val mse: 261999.1094
Epoch 171/1500
38 - mse: 314821.4375 - val loss: 261479.3906 - val mse: 261333.9688
Epoch 172/1500
70/70 [============================] - Os 3ms/step - loss: 314077.03
12 - mse: 313931.5625 - val loss: 261070.1562 - val mse: 260924.6094
Epoch 173/1500
50 - mse: 313153.8750 - val loss: 260717.1094 - val mse: 260571.5000
Epoch 174/1500
38 - mse: 312353.6875 - val loss: 260155.9375 - val mse: 260010.1719
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Epoch 175/1500
62 - mse: 311542.6875 - val loss: 259637.3281 - val mse: 259491.4844
Epoch 176/1500
88 - mse: 310739.3125 - val loss: 259302.0156 - val mse: 259156.0156
Epoch 177/1500
62 - mse: 309894.4375 - val loss: 258923.4531 - val mse: 258777.3594
Epoch 178/1500
88 - mse: 309231.0938 - val_loss: 258392.4062 - val_mse: 258246.1562
Epoch 179/1500
00 - mse: 308521.3125 - val loss: 258051.3125 - val mse: 257904.9688
Epoch 180/1500
00 - mse: 307832.6875 - val loss: 257710.5312 - val mse: 257564.0156
Epoch 181/1500
12 - mse: 307122.5312 - val loss: 257193.0625 - val mse: 257046.5312
Epoch 182/1500
75 - mse: 306459.3438 - val_loss: 256715.1094 - val_mse: 256568.4062
Epoch 183/1500
25 - mse: 305757.1875 - val loss: 256476.4219 - val mse: 256329.6562
Epoch 184/1500
50 - mse: 305047.3750 - val loss: 256079.3594 - val mse: 255932.3906
Epoch 185/1500
88 - mse: 304398.9062 - val loss: 255570.5156 - val mse: 255423.5781
Epoch 186/1500
00 - mse: 303771.3125 - val loss: 255340.6562 - val mse: 255193.5469
Epoch 187/1500
62 - mse: 302949.5938 - val loss: 255106.1875 - val mse: 254959.0156
Epoch 188/1500
00 - mse: 302507.3125 - val loss: 254645.7500 - val mse: 254498.5156
Epoch 189/1500
50 - mse: 301871.3750 - val loss: 254294.8281 - val mse: 254147.3750
Epoch 190/1500
50 - mse: 301226.7812 - val loss: 253769.7344 - val mse: 253622.1875
Epoch 191/1500
75 - mse: 300669.7188 - val loss: 253501.4531 - val mse: 253353.9062
Epoch 192/1500
12 - mse: 300062.2812 - val loss: 253287.2031 - val mse: 253139.5000
Epoch 193/1500
70/70 [============================] - Os 3ms/step - loss: 299731.75
00 - mse: 299584.0938 - val loss: 252986.4688 - val mse: 252838.7500
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Epoch 194/1500
38 - mse: 298841.5312 - val loss: 252671.2812 - val mse: 252523.4531
Epoch 195/1500
75 - mse: 298315.9375 - val loss: 252607.8906 - val mse: 252459.9375
Epoch 196/1500
12 - mse: 297708.4062 - val_loss: 252406.3125 - val_mse: 252258.2500
Epoch 197/1500
38 - mse: 296999.8438 - val_loss: 252324.3125 - val_mse: 252176.1875
Epoch 198/1500
00 - mse: 296710.2500 - val loss: 251748.0156 - val mse: 251599.8125
Epoch 199/1500
50 - mse: 296060.4062 - val loss: 251643.5000 - val mse: 251495.2969
Epoch 200/1500
50 - mse: 295500.6250 - val loss: 251339.5000 - val mse: 251191.0938
Epoch 201/1500
00 - mse: 295052.0000 - val_loss: 250928.1406 - val_mse: 250779.6875
Epoch 202/1500
75 - mse: 294474.7188 - val loss: 250737.0156 - val mse: 250588.5000
Epoch 203/1500
00 - mse: 293851.4688 - val loss: 250554.6562 - val mse: 250406.0156
Epoch 204/1500
62 - mse: 293550.7812 - val loss: 250051.2969 - val mse: 249902.5625
Epoch 205/1500
75 - mse: 292979.4375 - val loss: 249975.2969 - val mse: 249826.4844
Epoch 206/1500
38 - mse: 292440.6250 - val loss: 249679.5156 - val mse: 249530.6719
Epoch 207/1500
25 - mse: 291898.2500 - val loss: 249702.1562 - val mse: 249553.2344
Epoch 208/1500
75 - mse: 291489.3438 - val loss: 249247.2500 - val mse: 249098.2500
Epoch 209/1500
00 - mse: 291096.0000 - val loss: 248789.4375 - val mse: 248640.2656
Epoch 210/1500
75 - mse: 290569.0625 - val loss: 248616.4219 - val mse: 248467.2031
Epoch 211/1500
88 - mse: 290150.8438 - val loss: 248410.2812 - val mse: 248260.9531
Epoch 212/1500
62 - mse: 289620.2500 - val loss: 248085.5312 - val mse: 247936.2344
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Epoch 213/1500
50 - mse: 289140.0000 - val loss: 247717.3750 - val mse: 247567.9531
Epoch 214/1500
38 - mse: 288819.0000 - val loss: 247353.5469 - val mse: 247204.0938
Epoch 215/1500
50 - mse: 288403.4688 - val loss: 247114.2188 - val mse: 246964.6875
Epoch 216/1500
62 - mse: 287910.6562 - val_loss: 246749.1094 - val_mse: 246599.4688
Epoch 217/1500
38 - mse: 287502.3438 - val loss: 246708.2344 - val mse: 246558.5625
Epoch 218/1500
75 - mse: 287026.2812 - val loss: 246624.8906 - val mse: 246475.1094
Epoch 219/1500
62 - mse: 286531.7500 - val loss: 246381.0781 - val mse: 246231.2031
Epoch 220/1500
50 - mse: 286174.8750 - val_loss: 246086.3750 - val_mse: 245936.4531
Epoch 221/1500
88 - mse: 285739.3125 - val loss: 245842.6719 - val mse: 245692.6875
Epoch 222/1500
75 - mse: 285340.0312 - val loss: 245231.6562 - val mse: 245081.5781
Epoch 223/1500
38 - mse: 284857.0625 - val loss: 245099.7500 - val mse: 244949.5938
Epoch 224/1500
00 - mse: 284432.6562 - val loss: 244841.1719 - val mse: 244690.9688
Epoch 225/1500
88 - mse: 283955.5625 - val loss: 244831.8125 - val mse: 244681.5781
Epoch 226/1500
88 - mse: 283707.0625 - val loss: 244241.4219 - val mse: 244091.1094
Epoch 227/1500
25 - mse: 283242.0625 - val loss: 243997.4844 - val mse: 243847.0625
Epoch 228/1500
88 - mse: 282820.1875 - val loss: 243918.0781 - val mse: 243767.5938
Epoch 229/1500
12 - mse: 282546.1875 - val loss: 243543.8906 - val mse: 243393.4375
Epoch 230/1500
25 - mse: 282248.9062 - val loss: 243097.4219 - val mse: 242946.8906
Epoch 231/1500
50 - mse: 281698.8438 - val loss: 242826.7500 - val mse: 242676.2031
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Epoch 232/1500
25 - mse: 281350.7812 - val loss: 242596.7031 - val mse: 242446.0469
Epoch 233/1500
12 - mse: 280841.2500 - val loss: 242503.6250 - val mse: 242352.9062
Epoch 234/1500
88 - mse: 280646.3438 - val loss: 242103.7812 - val mse: 241952.9844
Epoch 235/1500
38 - mse: 280220.2812 - val_loss: 241765.2188 - val_mse: 241614.3438
Epoch 236/1500
62 - mse: 279889.4062 - val loss: 241453.3438 - val mse: 241302.4531
Epoch 237/1500
38 - mse: 279531.7188 - val loss: 241042.1875 - val mse: 240891.1875
Epoch 238/1500
38 - mse: 279265.1562 - val loss: 240599.2812 - val mse: 240448.1875
Epoch 239/1500
75 - mse: 278957.1250 - val_loss: 240312.1875 - val_mse: 240161.0469
Epoch 240/1500
88 - mse: 278613.6562 - val loss: 239783.4375 - val mse: 239632.2188
Epoch 241/1500
50 - mse: 278232.6562 - val loss: 239470.6875 - val mse: 239319.4688
Epoch 242/1500
50 - mse: 277965.5938 - val loss: 239189.0312 - val mse: 239037.7500
Epoch 243/1500
75 - mse: 277511.0000 - val loss: 239036.3594 - val mse: 238885.0000
Epoch 244/1500
38 - mse: 277351.3438 - val loss: 238607.0625 - val mse: 238455.7031
Epoch 245/1500
25 - mse: 277016.9062 - val loss: 238319.9531 - val mse: 238168.4844
Epoch 246/1500
25 - mse: 276784.0938 - val loss: 237974.5312 - val mse: 237822.9844
Epoch 247/1500
12 - mse: 276422.3750 - val loss: 237766.9375 - val mse: 237615.3594
Epoch 248/1500
25 - mse: 276139.5625 - val loss: 237497.5781 - val mse: 237345.9219
Epoch 249/1500
12 - mse: 275806.0938 - val loss: 237143.3281 - val mse: 236991.5781
Epoch 250/1500
75 - mse: 275453.8750 - val loss: 236982.7188 - val mse: 236830.9375
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Epoch 251/1500
75 - mse: 275284.5000 - val loss: 236550.5625 - val mse: 236398.6875
Epoch 252/1500
00 - mse: 274942.6562 - val loss: 236336.5938 - val mse: 236184.7031
Epoch 253/1500
62 - mse: 274738.5938 - val loss: 235966.9531 - val mse: 235815.0156
Epoch 254/1500
38 - mse: 274435.2500 - val_loss: 235649.6094 - val_mse: 235497.6094
Epoch 255/1500
88 - mse: 274164.5000 - val loss: 235337.9062 - val mse: 235185.7969
Epoch 256/1500
75 - mse: 273893.4062 - val loss: 235041.9531 - val mse: 234889.7969
Epoch 257/1500
00 - mse: 273667.8750 - val loss: 234720.5938 - val mse: 234568.3750
Epoch 258/1500
75 - mse: 273248.5938 - val_loss: 234576.8594 - val_mse: 234424.5938
Epoch 259/1500
12 - mse: 273217.8438 - val loss: 234138.5938 - val mse: 233986.2500
Epoch 260/1500
25 - mse: 272862.2812 - val loss: 233880.5156 - val mse: 233728.1406
Epoch 261/1500
12 - mse: 272596.4688 - val loss: 233550.0781 - val mse: 233397.5625
Epoch 262/1500
00 - mse: 272377.1250 - val loss: 233206.7656 - val mse: 233054.2656
Epoch 263/1500
75 - mse: 271951.0312 - val loss: 233056.1406 - val mse: 232903.6250
Epoch 264/1500
12 - mse: 271834.9375 - val loss: 232599.7344 - val mse: 232447.1406
Epoch 265/1500
70/70 [============================] - 0s 2ms/step - loss: 271684.87
50 - mse: 271532.3438 - val loss: 232272.5156 - val mse: 232119.8906
Epoch 266/1500
00 - mse: 271277.0625 - val loss: 232089.2031 - val mse: 231936.5156
Epoch 267/1500
70/70 [============================] - Os 2ms/step - loss: 271260.90
62 - mse: 271108.2812 - val loss: 231743.4844 - val mse: 231590.6875
Epoch 268/1500
00 - mse: 270747.5312 - val loss: 231457.7969 - val mse: 231304.9688
Epoch 269/1500
38 - mse: 270514.8750 - val loss: 231122.6250 - val mse: 230969.7188
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Epoch 270/1500
25 - mse: 270260.6562 - val loss: 230812.4219 - val mse: 230659.4219
Epoch 271/1500
50 - mse: 269927.3750 - val loss: 230680.0000 - val mse: 230526.9844
Epoch 272/1500
25 - mse: 269864.5938 - val loss: 230273.3438 - val mse: 230120.2344
Epoch 273/1500
25 - mse: 269605.4688 - val_loss: 230050.4375 - val_mse: 229897.2500
Epoch 274/1500
62 - mse: 269340.5000 - val loss: 229956.3906 - val mse: 229803.1562
Epoch 275/1500
12 - mse: 269015.8125 - val loss: 229921.3594 - val mse: 229768.1094
Epoch 276/1500
62 - mse: 268951.6250 - val loss: 229669.5938 - val mse: 229516.2812
Epoch 277/1500
62 - mse: 268631.5625 - val_loss: 229492.3281 - val_mse: 229338.8594
Epoch 278/1500
88 - mse: 268414.0000 - val loss: 229284.0469 - val mse: 229130.5625
Epoch 279/1500
50 - mse: 268278.1875 - val loss: 229103.4688 - val mse: 228949.9062
Epoch 280/1500
75 - mse: 267934.9062 - val loss: 229118.2031 - val mse: 228964.5781
Epoch 281/1500
62 - mse: 267721.1875 - val loss: 228850.5469 - val mse: 228696.8906
Epoch 282/1500
12 - mse: 267521.3750 - val loss: 228651.6875 - val mse: 228497.9062
Epoch 283/1500
38 - mse: 267286.6875 - val loss: 228389.9375 - val mse: 228236.1250
Epoch 284/1500
70/70 [============================] - 0s 2ms/step - loss: 267105.71
88 - mse: 266951.8750 - val loss: 228325.6406 - val mse: 228171.7500
Epoch 285/1500
50 - mse: 266875.7812 - val loss: 228108.7969 - val mse: 227954.8438
Epoch 286/1500
00 - mse: 266661.1875 - val loss: 227890.3594 - val mse: 227736.3438
Epoch 287/1500
75 - mse: 266389.2812 - val loss: 227726.5625 - val mse: 227572.5000
Epoch 288/1500
38 - mse: 266133.1250 - val loss: 227550.3906 - val mse: 227396.2500
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Epoch 289/1500
12 - mse: 265920.5000 - val loss: 227580.4688 - val mse: 227426.2500
Epoch 290/1500
50 - mse: 265698.6875 - val loss: 227266.1719 - val mse: 227111.8594
Epoch 291/1500
25 - mse: 265487.3438 - val loss: 227016.5312 - val mse: 226862.2031
Epoch 292/1500
88 - mse: 265159.6562 - val_loss: 227006.8281 - val_mse: 226852.3906
Epoch 293/1500
12 - mse: 265074.0625 - val loss: 226738.1094 - val mse: 226583.6250
Epoch 294/1500
62 - mse: 264985.7812 - val loss: 226571.4844 - val mse: 226416.9375
Epoch 295/1500
62 - mse: 264602.1562 - val loss: 226470.5000 - val mse: 226315.8750
Epoch 296/1500
38 - mse: 264399.5312 - val_loss: 226304.7188 - val_mse: 226150.0000
Epoch 297/1500
50 - mse: 264180.4688 - val loss: 226251.0781 - val mse: 226096.3438
Epoch 298/1500
25 - mse: 263958.0938 - val loss: 226007.8125 - val mse: 225853.0000
Epoch 299/1500
00 - mse: 263727.0312 - val loss: 225892.5156 - val mse: 225737.6250
Epoch 300/1500
38 - mse: 263578.0000 - val loss: 225666.0000 - val mse: 225511.0625
Epoch 301/1500
38 - mse: 263324.9375 - val loss: 225673.5000 - val mse: 225518.5000
Epoch 302/1500
25 - mse: 263272.6250 - val loss: 225516.4375 - val mse: 225361.3594
Epoch 303/1500
70/70 [============================] - 0s 2ms/step - loss: 263046.37
50 - mse: 262891.3438 - val loss: 225371.0156 - val mse: 225215.8906
Epoch 304/1500
00 - mse: 262682.4688 - val loss: 225256.9844 - val mse: 225101.8125
Epoch 305/1500
00 - mse: 262571.9062 - val loss: 225051.1875 - val mse: 224895.8906
Epoch 306/1500
75 - mse: 262292.0312 - val loss: 224852.3281 - val mse: 224696.9844
Epoch 307/1500
70/70 [============================] - 0s 2ms/step - loss: 262197.75
00 - mse: 262042.5000 - val loss: 224726.3125 - val mse: 224570.9688
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Epoch 308/1500
44 - mse: 261920.6719 - val loss: 224688.5938 - val mse: 224533.1562
Epoch 309/1500
88 - mse: 261744.1250 - val loss: 224549.8906 - val mse: 224394.3594
Epoch 310/1500
75 - mse: 261499.0625 - val loss: 224402.2656 - val mse: 224246.6719
Epoch 311/1500
75 - mse: 261249.1875 - val_loss: 224264.9062 - val_mse: 224109.2969
Epoch 312/1500
94 - mse: 261177.7969 - val loss: 223966.6250 - val mse: 223810.9219
Epoch 313/1500
88 - mse: 260919.0938 - val loss: 223925.6250 - val mse: 223769.8594
Epoch 314/1500
50 - mse: 260865.9531 - val loss: 223815.0156 - val mse: 223659.1875
Epoch 315/1500
12 - mse: 260358.2812 - val_loss: 223944.3906 - val_mse: 223788.4844
Epoch 316/1500
81 - mse: 260370.0625 - val loss: 223545.9844 - val mse: 223390.0000
Epoch 317/1500
25 - mse: 260039.6875 - val loss: 223512.0625 - val mse: 223356.0469
Epoch 318/1500
88 - mse: 260036.0000 - val loss: 223324.4688 - val mse: 223168.3750
Epoch 319/1500
38 - mse: 259715.4219 - val loss: 223247.6250 - val mse: 223091.4688
Epoch 320/1500
88 - mse: 259654.7188 - val loss: 223041.9062 - val mse: 222885.7344
Epoch 321/1500
94 - mse: 259339.5156 - val loss: 223047.9844 - val mse: 222891.7188
Epoch 322/1500
25 - mse: 259117.1406 - val loss: 222910.2031 - val mse: 222753.8906
Epoch 323/1500
81 - mse: 258887.6406 - val loss: 222823.5625 - val mse: 222667.2500
Epoch 324/1500
56 - mse: 258779.9219 - val loss: 222680.1094 - val mse: 222523.7031
Epoch 325/1500
00 - mse: 258569.3594 - val loss: 222589.5938 - val mse: 222433.1250
Epoch 326/1500
94 - mse: 258284.2188 - val loss: 222552.5000 - val mse: 222395.9062
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Epoch 327/1500
12 - mse: 258326.5625 - val loss: 222287.9062 - val mse: 222131.2500
Epoch 328/1500
12 - mse: 258008.5000 - val loss: 222212.8438 - val mse: 222056.1250
Epoch 329/1500
31 - mse: 257865.8438 - val loss: 222049.8438 - val mse: 221893.0781
Epoch 330/1500
31 - mse: 257566.7500 - val_loss: 221865.0469 - val_mse: 221708.1875
Epoch 331/1500
56 - mse: 257509.0781 - val loss: 221725.0312 - val mse: 221568.1406
Epoch 332/1500
44 - mse: 257223.3906 - val loss: 221654.6406 - val mse: 221497.7031
Epoch 333/1500
94 - mse: 257004.7500 - val loss: 221550.5625 - val mse: 221393.5312
Epoch 334/1500
25 - mse: 256866.0938 - val_loss: 221343.5156 - val_mse: 221186.4062
Epoch 335/1500
94 - mse: 256641.1875 - val loss: 221289.9531 - val mse: 221132.8438
Epoch 336/1500
00 - mse: 256408.6406 - val loss: 221166.6406 - val mse: 221009.4375
Epoch 337/1500
50 - mse: 256177.5469 - val loss: 220996.2656 - val mse: 220839.0312
Epoch 338/1500
06 - mse: 256115.4531 - val loss: 220736.4531 - val mse: 220579.1250
Epoch 339/1500
69 - mse: 255958.5781 - val loss: 220724.0000 - val mse: 220566.6094
Epoch 340/1500
44 - mse: 255622.7500 - val loss: 220679.9062 - val mse: 220522.4688
Epoch 341/1500
70/70 [============================] - 0s 2ms/step - loss: 255688.85
94 - mse: 255531.4375 - val loss: 220387.7656 - val mse: 220230.2812
Epoch 342/1500
94 - mse: 255335.4688 - val loss: 220385.7656 - val mse: 220228.2188
Epoch 343/1500
70/70 [============================] - 0s 2ms/step - loss: 255294.71
88 - mse: 255137.1406 - val loss: 220265.9219 - val mse: 220108.2969
Epoch 344/1500
75 - mse: 255041.8594 - val loss: 220051.9062 - val mse: 219894.2188
Epoch 345/1500
12 - mse: 254717.1562 - val loss: 220013.1250 - val mse: 219855.3438
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Epoch 346/1500
44 - mse: 254570.7500 - val loss: 219882.8906 - val mse: 219725.0625
Epoch 347/1500
12 - mse: 254428.4531 - val loss: 219613.7500 - val mse: 219455.8906
Epoch 348/1500
62 - mse: 254289.0312 - val_loss: 219586.1875 - val_mse: 219428.2344
Epoch 349/1500
94 - mse: 253933.2812 - val_loss: 219497.8438 - val_mse: 219339.8125
Epoch 350/1500
19 - mse: 253768.9531 - val loss: 219212.8906 - val mse: 219054.8125
Epoch 351/1500
31 - mse: 253768.3125 - val loss: 219131.8281 - val mse: 218973.6875
Epoch 352/1500
88 - mse: 253530.4531 - val loss: 219027.9844 - val mse: 218869.7812
Epoch 353/1500
62 - mse: 253416.7812 - val_loss: 218827.4219 - val_mse: 218669.1719
Epoch 354/1500
00 - mse: 253206.0469 - val loss: 218730.3281 - val mse: 218571.9844
Epoch 355/1500
69 - mse: 252994.3125 - val loss: 218676.5000 - val mse: 218518.1250
Epoch 356/1500
19 - mse: 252855.6406 - val loss: 218426.2969 - val mse: 218267.8594
Epoch 357/1500
69 - mse: 252686.9375 - val loss: 218314.1875 - val mse: 218155.7188
Epoch 358/1500
88 - mse: 252395.7656 - val loss: 218253.3438 - val mse: 218094.7812
Epoch 359/1500
06 - mse: 252383.4219 - val loss: 217952.2188 - val mse: 217793.6250
Epoch 360/1500
70/70 [============================] - Os 2ms/step - loss: 252404.04
69 - mse: 252245.5000 - val loss: 217864.8750 - val mse: 217706.2344
Epoch 361/1500
44 - mse: 251973.1250 - val loss: 217881.4062 - val mse: 217722.6875
Epoch 362/1500
70/70 [===========================] - 0s 2ms/step - loss: 252054.26
56 - mse: 251895.6875 - val loss: 217572.6406 - val mse: 217413.8594
Epoch 363/1500
44 - mse: 251583.3594 - val loss: 217494.7031 - val mse: 217335.8594
Epoch 364/1500
69 - mse: 251325.2656 - val loss: 217234.0000 - val mse: 217075.1250
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Epoch 365/1500
94 - mse: 251365.6094 - val loss: 217079.4375 - val mse: 216920.4688
Epoch 366/1500
25 - mse: 251024.1562 - val loss: 217041.8281 - val mse: 216882.8125
Epoch 367/1500
31 - mse: 250894.1875 - val loss: 216942.0156 - val mse: 216782.9062
Epoch 368/1500
94 - mse: 250826.7812 - val_loss: 216810.1406 - val_mse: 216650.9531
Epoch 369/1500
250 - mse: 250559.0312 - val loss: 216665.8125 - val mse: 216506.5781
Epoch 370/1500
19 - mse: 250475.2812 - val loss: 216507.1406 - val mse: 216347.8281
Epoch 371/1500
312 - mse: 250230.9062 - val loss: 216409.6875 - val mse: 216250.3125
Epoch 372/1500
906 - mse: 250036.6875 - val_loss: 216303.6094 - val_mse: 216144.2344
Epoch 373/1500
719 - mse: 250035.4219 - val loss: 216099.5312 - val mse: 215940.0625
Epoch 374/1500
625 - mse: 249691.1875 - val loss: 216134.9062 - val mse: 215975.3750
Epoch 375/1500
62 - mse: 249515.4688 - val loss: 216044.1094 - val mse: 215884.5312
Epoch 376/1500
38 - mse: 249476.6406 - val loss: 215789.7969 - val mse: 215630.1875
Epoch 377/1500
31 - mse: 249274.3594 - val loss: 215841.9531 - val mse: 215682.2812
Epoch 378/1500
94 - mse: 249106.3125 - val loss: 215676.9219 - val mse: 215517.1562
Epoch 379/1500
70/70 [===========================] - 0s 2ms/step - loss: 249135.09
38 - mse: 248975.3906 - val loss: 215656.0625 - val mse: 215496.2656
Epoch 380/1500
38 - mse: 248658.5938 - val loss: 215666.6406 - val mse: 215506.7969
Epoch 381/1500
70/70 [============================] - 0s 2ms/step - loss: 248888.07
81 - mse: 248728.3281 - val loss: 215402.1250 - val mse: 215242.2031
Epoch 382/1500
88 - mse: 248426.3594 - val loss: 215427.4688 - val mse: 215267.4844
Epoch 383/1500
75 - mse: 248430.4844 - val loss: 215279.8594 - val mse: 215119.8125
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Epoch 384/1500
88 - mse: 248140.7812 - val loss: 215320.2969 - val mse: 215160.2031
Epoch 385/1500
00 - mse: 248057.4844 - val loss: 215222.6094 - val mse: 215062.4688
Epoch 386/1500
06 - mse: 247873.3281 - val_loss: 215069.8281 - val_mse: 214909.6406
Epoch 387/1500
56 - mse: 247767.9531 - val_loss: 215011.2969 - val_mse: 214851.0469
Epoch 388/1500
44 - mse: 247608.4688 - val loss: 214878.3594 - val mse: 214718.0312
Epoch 389/1500
00 - mse: 247474.4688 - val loss: 214739.8906 - val mse: 214579.5312
Epoch 390/1500
75 - mse: 247230.6406 - val loss: 214653.6875 - val mse: 214493.2656
Epoch 391/1500
88 - mse: 247202.9531 - val_loss: 214391.5469 - val_mse: 214231.0625
Epoch 392/1500
12 - mse: 246895.3438 - val loss: 214420.4531 - val mse: 214259.8750
Epoch 393/1500
25 - mse: 246780.0781 - val loss: 214178.8438 - val mse: 214018.2500
Epoch 394/1500
56 - mse: 246679.0156 - val loss: 214108.5000 - val mse: 213947.8750
Epoch 395/1500
19 - mse: 246460.8281 - val loss: 214147.2500 - val mse: 213986.5469
Epoch 396/1500
94 - mse: 246509.5781 - val loss: 213940.2500 - val mse: 213779.4688
Epoch 397/1500
88 - mse: 246247.5000 - val loss: 213943.4531 - val mse: 213782.6250
Epoch 398/1500
75 - mse: 246148.1719 - val loss: 213781.9688 - val mse: 213621.0469
Epoch 399/1500
44 - mse: 246000.9219 - val loss: 213781.0781 - val mse: 213620.1250
Epoch 400/1500
70/70 [============================] - 0s 2ms/step - loss: 246102.65
62 - mse: 245941.8125 - val loss: 213664.7656 - val mse: 213503.7500
Epoch 401/1500
31 - mse: 245638.9688 - val loss: 213673.1562 - val mse: 213512.0625
Epoch 402/1500
12 - mse: 245661.9219 - val loss: 213496.6094 - val mse: 213335.4531
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Epoch 403/1500
31 - mse: 245421.6250 - val loss: 213537.2656 - val mse: 213376.0469
Epoch 404/1500
81 - mse: 245258.8281 - val loss: 213449.5781 - val mse: 213288.2969
Epoch 405/1500
12 - mse: 245063.6250 - val_loss: 213290.4062 - val_mse: 213129.0938
Epoch 406/1500
19 - mse: 245085.7188 - val_loss: 213187.0156 - val_mse: 213025.6250
Epoch 407/1500
75 - mse: 244781.4062 - val loss: 213138.3750 - val mse: 212976.8906
Epoch 408/1500
62 - mse: 244828.5938 - val loss: 213031.8125 - val mse: 212870.2969
Epoch 409/1500
44 - mse: 244573.1250 - val loss: 212999.2969 - val mse: 212837.7500
Epoch 410/1500
38 - mse: 244430.6250 - val_loss: 212853.8125 - val_mse: 212692.2344
Epoch 411/1500
38 - mse: 244263.8750 - val loss: 212782.2188 - val mse: 212620.6094
Epoch 412/1500
75 - mse: 244181.4062 - val loss: 212796.7969 - val mse: 212635.0938
Epoch 413/1500
12 - mse: 244079.4062 - val loss: 212706.4844 - val mse: 212544.7344
Epoch 414/1500
281 - mse: 243954.1406 - val loss: 212677.6875 - val mse: 212515.8281
Epoch 415/1500
438 - mse: 243802.1406 - val loss: 212570.3125 - val mse: 212408.4688
Epoch 416/1500
500 - mse: 243630.4688 - val loss: 212530.2656 - val mse: 212368.3281
Epoch 417/1500
625 - mse: 243644.2188 - val loss: 212378.5000 - val mse: 212216.5156
Epoch 418/1500
719 - mse: 243437.2812 - val loss: 212510.9375 - val mse: 212348.8906
Epoch 419/1500
125 - mse: 243371.2344 - val loss: 212286.6875 - val mse: 212124.5625
Epoch 420/1500
38 - mse: 243088.3594 - val loss: 212316.9062 - val mse: 212154.7500
Epoch 421/1500
62 - mse: 243153.6719 - val loss: 212120.7812 - val mse: 211958.5938
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Epoch 422/1500
81 - mse: 242908.6562 - val loss: 212106.4531 - val mse: 211944.1719
Epoch 423/1500
50 - mse: 242813.6562 - val loss: 211970.8281 - val mse: 211808.5156
Epoch 424/1500
25 - mse: 242598.5781 - val loss: 211938.4844 - val mse: 211776.1094
Epoch 425/1500
38 - mse: 242730.0781 - val_loss: 211806.5312 - val_mse: 211644.1094
Epoch 426/1500
50 - mse: 242339.0938 - val loss: 211926.7969 - val mse: 211764.2656
Epoch 427/1500
31 - mse: 242352.0312 - val loss: 211709.5312 - val mse: 211547.0000
Epoch 428/1500
25 - mse: 242091.8906 - val loss: 211763.3281 - val mse: 211600.7188
Epoch 429/1500
12 - mse: 242258.5469 - val_loss: 211613.1562 - val_mse: 211450.5625
Epoch 430/1500
38 - mse: 241898.3125 - val loss: 211705.5625 - val mse: 211542.9375
Epoch 431/1500
44 - mse: 241925.8750 - val loss: 211513.5781 - val mse: 211350.8750
Epoch 432/1500
12 - mse: 241729.7031 - val loss: 211540.7969 - val mse: 211378.0000
Epoch 433/1500
00 - mse: 241532.2656 - val loss: 211468.6875 - val mse: 211305.8125
Epoch 434/1500
25 - mse: 241671.5938 - val loss: 211290.2344 - val mse: 211127.3125
Epoch 435/1500
88 - mse: 241288.9531 - val loss: 211439.2656 - val mse: 211276.3750
Epoch 436/1500
81 - mse: 241355.5000 - val loss: 211232.6406 - val mse: 211069.6250
Epoch 437/1500
88 - mse: 241103.7812 - val loss: 211311.0469 - val mse: 211148.0469
Epoch 438/1500
70/70 [===========================] - 0s 4ms/step - loss: 241227.12
50 - mse: 241064.1875 - val loss: 211092.7500 - val mse: 210929.6406
Epoch 439/1500
56 - mse: 240891.5312 - val loss: 211091.1719 - val mse: 210928.0625
Epoch 440/1500
69 - mse: 240899.4688 - val loss: 210927.6250 - val mse: 210764.4844
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Epoch 441/1500
38 - mse: 240607.0469 - val loss: 211008.0625 - val mse: 210844.8281
Epoch 442/1500
31 - mse: 240590.5938 - val loss: 210862.2812 - val mse: 210699.0000
Epoch 443/1500
56 - mse: 240635.0938 - val_loss: 210810.2188 - val mse: 210646.8594
Epoch 444/1500
812 - mse: 240259.5625 - val_loss: 210967.5312 - val_mse: 210804.2656
Epoch 445/1500
938 - mse: 240221.3750 - val loss: 210723.5781 - val mse: 210560.2031
Epoch 446/1500
906 - mse: 240067.0938 - val loss: 210692.8438 - val mse: 210529.4062
Epoch 447/1500
688 - mse: 240044.1094 - val loss: 210613.0000 - val mse: 210449.5469
Epoch 448/1500
19 - mse: 239702.0781 - val_loss: 210679.2188 - val_mse: 210515.7344
Epoch 449/1500
00 - mse: 239872.5312 - val loss: 210516.0469 - val mse: 210352.5000
Epoch 450/1500
19 - mse: 239660.2656 - val loss: 210612.4531 - val mse: 210448.8281
Epoch 451/1500
38 - mse: 239661.2812 - val loss: 210496.1406 - val mse: 210332.4219
Epoch 452/1500
06 - mse: 239493.0312 - val loss: 210397.1094 - val mse: 210233.4062
Epoch 453/1500
69 - mse: 239262.4062 - val loss: 210473.1562 - val mse: 210309.3906
Epoch 454/1500
62 - mse: 239209.7656 - val loss: 210312.7812 - val mse: 210148.9688
Epoch 455/1500
31 - mse: 239205.3281 - val loss: 210292.0938 - val mse: 210128.2031
Epoch 456/1500
62 - mse: 239010.6094 - val loss: 210207.8125 - val mse: 210043.9062
Epoch 457/1500
70/70 [============================] - 0s 3ms/step - loss: 239062.85
94 - mse: 238899.1250 - val loss: 210255.7656 - val mse: 210091.7969
Epoch 458/1500
19 - mse: 238870.1406 - val loss: 210207.8594 - val mse: 210043.8594
Epoch 459/1500
44 - mse: 238746.1094 - val loss: 210172.1406 - val mse: 210008.0469
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Epoch 460/1500
38 - mse: 238500.1719 - val loss: 210213.4531 - val mse: 210049.3438
Epoch 461/1500
44 - mse: 238453.2344 - val loss: 209933.4844 - val mse: 209769.3594
Epoch 462/1500
75 - mse: 238409.3594 - val loss: 210042.6562 - val mse: 209878.4375
Epoch 463/1500
81 - mse: 238144.0938 - val_loss: 209903.2031 - val_mse: 209739.0000
Epoch 464/1500
50 - mse: 238211.8750 - val loss: 209735.9688 - val mse: 209571.7344
Epoch 465/1500
62 - mse: 238098.3594 - val loss: 209923.9844 - val mse: 209759.7656
Epoch 466/1500
25 - mse: 237896.4219 - val loss: 209721.5156 - val mse: 209557.2500
Epoch 467/1500
75 - mse: 237796.0000 - val_loss: 209773.4375 - val_mse: 209609.1562
Epoch 468/1500
38 - mse: 237741.2031 - val loss: 209532.5000 - val mse: 209368.1562
Epoch 469/1500
81 - mse: 237746.3906 - val loss: 209626.3750 - val mse: 209461.9844
Epoch 470/1500
62 - mse: 237449.0938 - val loss: 209640.5469 - val mse: 209476.1250
Epoch 471/1500
69 - mse: 237365.1719 - val loss: 209475.4844 - val mse: 209310.9531
Epoch 472/1500
12 - mse: 237423.5625 - val loss: 209447.8906 - val mse: 209283.3281
Epoch 473/1500
38 - mse: 237025.0469 - val loss: 209425.7656 - val mse: 209261.0938
Epoch 474/1500
81 - mse: 237238.7344 - val loss: 209251.6250 - val mse: 209086.8906
Epoch 475/1500
00 - mse: 237016.3750 - val loss: 209300.3906 - val mse: 209135.5781
Epoch 476/1500
50 - mse: 236828.6406 - val loss: 209292.6094 - val mse: 209127.7500
Epoch 477/1500
25 - mse: 236829.3281 - val loss: 209109.7344 - val mse: 208944.7969
Epoch 478/1500
69 - mse: 236592.6875 - val loss: 209149.4844 - val mse: 208984.4688
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Epoch 479/1500
19 - mse: 236534.3438 - val loss: 208978.6875 - val mse: 208813.6406
Epoch 480/1500
38 - mse: 236484.2500 - val loss: 208888.5156 - val mse: 208723.3906
Epoch 481/1500
62 - mse: 236304.8438 - val loss: 208957.4688 - val mse: 208792.3281
Epoch 482/1500
25 - mse: 236344.8125 - val_loss: 208775.5000 - val_mse: 208610.3281
Epoch 483/1500
88 - mse: 236174.6562 - val loss: 208733.1406 - val mse: 208567.8594
Epoch 484/1500
75 - mse: 235925.9844 - val loss: 208666.7812 - val mse: 208501.5312
Epoch 485/1500
38 - mse: 236026.4062 - val loss: 208631.7656 - val mse: 208466.4375
Epoch 486/1500
19 - mse: 235767.8594 - val_loss: 208496.5312 - val_mse: 208331.1406
Epoch 487/1500
38 - mse: 235772.7656 - val loss: 208487.2969 - val mse: 208321.8125
Epoch 488/1500
12 - mse: 235547.9688 - val loss: 208467.9531 - val mse: 208302.4375
Epoch 489/1500
62 - mse: 235612.6875 - val loss: 208327.0938 - val mse: 208161.5156
Epoch 490/1500
19 - mse: 235460.9531 - val loss: 208374.9375 - val mse: 208209.2812
Epoch 491/1500
69 - mse: 235352.9688 - val loss: 208383.7656 - val mse: 208218.0938
Epoch 492/1500
25 - mse: 235163.8281 - val loss: 208271.1094 - val mse: 208105.3750
Epoch 493/1500
62 - mse: 235292.0156 - val loss: 208027.3594 - val mse: 207861.6250
Epoch 494/1500
94 - mse: 235042.9531 - val loss: 208231.6406 - val mse: 208065.8125
Epoch 495/1500
56 - mse: 234870.2969 - val loss: 208050.1094 - val mse: 207884.2656
Epoch 496/1500
50 - mse: 234917.4219 - val loss: 207996.7344 - val mse: 207830.8438
Epoch 497/1500
19 - mse: 234589.6250 - val loss: 207928.3281 - val mse: 207762.3594
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Epoch 498/1500
25 - mse: 234667.9844 - val loss: 207749.4219 - val mse: 207583.4531
Epoch 499/1500
56 - mse: 234533.1562 - val loss: 207752.4844 - val mse: 207586.4688
Epoch 500/1500
88 - mse: 234378.3438 - val loss: 207746.6562 - val mse: 207580.5781
Epoch 501/1500
62 - mse: 234353.4219 - val_loss: 207578.1406 - val_mse: 207412.0312
Epoch 502/1500
50 - mse: 234331.5781 - val loss: 207589.7344 - val mse: 207423.6094
Epoch 503/1500
56 - mse: 234014.4531 - val loss: 207529.3438 - val mse: 207363.1719
Epoch 504/1500
44 - mse: 234087.0781 - val loss: 207461.7969 - val mse: 207295.5469
Epoch 505/1500
31 - mse: 233919.0625 - val_loss: 207432.2969 - val_mse: 207266.0000
Epoch 506/1500
50 - mse: 233807.1406 - val loss: 207336.7812 - val mse: 207170.3906
Epoch 507/1500
06 - mse: 233666.8906 - val loss: 207306.6562 - val mse: 207140.2188
Epoch 508/1500
06 - mse: 233708.3281 - val loss: 207172.9375 - val mse: 207006.4062
Epoch 509/1500
44 - mse: 233512.5469 - val loss: 207339.2344 - val mse: 207172.6562
Epoch 510/1500
38 - mse: 233371.6094 - val loss: 207239.5781 - val mse: 207072.9688
Epoch 511/1500
69 - mse: 233295.4844 - val loss: 206945.1562 - val mse: 206778.4688
Epoch 512/1500
70/70 [===========================] - 0s 3ms/step - loss: 233472.29
69 - mse: 233305.6719 - val loss: 207027.0625 - val mse: 206860.3750
Epoch 513/1500
00 - mse: 233056.9219 - val loss: 207113.4688 - val mse: 206946.7344
Epoch 514/1500
70/70 [============================] - Os 2ms/step - loss: 233181.95
31 - mse: 233015.2812 - val loss: 206972.0469 - val mse: 206805.2500
Epoch 515/1500
94 - mse: 232868.2812 - val loss: 206746.8281 - val mse: 206579.9375
Epoch 516/1500
70/70 [===========================] - 0s 3ms/step - loss: 233032.07
81 - mse: 232865.3125 - val loss: 206836.9844 - val mse: 206670.0938
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Epoch 517/1500
25 - mse: 232671.0000 - val loss: 206739.3594 - val mse: 206572.3906
Epoch 518/1500
75 - mse: 232605.8281 - val loss: 206741.8438 - val mse: 206574.8438
Epoch 519/1500
69 - mse: 232479.5469 - val loss: 206592.7188 - val mse: 206425.6875
Epoch 520/1500
31 - mse: 232356.1406 - val_loss: 206543.3906 - val_mse: 206376.2969
Epoch 521/1500
88 - mse: 232294.0938 - val loss: 206445.6875 - val mse: 206278.5312
Epoch 522/1500
31 - mse: 232126.5781 - val loss: 206526.2500 - val mse: 206359.0312
Epoch 523/1500
44 - mse: 232082.3281 - val loss: 206401.3438 - val mse: 206234.0625
Epoch 524/1500
50 - mse: 232022.9531 - val_loss: 206314.8906 - val_mse: 206147.5625
Epoch 525/1500
62 - mse: 231678.2031 - val loss: 206326.8906 - val mse: 206159.4844
Epoch 526/1500
12 - mse: 231841.2344 - val loss: 206099.3281 - val mse: 205931.8750
Epoch 527/1500
12 - mse: 231644.5312 - val loss: 206237.2031 - val mse: 206069.6875
Epoch 528/1500
31 - mse: 231595.6250 - val loss: 206285.6719 - val mse: 206118.1094
Epoch 529/1500
62 - mse: 231449.9375 - val loss: 206193.5156 - val mse: 206025.8438
Epoch 530/1500
19 - mse: 231411.5625 - val loss: 206026.4219 - val mse: 205858.7344
Epoch 531/1500
31 - mse: 231365.6250 - val loss: 206046.2812 - val mse: 205878.5000
Epoch 532/1500
56 - mse: 231106.3125 - val loss: 205992.6562 - val mse: 205824.8438
Epoch 533/1500
25 - mse: 231144.8281 - val loss: 205863.1250 - val mse: 205695.2344
Epoch 534/1500
44 - mse: 230930.1250 - val loss: 205922.0000 - val mse: 205754.0781
Epoch 535/1500
06 - mse: 230794.5625 - val loss: 205752.0625 - val mse: 205584.0938
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Epoch 536/1500
88 - mse: 230754.2812 - val loss: 205651.1406 - val mse: 205483.0469
Epoch 537/1500
19 - mse: 230758.0000 - val loss: 205715.9531 - val mse: 205547.8594
Epoch 538/1500
12 - mse: 230408.7656 - val loss: 205790.7812 - val mse: 205622.6406
Epoch 539/1500
69 - mse: 230538.5156 - val_loss: 205632.9688 - val_mse: 205464.7344
Epoch 540/1500
69 - mse: 230343.9375 - val loss: 205487.0156 - val mse: 205318.7969
Epoch 541/1500
25 - mse: 230230.6719 - val loss: 205622.6562 - val mse: 205454.3125
Epoch 542/1500
44 - mse: 230088.2656 - val loss: 205516.9844 - val mse: 205348.5938
Epoch 543/1500
94 - mse: 230061.1094 - val_loss: 205550.4062 - val_mse: 205381.9844
Epoch 544/1500
00 - mse: 229933.1875 - val loss: 205380.1250 - val mse: 205211.6562
Epoch 545/1500
88 - mse: 229906.3594 - val loss: 205373.8281 - val_mse: 205205.3125
Epoch 546/1500
31 - mse: 229668.0469 - val loss: 205406.9844 - val mse: 205238.3906
Epoch 547/1500
00 - mse: 229643.5156 - val loss: 205338.9531 - val mse: 205170.2812
Epoch 548/1500
75 - mse: 229615.1094 - val loss: 205326.9375 - val mse: 205158.2344
Epoch 549/1500
62 - mse: 229458.0156 - val loss: 205280.9219 - val mse: 205112.1875
Epoch 550/1500
70/70 [============================] - Os 3ms/step - loss: 229460.84
38 - mse: 229292.1562 - val loss: 205239.3906 - val mse: 205070.5781
Epoch 551/1500
38 - mse: 229257.3438 - val loss: 205043.7031 - val mse: 204874.8438
Epoch 552/1500
50 - mse: 229212.8438 - val loss: 205047.4219 - val mse: 204878.4844
Epoch 553/1500
75 - mse: 229172.0938 - val loss: 205089.0000 - val mse: 204920.0000
Epoch 554/1500
12 - mse: 228899.7969 - val loss: 205032.9688 - val mse: 204863.9375
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Epoch 555/1500
94 - mse: 228876.5781 - val loss: 204896.9531 - val mse: 204727.8594
Epoch 556/1500
00 - mse: 228925.2031 - val loss: 204817.5938 - val mse: 204648.4375
Epoch 557/1500
31 - mse: 228560.1562 - val_loss: 204791.8906 - val mse: 204622.6875
Epoch 558/1500
62 - mse: 228716.2500 - val_loss: 204707.3594 - val_mse: 204538.0781
Epoch 559/1500
19 - mse: 228497.7656 - val loss: 204800.3281 - val mse: 204630.9531
Epoch 560/1500
81 - mse: 228435.2812 - val loss: 204772.0469 - val mse: 204602.6094
Epoch 561/1500
19 - mse: 228148.7500 - val loss: 204531.8594 - val mse: 204362.3750
Epoch 562/1500
31 - mse: 228329.7188 - val_loss: 204397.2500 - val_mse: 204227.6719
Epoch 563/1500
56 - mse: 227971.0000 - val loss: 204438.5000 - val mse: 204268.8906
Epoch 564/1500
75 - mse: 228032.1406 - val loss: 204437.6250 - val mse: 204267.9375
Epoch 565/1500
12 - mse: 227797.1562 - val loss: 204247.5625 - val mse: 204077.8125
Epoch 566/1500
75 - mse: 227888.2344 - val loss: 204235.6094 - val mse: 204065.7812
Epoch 567/1500
31 - mse: 227706.4531 - val loss: 204241.4688 - val mse: 204071.5781
Epoch 568/1500
94 - mse: 227664.9844 - val loss: 204193.9375 - val mse: 204023.9531
Epoch 569/1500
88 - mse: 227413.5781 - val loss: 204134.9844 - val mse: 203964.9531
Epoch 570/1500
44 - mse: 227350.3125 - val loss: 204073.0781 - val mse: 203902.9688
Epoch 571/1500
25 - mse: 227413.4844 - val loss: 203930.0469 - val mse: 203759.9062
Epoch 572/1500
00 - mse: 227082.6406 - val loss: 203893.2031 - val mse: 203722.9688
Epoch 573/1500
50 - mse: 227135.1562 - val loss: 203666.4531 - val mse: 203496.1406
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Epoch 574/1500
62 - mse: 226999.3906 - val loss: 203680.0938 - val mse: 203509.7500
Epoch 575/1500
88 - mse: 226938.4219 - val loss: 203666.8594 - val mse: 203496.4062
Epoch 576/1500
00 - mse: 226759.1406 - val loss: 203648.0469 - val mse: 203477.5625
Epoch 577/1500
31 - mse: 226663.7188 - val_loss: 203422.7500 - val_mse: 203252.1562
Epoch 578/1500
81 - mse: 226523.3281 - val loss: 203299.7188 - val mse: 203129.0781
Epoch 579/1500
69 - mse: 226555.4531 - val loss: 203270.1875 - val mse: 203099.5156
Epoch 580/1500
06 - mse: 226182.1250 - val loss: 203248.9375 - val mse: 203078.1875
Epoch 581/1500
44 - mse: 226376.0469 - val_loss: 203089.6875 - val_mse: 202918.8125
Epoch 582/1500
75 - mse: 226240.6875 - val loss: 203204.1406 - val mse: 203033.2344
Epoch 583/1500
75 - mse: 225974.9062 - val loss: 203171.4062 - val mse: 203000.4688
Epoch 584/1500
19 - mse: 225816.0312 - val loss: 203092.4844 - val mse: 202921.4375
Epoch 585/1500
88 - mse: 225748.0312 - val loss: 202873.0938 - val mse: 202701.9844
Epoch 586/1500
31 - mse: 225807.7188 - val loss: 202866.6250 - val mse: 202695.4844
Epoch 587/1500
56 - mse: 225695.7188 - val loss: 202879.1406 - val mse: 202707.8750
Epoch 588/1500
69 - mse: 225459.3594 - val loss: 202874.9688 - val mse: 202703.5781
Epoch 589/1500
31 - mse: 225463.9531 - val loss: 202796.8906 - val mse: 202625.5312
Epoch 590/1500
70/70 [============================] - Os 3ms/step - loss: 225630.59
38 - mse: 225459.2656 - val loss: 202739.9375 - val mse: 202568.5156
Epoch 591/1500
50 - mse: 225189.6719 - val loss: 202783.3906 - val mse: 202611.8594
Epoch 592/1500
56 - mse: 225100.2969 - val loss: 202704.0312 - val mse: 202532.4219
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Epoch 593/1500
38 - mse: 224938.5000 - val loss: 202533.3125 - val mse: 202361.6562
Epoch 594/1500
81 - mse: 224995.3906 - val loss: 202506.9062 - val mse: 202335.1250
Epoch 595/1500
56 - mse: 224941.0469 - val loss: 202529.4062 - val mse: 202357.6250
Epoch 596/1500
38 - mse: 224682.5938 - val_loss: 202507.2812 - val_mse: 202335.3594
Epoch 597/1500
44 - mse: 224741.8438 - val loss: 202374.6094 - val mse: 202202.6406
Epoch 598/1500
19 - mse: 224571.9688 - val loss: 202383.0781 - val mse: 202211.0469
Epoch 599/1500
62 - mse: 224406.4375 - val loss: 202303.7188 - val mse: 202131.6094
Epoch 600/1500
75 - mse: 224492.1562 - val_loss: 202286.3438 - val_mse: 202114.0938
Epoch 601/1500
25 - mse: 224059.9375 - val loss: 202275.8750 - val mse: 202103.5938
Epoch 602/1500
81 - mse: 224255.5938 - val loss: 201981.5156 - val mse: 201809.1406
Epoch 603/1500
12 - mse: 224215.4531 - val loss: 202168.7969 - val mse: 201996.3438
Epoch 604/1500
56 - mse: 223999.2812 - val loss: 201999.7344 - val mse: 201827.1719
Epoch 605/1500
94 - mse: 223903.3750 - val loss: 202022.0469 - val mse: 201849.3906
Epoch 606/1500
50 - mse: 223945.5625 - val loss: 201946.3750 - val mse: 201773.7031
Epoch 607/1500
44 - mse: 223702.5156 - val loss: 201989.1562 - val mse: 201816.3594
Epoch 608/1500
38 - mse: 223765.6094 - val loss: 201880.0469 - val mse: 201707.1406
Epoch 609/1500
70/70 [============================] - 0s 2ms/step - loss: 223876.12
50 - mse: 223703.3125 - val loss: 201901.5938 - val mse: 201728.7031
Epoch 610/1500
06 - mse: 223423.0625 - val loss: 201841.4531 - val mse: 201668.3906
Epoch 611/1500
19 - mse: 223279.0625 - val loss: 201667.5625 - val mse: 201494.5156
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Epoch 612/1500
81 - mse: 223323.7969 - val loss: 201483.4062 - val mse: 201310.2344
Epoch 613/1500
00 - mse: 223271.6562 - val loss: 201571.6875 - val mse: 201398.4375
Epoch 614/1500
62 - mse: 223257.5000 - val loss: 201665.1875 - val mse: 201491.8594
Epoch 615/1500
06 - mse: 222982.6094 - val_loss: 201557.3438 - val_mse: 201383.9375
Epoch 616/1500
00 - mse: 223058.4219 - val loss: 201435.8438 - val mse: 201262.3594
Epoch 617/1500
12 - mse: 223035.8438 - val loss: 201432.2344 - val mse: 201258.6406
Epoch 618/1500
31 - mse: 222735.4688 - val loss: 201430.8125 - val mse: 201257.1562
Epoch 619/1500
50 - mse: 222805.4062 - val_loss: 201332.2344 - val_mse: 201158.5000
Epoch 620/1500
56 - mse: 222645.2656 - val loss: 201388.5625 - val mse: 201214.7500
Epoch 621/1500
25 - mse: 222517.0781 - val loss: 201157.7500 - val mse: 200983.8438
Epoch 622/1500
00 - mse: 222529.1250 - val loss: 201061.3906 - val mse: 200887.4688
Epoch 623/1500
81 - mse: 222558.5625 - val loss: 201131.5000 - val mse: 200957.4844
Epoch 624/1500
75 - mse: 222317.2969 - val loss: 201163.0469 - val mse: 200989.0156
Epoch 625/1500
69 - mse: 222361.3125 - val loss: 201002.2031 - val mse: 200828.1094
Epoch 626/1500
70/70 [============================] - 0s 2ms/step - loss: 222489.90
62 - mse: 222315.8281 - val loss: 201059.7031 - val mse: 200885.5156
Epoch 627/1500
75 - mse: 222045.4844 - val loss: 201021.2188 - val mse: 200846.9688
Epoch 628/1500
70/70 [============================] - 0s 2ms/step - loss: 222235.57
81 - mse: 222061.3438 - val loss: 200961.7656 - val mse: 200787.4688
Epoch 629/1500
88 - mse: 222053.4531 - val loss: 200969.0781 - val mse: 200794.7344
Epoch 630/1500
44 - mse: 221801.4375 - val loss: 200986.9688 - val mse: 200812.5156
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Epoch 631/1500
25 - mse: 221818.9219 - val loss: 200803.7031 - val mse: 200629.2188
Epoch 632/1500
62 - mse: 221848.6719 - val loss: 200848.5312 - val mse: 200673.9219
Epoch 633/1500
56 - mse: 221568.5312 - val_loss: 200823.2031 - val_mse: 200648.5469
Epoch 634/1500
00 - mse: 221546.9531 - val_loss: 200815.2031 - val_mse: 200640.5156
Epoch 635/1500
00 - mse: 221491.0625 - val loss: 200758.9062 - val mse: 200584.1250
Epoch 636/1500
25 - mse: 221331.8438 - val loss: 200614.3125 - val mse: 200439.4844
Epoch 637/1500
00 - mse: 221405.7188 - val loss: 200545.5000 - val mse: 200370.5625
Epoch 638/1500
62 - mse: 221302.9844 - val_loss: 200571.5312 - val_mse: 200396.5156
Epoch 639/1500
62 - mse: 221041.9375 - val loss: 200415.4688 - val mse: 200240.4375
Epoch 640/1500
25 - mse: 221041.8594 - val loss: 200285.2500 - val_mse: 200110.1250
Epoch 641/1500
75 - mse: 221055.1719 - val loss: 200301.7812 - val mse: 200126.6250
Epoch 642/1500
88 - mse: 220918.4375 - val loss: 200334.1406 - val mse: 200158.9375
Epoch 643/1500
56 - mse: 220668.9219 - val loss: 200191.2812 - val mse: 200015.9688
Epoch 644/1500
06 - mse: 220786.8750 - val loss: 200024.7812 - val mse: 199849.4375
Epoch 645/1500
56 - mse: 220611.9688 - val loss: 199778.6719 - val mse: 199603.2656
Epoch 646/1500
81 - mse: 220065.9688 - val loss: 198096.5469 - val mse: 197921.0000
Epoch 647/1500
70/70 [============================] - Os 2ms/step - loss: 219821.54
69 - mse: 219646.1250 - val loss: 197365.8125 - val mse: 197190.1875
Epoch 648/1500
12 - mse: 219247.9062 - val loss: 196274.3438 - val mse: 196098.6250
Epoch 649/1500
62 - mse: 218545.9375 - val loss: 193334.6562 - val mse: 193158.8438
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Epoch 650/1500
62 - mse: 217208.2969 - val loss: 192051.8594 - val mse: 191875.9062
Epoch 651/1500
56 - mse: 216292.0469 - val loss: 190022.7031 - val mse: 189846.6406
Epoch 652/1500
75 - mse: 215223.1406 - val loss: 186548.4375 - val mse: 186372.2188
Epoch 653/1500
44 - mse: 214368.5000 - val_loss: 186500.0312 - val_mse: 186323.6562
Epoch 654/1500
94 - mse: 214019.5625 - val loss: 186033.6406 - val mse: 185857.1875
Epoch 655/1500
94 - mse: 213386.8281 - val loss: 185769.3750 - val mse: 185592.7969
Epoch 656/1500
19 - mse: 213015.6875 - val loss: 184976.7031 - val mse: 184800.0000
Epoch 657/1500
06 - mse: 212625.7656 - val_loss: 184521.5312 - val_mse: 184344.7344
Epoch 658/1500
62 - mse: 212129.1406 - val loss: 184173.2500 - val mse: 183996.3438
Epoch 659/1500
88 - mse: 211553.6250 - val loss: 183552.3594 - val mse: 183375.3281
Epoch 660/1500
81 - mse: 211045.2500 - val loss: 183169.0625 - val mse: 182991.8906
Epoch 661/1500
75 - mse: 210496.5781 - val loss: 182783.7188 - val mse: 182606.4375
Epoch 662/1500
81 - mse: 210028.5938 - val loss: 182301.2188 - val mse: 182123.7969
Epoch 663/1500
19 - mse: 209656.3594 - val loss: 181792.2656 - val mse: 181614.7344
Epoch 664/1500
70/70 [============================] - 0s 2ms/step - loss: 209259.46
88 - mse: 209082.0156 - val loss: 181430.2188 - val mse: 181252.5938
Epoch 665/1500
06 - mse: 208823.5156 - val loss: 181025.2500 - val mse: 180847.4844
Epoch 666/1500
70/70 [============================] - 0s 2ms/step - loss: 208403.82
81 - mse: 208226.0781 - val loss: 180705.3438 - val mse: 180527.4844
Epoch 667/1500
06 - mse: 207848.3594 - val loss: 180352.4375 - val mse: 180174.5000
Epoch 668/1500
70/70 [============================] - Os 2ms/step - loss: 207460.59
38 - mse: 207282.5938 - val loss: 180080.9844 - val mse: 179902.9375
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Epoch 669/1500
88 - mse: 207130.6875 - val loss: 179528.0156 - val mse: 179349.7656
Epoch 670/1500
88 - mse: 206489.2812 - val loss: 179274.2031 - val mse: 179095.8906
Epoch 671/1500
38 - mse: 206280.7656 - val loss: 178737.5312 - val mse: 178559.0781
Epoch 672/1500
19 - mse: 206001.9375 - val_loss: 178336.5938 - val_mse: 178158.0469
Epoch 673/1500
94 - mse: 205485.5000 - val loss: 178098.0938 - val mse: 177919.4375
Epoch 674/1500
69 - mse: 205038.1250 - val loss: 177899.2812 - val mse: 177720.4688
Epoch 675/1500
12 - mse: 204900.0469 - val loss: 177355.8125 - val mse: 177176.8906
Epoch 676/1500
31 - mse: 204191.8125 - val_loss: 177227.4688 - val_mse: 177048.4219
Epoch 677/1500
12 - mse: 203948.5156 - val loss: 176827.8594 - val mse: 176648.7031
Epoch 678/1500
88 - mse: 203600.8594 - val loss: 176371.8594 - val mse: 176192.5625
Epoch 679/1500
81 - mse: 203294.0312 - val loss: 176097.6875 - val mse: 175918.2812
Epoch 680/1500
06 - mse: 202877.2500 - val loss: 175668.1406 - val mse: 175488.7031
Epoch 681/1500
88 - mse: 202511.9688 - val loss: 175356.0000 - val mse: 175176.3750
Epoch 682/1500
88 - mse: 202061.6719 - val loss: 175023.0156 - val mse: 174843.2812
Epoch 683/1500
44 - mse: 201880.2344 - val loss: 174522.7812 - val mse: 174342.8750
Epoch 684/1500
75 - mse: 201667.5781 - val loss: 174176.7656 - val mse: 173996.7500
Epoch 685/1500
70/70 [============================] - 0s 2ms/step - loss: 201547.25
00 - mse: 201367.2500 - val loss: 173826.8438 - val mse: 173646.7188
Epoch 686/1500
06 - mse: 200656.7812 - val loss: 173607.6250 - val mse: 173427.3281
Epoch 687/1500
19 - mse: 200613.2188 - val loss: 173180.2344 - val mse: 172999.8750
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Epoch 688/1500
00 - mse: 200218.6719 - val loss: 172856.3594 - val mse: 172675.8594
Epoch 689/1500
88 - mse: 199848.7344 - val loss: 172515.8594 - val mse: 172335.2656
Epoch 690/1500
62 - mse: 199574.8125 - val loss: 172189.2656 - val mse: 172008.5156
Epoch 691/1500
12 - mse: 198794.5625 - val_loss: 171809.4531 - val_mse: 171628.5312
Epoch 692/1500
44 - mse: 198947.1250 - val loss: 171348.2812 - val mse: 171167.2969
Epoch 693/1500
50 - mse: 198437.9062 - val loss: 171053.9688 - val mse: 170872.8438
Epoch 694/1500
69 - mse: 198255.1406 - val loss: 170671.9219 - val mse: 170490.6875
Epoch 695/1500
50 - mse: 197347.2188 - val_loss: 170414.8281 - val_mse: 170233.4062
Epoch 696/1500
25 - mse: 197494.7031 - val loss: 170205.7188 - val mse: 170024.2344
Epoch 697/1500
81 - mse: 196666.8750 - val loss: 169847.1094 - val mse: 169665.4531
Epoch 698/1500
38 - mse: 197064.4844 - val loss: 169445.5469 - val mse: 169263.7812
Epoch 699/1500
75 - mse: 196541.2188 - val loss: 169168.7031 - val mse: 168986.7812
Epoch 700/1500
06 - mse: 196174.8438 - val loss: 169064.9844 - val mse: 168882.9688
Epoch 701/1500
06 - mse: 196018.4219 - val loss: 168601.7188 - val mse: 168419.5938
Epoch 702/1500
70/70 [============================] - Os 2ms/step - loss: 195677.14
06 - mse: 195495.0312 - val loss: 168513.0625 - val mse: 168330.7969
Epoch 703/1500
56 - mse: 195093.0469 - val loss: 168529.4531 - val mse: 168347.1094
Epoch 704/1500
70/70 [============================] - Os 2ms/step - loss: 195180.84
38 - mse: 194998.5469 - val loss: 167918.6562 - val mse: 167736.1875
Epoch 705/1500
50 - mse: 194534.9688 - val loss: 167789.1875 - val mse: 167606.6406
Epoch 706/1500
44 - mse: 194423.8750 - val loss: 167387.7188 - val mse: 167205.0625
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Epoch 707/1500
62 - mse: 194016.5156 - val loss: 167218.0469 - val mse: 167035.2344
Epoch 708/1500
81 - mse: 193585.8125 - val loss: 166999.4375 - val mse: 166816.5625
Epoch 709/1500
50 - mse: 193305.0312 - val_loss: 166749.1406 - val mse: 166566.0938
Epoch 710/1500
56 - mse: 193122.5156 - val_loss: 166398.4688 - val_mse: 166215.3281
Epoch 711/1500
56 - mse: 192697.6719 - val loss: 166121.2656 - val mse: 165938.0312
Epoch 712/1500
12 - mse: 192414.9844 - val loss: 165881.7812 - val mse: 165698.4531
Epoch 713/1500
12 - mse: 191946.4688 - val loss: 165728.2500 - val mse: 165544.7656
Epoch 714/1500
31 - mse: 191866.0156 - val_loss: 165574.2969 - val_mse: 165390.7188
Epoch 715/1500
12 - mse: 191352.7031 - val loss: 165257.2656 - val mse: 165073.5938
Epoch 716/1500
38 - mse: 191238.6250 - val loss: 165118.5469 - val mse: 164934.6562
Epoch 717/1500
50 - mse: 190788.3281 - val loss: 164926.5781 - val mse: 164742.6250
Epoch 718/1500
88 - mse: 190475.2969 - val loss: 164618.1875 - val mse: 164434.1406
Epoch 719/1500
94 - mse: 189694.8125 - val loss: 164100.3594 - val mse: 163916.1406
Epoch 720/1500
69 - mse: 189839.8906 - val loss: 163910.2344 - val mse: 163725.9531
Epoch 721/1500
70/70 [=============================] - Os 2ms/step - loss: 189457.73
44 - mse: 189273.5312 - val loss: 163790.2812 - val mse: 163605.9219
Epoch 722/1500
00 - mse: 188640.6562 - val loss: 163177.8438 - val mse: 162993.3438
Epoch 723/1500
70/70 [============================] - 0s 2ms/step - loss: 188758.07
81 - mse: 188573.5625 - val loss: 163232.6719 - val mse: 163048.0781
Epoch 724/1500
44 - mse: 187831.6250 - val loss: 162581.7031 - val mse: 162396.9219
Epoch 725/1500
62 - mse: 187693.4531 - val loss: 162707.6562 - val mse: 162522.7656
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Epoch 726/1500
06 - mse: 187268.0781 - val loss: 162519.6094 - val mse: 162334.6562
Epoch 727/1500
50 - mse: 186961.6406 - val loss: 162282.4062 - val mse: 162097.2500
Epoch 728/1500
25 - mse: 186228.2188 - val loss: 161644.6562 - val mse: 161459.4375
Epoch 729/1500
12 - mse: 186298.0781 - val_loss: 161740.7031 - val_mse: 161555.3906
Epoch 730/1500
06 - mse: 185854.0781 - val loss: 161472.1406 - val mse: 161286.6719
Epoch 731/1500
12 - mse: 185417.3750 - val loss: 161422.2031 - val mse: 161236.6250
Epoch 732/1500
94 - mse: 185033.0469 - val loss: 161344.2656 - val mse: 161158.6406
Epoch 733/1500
25 - mse: 184422.1250 - val_loss: 160516.8906 - val_mse: 160331.1094
Epoch 734/1500
44 - mse: 184192.9688 - val loss: 160806.7500 - val mse: 160620.8438
Epoch 735/1500
56 - mse: 183988.6562 - val loss: 160444.5938 - val mse: 160258.5156
Epoch 736/1500
50 - mse: 183536.1562 - val loss: 160380.6406 - val mse: 160194.4844
Epoch 737/1500
50 - mse: 182721.0000 - val loss: 159970.0000 - val mse: 159783.7656
Epoch 738/1500
06 - mse: 182853.6406 - val loss: 159789.8906 - val mse: 159603.5625
Epoch 739/1500
62 - mse: 182445.5625 - val loss: 159570.3750 - val mse: 159383.8906
Epoch 740/1500
70/70 [============================] - 0s 2ms/step - loss: 182227.12
50 - mse: 182040.6406 - val loss: 159497.9062 - val mse: 159311.3125
Epoch 741/1500
06 - mse: 181171.8438 - val loss: 159150.6562 - val mse: 158963.9375
Epoch 742/1500
70/70 [============================] - 0s 2ms/step - loss: 181504.45
31 - mse: 181317.7500 - val loss: 158787.5625 - val mse: 158600.7188
Epoch 743/1500
62 - mse: 181010.8281 - val loss: 158573.8750 - val mse: 158386.8750
Epoch 744/1500
31 - mse: 180337.0312 - val loss: 158691.3750 - val mse: 158504.3438
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Epoch 745/1500
69 - mse: 179753.5312 - val loss: 157846.0781 - val mse: 157658.9375
Epoch 746/1500
19 - mse: 179857.0312 - val loss: 157671.5781 - val mse: 157484.2812
Epoch 747/1500
06 - mse: 179193.9062 - val loss: 157995.6719 - val mse: 157808.2500
Epoch 748/1500
31 - mse: 178897.5938 - val_loss: 157596.6094 - val_mse: 157409.0625
Epoch 749/1500
44 - mse: 178140.4531 - val loss: 157116.4062 - val mse: 156928.7188
Epoch 750/1500
44 - mse: 178207.5625 - val loss: 156872.0000 - val mse: 156684.1719
Epoch 751/1500
25 - mse: 177746.5156 - val loss: 156687.0000 - val mse: 156499.0469
Epoch 752/1500
44 - mse: 177347.8281 - val_loss: 156381.8594 - val_mse: 156193.8281
Epoch 753/1500
56 - mse: 176942.9844 - val loss: 156229.5781 - val mse: 156041.3906
Epoch 754/1500
06 - mse: 176627.4531 - val loss: 155850.3281 - val mse: 155662.0781
Epoch 755/1500
31 - mse: 176184.2500 - val loss: 155738.7344 - val mse: 155550.3281
Epoch 756/1500
06 - mse: 175864.2344 - val loss: 155260.5781 - val mse: 155072.0469
Epoch 757/1500
06 - mse: 175435.3125 - val loss: 155241.9219 - val mse: 155053.2812
Epoch 758/1500
38 - mse: 175037.7344 - val loss: 155054.0938 - val mse: 154865.3125
Epoch 759/1500
44 - mse: 174738.9375 - val loss: 154538.9375 - val mse: 154350.0625
Epoch 760/1500
88 - mse: 174126.6406 - val loss: 154731.8594 - val mse: 154542.8438
Epoch 761/1500
70/70 [=============================] - Os 2ms/step - loss: 173648.89
06 - mse: 173459.8438 - val loss: 153948.1719 - val mse: 153759.0156
Epoch 762/1500
75 - mse: 173547.0781 - val loss: 153563.6250 - val mse: 153374.3750
Epoch 763/1500
12 - mse: 172980.4688 - val loss: 153737.9844 - val mse: 153548.5625
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Epoch 764/1500
88 - mse: 172620.7812 - val loss: 153524.3281 - val mse: 153334.7812
Epoch 765/1500
12 - mse: 172445.7500 - val loss: 153039.9219 - val mse: 152850.2969
Epoch 766/1500
50 - mse: 171901.7188 - val loss: 153075.6250 - val mse: 152885.8906
Epoch 767/1500
50 - mse: 171499.1719 - val_loss: 152842.4531 - val_mse: 152652.5781
Epoch 768/1500
94 - mse: 170617.9375 - val loss: 152374.2188 - val mse: 152184.2031
Epoch 769/1500
06 - mse: 170731.3906 - val loss: 151942.1094 - val mse: 151752.0000
Epoch 770/1500
38 - mse: 169936.0000 - val loss: 152396.3750 - val mse: 152206.1406
Epoch 771/1500
94 - mse: 169573.1875 - val_loss: 151529.0625 - val_mse: 151338.7188
Epoch 772/1500
81 - mse: 169013.7969 - val loss: 151213.9062 - val mse: 151023.4688
Epoch 773/1500
00 - mse: 167784.0781 - val loss: 150702.8438 - val mse: 150512.2969
Epoch 774/1500
69 - mse: 167710.7188 - val loss: 149853.7188 - val mse: 149663.0469
Epoch 775/1500
69 - mse: 166873.6250 - val loss: 149644.9375 - val mse: 149454.1250
Epoch 776/1500
19 - mse: 165673.3438 - val loss: 148701.0781 - val mse: 148510.1094
Epoch 777/1500
00 - mse: 165317.3125 - val loss: 148315.0156 - val mse: 148123.9375
Epoch 778/1500
70/70 [============================] - 0s 2ms/step - loss: 164980.39
06 - mse: 164789.3125 - val loss: 147429.5312 - val mse: 147238.3281
Epoch 779/1500
00 - mse: 163230.2656 - val loss: 146860.3438 - val mse: 146668.9844
Epoch 780/1500
69 - mse: 162908.9062 - val loss: 146551.2500 - val mse: 146359.7656
Epoch 781/1500
88 - mse: 162014.2500 - val loss: 145997.5312 - val mse: 145805.8750
Epoch 782/1500
75 - mse: 160925.0000 - val loss: 145166.9688 - val mse: 144975.1094
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Epoch 783/1500
62 - mse: 159738.5781 - val loss: 145436.7344 - val mse: 145244.7344
Epoch 784/1500
25 - mse: 159155.3125 - val loss: 144443.2500 - val mse: 144251.0938
Epoch 785/1500
44 - mse: 158425.8906 - val loss: 143764.8281 - val mse: 143572.4844
Epoch 786/1500
94 - mse: 157485.0469 - val_loss: 143494.4375 - val_mse: 143301.9375
Epoch 787/1500
31 - mse: 156414.0312 - val loss: 143479.6406 - val mse: 143287.0156
Epoch 788/1500
69 - mse: 155847.6719 - val loss: 142779.4062 - val mse: 142586.6250
Epoch 789/1500
56 - mse: 155341.4688 - val loss: 141822.1875 - val mse: 141629.2500
Epoch 790/1500
44 - mse: 154490.2812 - val_loss: 141740.5469 - val_mse: 141547.4219
Epoch 791/1500
81 - mse: 153705.9531 - val loss: 141394.0156 - val mse: 141200.7188
Epoch 792/1500
75 - mse: 153118.6875 - val loss: 140693.4531 - val mse: 140499.9531
Epoch 793/1500
25 - mse: 152513.3438 - val loss: 139930.7188 - val mse: 139737.0625
Epoch 794/1500
94 - mse: 151727.2656 - val loss: 139645.3438 - val mse: 139451.5312
Epoch 795/1500
69 - mse: 151114.9688 - val loss: 138895.1562 - val mse: 138701.1562
Epoch 796/1500
19 - mse: 150539.9375 - val loss: 138220.3125 - val mse: 138026.0938
Epoch 797/1500
44 - mse: 149716.8281 - val loss: 138040.2500 - val mse: 137845.9062
Epoch 798/1500
38 - mse: 149117.0000 - val loss: 137437.6250 - val mse: 137243.1094
Epoch 799/1500
12 - mse: 148327.2969 - val loss: 137278.4531 - val mse: 137083.7656
Epoch 800/1500
19 - mse: 147751.5000 - val loss: 136547.3438 - val mse: 136352.5156
Epoch 801/1500
06 - mse: 147179.3281 - val loss: 136008.3438 - val mse: 135813.3281
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Epoch 802/1500
19 - mse: 146510.6719 - val loss: 135592.0781 - val mse: 135396.8906
Epoch 803/1500
81 - mse: 145867.6875 - val loss: 135183.2344 - val mse: 134987.8594
Epoch 804/1500
69 - mse: 145190.7188 - val loss: 134585.2969 - val mse: 134389.7969
Epoch 805/1500
62 - mse: 144467.6562 - val_loss: 134409.6562 - val_mse: 134214.0000
Epoch 806/1500
38 - mse: 143913.9219 - val loss: 133732.7656 - val mse: 133536.8906
Epoch 807/1500
56 - mse: 143226.9531 - val loss: 133631.8438 - val mse: 133435.8281
Epoch 808/1500
44 - mse: 142549.0000 - val loss: 133028.7188 - val mse: 132832.5156
Epoch 809/1500
31 - mse: 142108.5625 - val_loss: 132524.3594 - val_mse: 132327.9844
Epoch 810/1500
69 - mse: 141289.4531 - val loss: 132475.2031 - val mse: 132278.7188
Epoch 811/1500
38 - mse: 140727.3438 - val loss: 132022.1875 - val mse: 131825.5000
Epoch 812/1500
50 - mse: 140048.1719 - val loss: 131747.7031 - val mse: 131550.8438
Epoch 813/1500
25 - mse: 139418.4688 - val loss: 130987.0234 - val mse: 130789.9688
Epoch 814/1500
06 - mse: 138852.1094 - val loss: 130757.3906 - val mse: 130560.1719
Epoch 815/1500
69 - mse: 138171.6094 - val loss: 130380.2266 - val mse: 130182.8594
Epoch 816/1500
25 - mse: 137536.4688 - val loss: 130045.9766 - val mse: 129848.4141
Epoch 817/1500
12 - mse: 136995.7344 - val loss: 129726.4375 - val mse: 129528.7109
Epoch 818/1500
88 - mse: 136262.2656 - val loss: 129795.5312 - val mse: 129597.6172
Epoch 819/1500
81 - mse: 135766.9844 - val loss: 129273.7891 - val mse: 129075.7422
Epoch 820/1500
25 - mse: 135182.3125 - val loss: 128391.2266 - val mse: 128193.0312
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Epoch 821/1500
38 - mse: 134484.6562 - val loss: 128430.1172 - val mse: 128231.7422
Epoch 822/1500
44 - mse: 133919.3750 - val loss: 128242.4219 - val mse: 128043.9219
Epoch 823/1500
88 - mse: 133446.4375 - val loss: 127862.5156 - val mse: 127663.8281
Epoch 824/1500
06 - mse: 132784.2188 - val_loss: 127641.5781 - val_mse: 127442.7422
Epoch 825/1500
69 - mse: 132281.2344 - val loss: 127187.0391 - val mse: 126988.0391
Epoch 826/1500
69 - mse: 131699.8438 - val loss: 127099.6953 - val mse: 126900.5312
Epoch 827/1500
50 - mse: 131041.7578 - val loss: 126794.3047 - val mse: 126595.0000
Epoch 828/1500
19 - mse: 130600.3750 - val_loss: 126434.7812 - val_mse: 126235.3281
Epoch 829/1500
12 - mse: 129999.8828 - val loss: 126335.9844 - val mse: 126136.3906
Epoch 830/1500
53 - mse: 129535.8594 - val loss: 125784.6562 - val mse: 125584.9375
Epoch 831/1500
03 - mse: 128879.8672 - val loss: 125520.7500 - val mse: 125320.8594
Epoch 832/1500
62 - mse: 128397.0234 - val loss: 125135.0625 - val mse: 124935.0469
Epoch 833/1500
72 - mse: 127718.3359 - val loss: 124953.4609 - val mse: 124753.2578
Epoch 834/1500
34 - mse: 127314.3672 - val loss: 124488.4922 - val mse: 124288.1328
Epoch 835/1500
78 - mse: 126842.9531 - val loss: 124386.1172 - val mse: 124185.6172
Epoch 836/1500
22 - mse: 126345.5547 - val loss: 124160.1484 - val mse: 123959.5156
Epoch 837/1500
00 - mse: 125561.8984 - val loss: 123904.2422 - val mse: 123703.4531
Epoch 838/1500
81 - mse: 125411.8516 - val loss: 123253.2812 - val mse: 123052.3516
Epoch 839/1500
81 - mse: 124821.4297 - val loss: 122925.4844 - val mse: 122724.3984
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Epoch 840/1500
91 - mse: 124261.7500 - val loss: 122834.2188 - val mse: 122633.0703
Epoch 841/1500
72 - mse: 123744.7422 - val loss: 122007.9609 - val mse: 121806.6641
Epoch 842/1500
78 - mse: 123357.2266 - val loss: 122294.3047 - val mse: 122092.8828
Epoch 843/1500
06 - mse: 122790.2188 - val_loss: 121905.5078 - val_mse: 121703.9062
Epoch 844/1500
06 - mse: 122437.1094 - val loss: 121194.2734 - val mse: 120992.5625
Epoch 845/1500
88 - mse: 121754.5469 - val loss: 121363.9844 - val mse: 121162.1250
Epoch 846/1500
59 - mse: 121357.0078 - val loss: 120873.1641 - val mse: 120671.1953
Epoch 847/1500
91 - mse: 120840.3438 - val_loss: 120289.8359 - val_mse: 120087.7031
Epoch 848/1500
06 - mse: 120469.0234 - val loss: 119524.6719 - val mse: 119322.4219
Epoch 849/1500
00 - mse: 119938.5156 - val loss: 119912.5469 - val_mse: 119710.1641
Epoch 850/1500
25 - mse: 119446.2031 - val loss: 119122.3281 - val mse: 118919.7969
Epoch 851/1500
84 - mse: 119031.8750 - val loss: 119421.5000 - val mse: 119218.7969
Epoch 852/1500
94 - mse: 118595.2734 - val loss: 118522.6328 - val mse: 118319.8672
Epoch 853/1500
84 - mse: 118085.9453 - val loss: 117962.9141 - val mse: 117760.0547
Epoch 854/1500
62 - mse: 117662.5625 - val loss: 118290.7422 - val mse: 118087.7344
Epoch 855/1500
81 - mse: 117225.1094 - val loss: 117378.7812 - val mse: 117175.6406
Epoch 856/1500
70/70 [===========================] - 0s 2ms/step - loss: 117018.59
38 - mse: 116815.5234 - val loss: 116772.2969 - val mse: 116569.0312
Epoch 857/1500
50 - mse: 116073.1562 - val loss: 117008.6250 - val mse: 116805.2422
Epoch 858/1500
53 - mse: 115483.8203 - val loss: 116206.7578 - val mse: 116003.2266
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Epoch 859/1500
97 - mse: 115062.6719 - val loss: 116513.8438 - val mse: 116310.2109
Epoch 860/1500
50 - mse: 114605.5156 - val loss: 115755.6641 - val mse: 115551.8906
Epoch 861/1500
19 - mse: 113906.1875 - val loss: 115148.8047 - val mse: 114944.9062
Epoch 862/1500
41 - mse: 113587.8047 - val_loss: 115313.7109 - val_mse: 115109.6875
Epoch 863/1500
375 - mse: 112866.4062 - val loss: 115080.8594 - val mse: 114876.6797
Epoch 864/1500
250 - mse: 112422.4922 - val loss: 114233.0547 - val mse: 114028.7656
Epoch 865/1500
56 - mse: 112107.0391 - val loss: 114779.4688 - val mse: 114575.0781
Epoch 866/1500
56 - mse: 111516.6719 - val_loss: 114395.7578 - val_mse: 114191.2656
Epoch 867/1500
016 - mse: 111174.6328 - val loss: 113780.0703 - val mse: 113575.4219
Epoch 868/1500
000 - mse: 110658.8906 - val loss: 114118.8516 - val mse: 113914.1016
Epoch 869/1500
625 - mse: 110299.3438 - val loss: 113299.5156 - val mse: 113094.6641
Epoch 870/1500
203 - mse: 109961.9844 - val loss: 113461.0859 - val mse: 113256.1172
Epoch 871/1500
500 - mse: 109411.7969 - val loss: 112756.9375 - val mse: 112551.8516
Epoch 872/1500
66 - mse: 108946.9219 - val loss: 112173.9766 - val mse: 111968.7891
Epoch 873/1500
70/70 [===========================] - 0s 7ms/step - loss: 108764.35
16 - mse: 108559.1484 - val loss: 112986.5156 - val mse: 112781.2031
Epoch 874/1500
22 - mse: 108185.9531 - val loss: 112013.9766 - val mse: 111808.5312
Epoch 875/1500
25 - mse: 107847.1250 - val loss: 111924.4766 - val mse: 111718.9062
Epoch 876/1500
344 - mse: 107377.1875 - val loss: 111961.0234 - val mse: 111755.3281
Epoch 877/1500
22 - mse: 106950.8047 - val loss: 111815.6094 - val mse: 111609.7969
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Epoch 878/1500
03 - mse: 106781.0781 - val loss: 111834.8125 - val mse: 111628.9062
Epoch 879/1500
41 - mse: 106232.5859 - val loss: 111060.3359 - val mse: 110854.3203
Epoch 880/1500
16 - mse: 105940.3984 - val loss: 110922.6328 - val mse: 110716.5156
Epoch 881/1500
88 - mse: 105714.3672 - val_loss: 111149.3594 - val_mse: 110943.0547
Epoch 882/1500
44 - mse: 105180.2578 - val loss: 110309.4297 - val mse: 110103.0312
Epoch 883/1500
59 - mse: 104900.9766 - val loss: 110753.3359 - val mse: 110546.7969
Epoch 884/1500
28 - mse: 104483.1406 - val loss: 110348.6484 - val mse: 110142.0391
Epoch 885/1500
69 - mse: 104360.9375 - val_loss: 110283.1562 - val_mse: 110076.4375
Epoch 886/1500
84 - mse: 103963.9766 - val loss: 109791.1094 - val mse: 109584.2891
Epoch 887/1500
31 - mse: 103448.3828 - val loss: 109752.5000 - val mse: 109545.5469
Epoch 888/1500
53 - mse: 103182.9922 - val loss: 109430.9766 - val mse: 109223.9062
Epoch 889/1500
62 - mse: 102799.8672 - val loss: 108928.4453 - val mse: 108721.2500
Epoch 890/1500
50 - mse: 102677.2109 - val loss: 109020.3828 - val mse: 108813.1094
Epoch 891/1500
66 - mse: 102228.2500 - val loss: 109082.6875 - val mse: 108875.3281
Epoch 892/1500
70/70 [============================] - 0s 3ms/step - loss: 102142.67
97 - mse: 101935.3516 - val loss: 108032.8516 - val mse: 107825.3750
Epoch 893/1500
88 - mse: 101564.5234 - val loss: 108030.9844 - val mse: 107823.4219
Epoch 894/1500
22 - mse: 101331.4375 - val loss: 108391.7891 - val mse: 108184.1016
Epoch 895/1500
22 - mse: 100892.5469 - val loss: 107203.2031 - val mse: 106995.4219
Epoch 896/1500
66 - mse: 100657.7266 - val loss: 107624.3047 - val mse: 107416.3984
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Epoch 897/1500
22 - mse: 100305.6328 - val loss: 107847.4688 - val mse: 107639.4766
Epoch 898/1500
12 - mse: 100053.8203 - val loss: 106545.8984 - val mse: 106337.8203
Epoch 899/1500
1 - mse: 99664.6172 - val_loss: 106664.4219 - val_mse: 106456.2422
Epoch 900/1500
9 - mse: 99313.8672 - val_loss: 107081.3906 - val_mse: 106873.1094
Epoch 901/1500
2 - mse: 98685.3750 - val loss: 105499.1406 - val mse: 105290.7656
Epoch 902/1500
2 - mse: 98823.6562 - val loss: 105903.6094 - val mse: 105695.1250
Epoch 903/1500
5 - mse: 98066.4922 - val loss: 105800.1484 - val mse: 105591.5781
Epoch 904/1500
2 - mse: 98198.5234 - val_loss: 105725.0625 - val_mse: 105516.4141
Epoch 905/1500
8 - mse: 97444.6094 - val loss: 104565.0469 - val mse: 104356.2578
Epoch 906/1500
8 - mse: 97706.2812 - val loss: 105058.1719 - val mse: 104849.2969
Epoch 907/1500
5 - mse: 97493.8594 - val loss: 104819.3047 - val mse: 104610.3594
Epoch 908/1500
6 - mse: 96660.2266 - val loss: 104518.1875 - val mse: 104309.1406
Epoch 909/1500
8 - mse: 96840.4531 - val loss: 104517.9219 - val mse: 104308.8047
Epoch 910/1500
3 - mse: 96119.3438 - val loss: 104133.4062 - val mse: 103924.1562
Epoch 911/1500
1 - mse: 95773.5312 - val loss: 103041.7812 - val mse: 102832.4453
Epoch 912/1500
2 - mse: 96072.9375 - val loss: 103576.6719 - val mse: 103367.2500
Epoch 913/1500
2 - mse: 95371.9375 - val loss: 103195.1875 - val mse: 102985.6484
Epoch 914/1500
6 - mse: 95127.6797 - val loss: 102988.6875 - val mse: 102779.0547
Epoch 915/1500
7 - mse: 94940.8125 - val loss: 102588.7812 - val mse: 102379.0625
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Epoch 916/1500
5 - mse: 94560.3594 - val loss: 102353.4766 - val mse: 102143.6484
Epoch 917/1500
2 - mse: 94349.7422 - val_loss: 102172.3906 - val_mse: 101962.4922
Epoch 918/1500
1 - mse: 94052.1172 - val_loss: 101987.8750 - val_mse: 101777.8516
Epoch 919/1500
7 - mse: 93828.6719 - val_loss: 101714.8203 - val_mse: 101504.7031
Epoch 920/1500
6 - mse: 93595.7812 - val loss: 101504.4062 - val mse: 101294.2109
Epoch 921/1500
6 - mse: 93350.4844 - val loss: 101445.9375 - val mse: 101235.6406
Epoch 922/1500
9 - mse: 93096.9141 - val loss: 101227.0781 - val mse: 101016.6719
Epoch 923/1500
2 - mse: 93193.1328 - val_loss: 100263.5781 - val_mse: 100053.1016
Epoch 924/1500
7 - mse: 92931.7188 - val loss: 100557.3047 - val mse: 100346.7266
Epoch 925/1500
7 - mse: 92482.7734 - val loss: 100389.7500 - val mse: 100179.0859
Epoch 926/1500
9 - mse: 92206.5391 - val loss: 99868.9375 - val mse: 99658.1562
Epoch 927/1500
8 - mse: 91885.0547 - val loss: 99316.4531 - val mse: 99105.6094
Epoch 928/1500
1 - mse: 91753.7422 - val loss: 99326.4453 - val mse: 99115.5000
Epoch 929/1500
7 - mse: 91509.4062 - val loss: 98549.5703 - val mse: 98338.5312
Epoch 930/1500
7 - mse: 91139.4141 - val loss: 98354.1719 - val mse: 98143.0234
Epoch 931/1500
7 - mse: 90985.8594 - val loss: 98186.1641 - val mse: 97974.9219
Epoch 932/1500
70/70 [============================] - Os 3ms/step - loss: 90860.195
3 - mse: 90649.0391 - val loss: 97753.5938 - val mse: 97542.2969
Epoch 933/1500
0 - mse: 90394.6016 - val loss: 97273.6328 - val mse: 97062.2344
Epoch 934/1500
6 - mse: 90278.8984 - val loss: 97218.9375 - val mse: 97007.4609
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Epoch 935/1500
8 - mse: 90012.3359 - val loss: 96551.1641 - val mse: 96339.6016
Epoch 936/1500
9 - mse: 89927.5469 - val loss: 96818.7344 - val mse: 96607.1094
Epoch 937/1500
9 - mse: 89566.4609 - val loss: 96253.4609 - val mse: 96041.7422
Epoch 938/1500
6 - mse: 89308.4531 - val_loss: 95765.4219 - val_mse: 95553.6328
Epoch 939/1500
3 - mse: 89226.2891 - val loss: 96259.7656 - val mse: 96047.9062
Epoch 940/1500
4 - mse: 88982.5469 - val loss: 95457.1172 - val mse: 95245.1641
Epoch 941/1500
4 - mse: 88637.0938 - val loss: 95234.9531 - val mse: 95022.9375
Epoch 942/1500
4 - mse: 88602.6719 - val_loss: 95525.9609 - val_mse: 95313.8750
Epoch 943/1500
2 - mse: 88287.0547 - val loss: 94866.0469 - val mse: 94653.8359
Epoch 944/1500
6 - mse: 88024.3438 - val loss: 94306.6562 - val mse: 94094.3516
Epoch 945/1500
2 - mse: 87981.0312 - val loss: 94434.1719 - val mse: 94221.8125
Epoch 946/1500
2 - mse: 87648.1719 - val loss: 93760.6094 - val mse: 93548.1797
Epoch 947/1500
3 - mse: 87564.9219 - val loss: 94321.1484 - val mse: 94108.6641
Epoch 948/1500
6 - mse: 87313.3594 - val loss: 93412.2109 - val mse: 93199.6172
Epoch 949/1500
6 - mse: 87061.6719 - val loss: 93465.8516 - val mse: 93253.1719
Epoch 950/1500
4 - mse: 87058.6484 - val loss: 93108.0938 - val mse: 92895.3594
Epoch 951/1500
4 - mse: 86715.1953 - val loss: 93093.8750 - val mse: 92881.0547
Epoch 952/1500
4 - mse: 86659.8047 - val loss: 93118.5859 - val mse: 92905.6953
Epoch 953/1500
5 - mse: 86423.8281 - val loss: 92914.9531 - val mse: 92702.0000
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Epoch 954/1500
9 - mse: 86344.5391 - val loss: 92855.1797 - val mse: 92642.1328
Epoch 955/1500
1 - mse: 86132.9766 - val_loss: 92149.9766 - val_mse: 91936.8828
Epoch 956/1500
0 - mse: 85859.9453 - val loss: 92443.7734 - val mse: 92230.5938
Epoch 957/1500
0 - mse: 85827.1250 - val_loss: 92298.3984 - val_mse: 92085.1797
Epoch 958/1500
6 - mse: 85651.3125 - val loss: 91602.1406 - val mse: 91388.8125
Epoch 959/1500
6 - mse: 85461.7031 - val loss: 91898.3984 - val mse: 91685.0000
Epoch 960/1500
6 - mse: 85276.7344 - val loss: 91449.6562 - val mse: 91236.1875
Epoch 961/1500
9 - mse: 85084.6406 - val_loss: 90852.0625 - val_mse: 90638.5312
Epoch 962/1500
4 - mse: 84988.5469 - val loss: 91167.0078 - val mse: 90953.4219
Epoch 963/1500
1 - mse: 84765.3594 - val loss: 90944.0078 - val mse: 90730.3672
Epoch 964/1500
8 - mse: 84587.7422 - val loss: 90402.5000 - val mse: 90188.7891
Epoch 965/1500
7 - mse: 84498.7422 - val loss: 90694.2422 - val mse: 90480.4531
Epoch 966/1500
7 - mse: 84341.0312 - val loss: 89994.0391 - val mse: 89780.1797
Epoch 967/1500
8 - mse: 84189.0547 - val loss: 90165.2109 - val mse: 89951.3047
Epoch 968/1500
8 - mse: 83980.3984 - val loss: 90152.1641 - val mse: 89938.1719
Epoch 969/1500
9 - mse: 83759.6406 - val loss: 89497.6406 - val mse: 89283.5781
Epoch 970/1500
6 - mse: 83777.2188 - val loss: 89470.5703 - val mse: 89256.4766
Epoch 971/1500
9 - mse: 83502.3828 - val loss: 89583.5547 - val mse: 89369.3828
Epoch 972/1500
1 - mse: 83334.5156 - val loss: 89065.8359 - val mse: 88851.6016
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Epoch 973/1500
2 - mse: 83232.6953 - val loss: 88596.4688 - val mse: 88382.1562
Epoch 974/1500
4 - mse: 83130.3359 - val loss: 88715.7656 - val mse: 88501.3672
Epoch 975/1500
9 - mse: 83024.5938 - val loss: 88208.5781 - val mse: 87994.1250
Epoch 976/1500
2 - mse: 82802.7344 - val_loss: 88017.1016 - val_mse: 87802.5703
Epoch 977/1500
3 - mse: 82601.9688 - val loss: 87919.9766 - val mse: 87705.3750
Epoch 978/1500
2 - mse: 82586.9609 - val loss: 87904.1484 - val mse: 87689.4766
Epoch 979/1500
2 - mse: 82449.3750 - val loss: 87463.5547 - val mse: 87248.8125
Epoch 980/1500
8 - mse: 82248.9609 - val_loss: 87260.9922 - val_mse: 87046.2109
Epoch 981/1500
8 - mse: 82155.6562 - val loss: 87447.1094 - val mse: 87232.2422
Epoch 982/1500
6 - mse: 82048.7812 - val loss: 87020.4844 - val mse: 86805.5703
Epoch 983/1500
5 - mse: 81792.0703 - val loss: 86866.7500 - val mse: 86651.7734
Epoch 984/1500
6 - mse: 81591.2891 - val loss: 86664.8281 - val mse: 86449.7891
Epoch 985/1500
6 - mse: 81644.1641 - val loss: 86556.2656 - val mse: 86341.1797
Epoch 986/1500
2 - mse: 81383.4922 - val loss: 86294.3047 - val mse: 86079.1641
Epoch 987/1500
8 - mse: 81162.0078 - val loss: 86236.5312 - val mse: 86021.2812
Epoch 988/1500
1 - mse: 81186.5312 - val loss: 86221.2266 - val mse: 86005.9766
Epoch 989/1500
1 - mse: 80952.5938 - val loss: 86060.0859 - val mse: 85844.7500
Epoch 990/1500
3 - mse: 80834.3594 - val loss: 85832.8438 - val mse: 85617.4375
Epoch 991/1500
0 - mse: 80783.7500 - val loss: 85946.4922 - val mse: 85731.0469
```

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Epoch 992/1500
9 - mse: 80565.4062 - val loss: 85730.5703 - val mse: 85515.0547
Epoch 993/1500
6 - mse: 80426.2891 - val_loss: 85591.1094 - val_mse: 85375.5078
Epoch 994/1500
6 - mse: 80277.9453 - val loss: 85687.5078 - val mse: 85471.8672
Epoch 995/1500
2 - mse: 80155.7891 - val_loss: 85532.5000 - val_mse: 85316.7812
Epoch 996/1500
8 - mse: 80126.0703 - val loss: 85065.6562 - val mse: 84849.8828
Epoch 997/1500
1 - mse: 79935.4531 - val loss: 85642.9531 - val mse: 85427.1172
Epoch 998/1500
4 - mse: 79882.4531 - val loss: 85069.4297 - val mse: 84853.5547
Epoch 999/1500
6 - mse: 79672.3906 - val_loss: 84897.0234 - val_mse: 84681.0625
Epoch 1000/1500
4 - mse: 79656.2188 - val loss: 84981.0312 - val mse: 84765.0469
Epoch 1001/1500
1 - mse: 79451.2578 - val loss: 85053.9375 - val mse: 84837.8828
Epoch 1002/1500
8 - mse: 79360.8672 - val loss: 84693.5000 - val mse: 84477.4141
Epoch 1003/1500
9 - mse: 79191.2891 - val loss: 84793.7734 - val mse: 84577.6406
Epoch 1004/1500
4 - mse: 79075.7891 - val loss: 84524.4297 - val mse: 84308.2109
Epoch 1005/1500
6 - mse: 79033.1875 - val loss: 84790.3594 - val mse: 84574.1094
Epoch 1006/1500
6 - mse: 78925.1641 - val loss: 84275.0859 - val mse: 84058.7891
Epoch 1007/1500
4 - mse: 78720.5000 - val loss: 84315.9453 - val mse: 84099.6016
Epoch 1008/1500
70/70 [===========================] - 0s 2ms/step - loss: 78794.140
6 - mse: 78577.8281 - val loss: 84526.2969 - val mse: 84309.8984
Epoch 1009/1500
3 - mse: 78436.5703 - val loss: 84139.7344 - val mse: 83923.2422
Epoch 1010/1500
6 - mse: 78354.0156 - val loss: 84103.2344 - val mse: 83886.7031
```

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Epoch 1011/1500
3 - mse: 78194.2031 - val_loss: 84187.7891 - val_mse: 83971.2188
Epoch 1012/1500
7 - mse: 78165.2500 - val_loss: 83875.8125 - val_mse: 83659.1875
Epoch 1013/1500
1 - mse: 77987.8281 - val loss: 83796.4219 - val mse: 83579.7422
Epoch 1014/1500
6 - mse: 77824.7344 - val_loss: 83995.5234 - val_mse: 83778.7734
Epoch 1015/1500
0 - mse: 77767.6719 - val loss: 83770.2031 - val mse: 83553.4062
Epoch 1016/1500
9 - mse: 77621.1719 - val loss: 83602.2109 - val mse: 83385.3672
Epoch 1017/1500
4 - mse: 77497.7188 - val loss: 83672.0781 - val mse: 83455.1797
Epoch 1018/1500
1 - mse: 77456.3359 - val_loss: 83399.3359 - val_mse: 83182.4062
Epoch 1019/1500
2 - mse: 77281.7422 - val loss: 83216.9219 - val mse: 82999.9297
Epoch 1020/1500
3 - mse: 77263.3828 - val loss: 83089.4688 - val mse: 82872.4219
Epoch 1021/1500
6 - mse: 77104.6328 - val loss: 83006.5312 - val mse: 82789.4297
Epoch 1022/1500
1 - mse: 77021.6328 - val loss: 82986.9297 - val mse: 82769.7656
Epoch 1023/1500
5 - mse: 76847.0469 - val loss: 82962.6719 - val mse: 82745.4531
Epoch 1024/1500
9 - mse: 76750.1328 - val loss: 82904.8594 - val mse: 82687.5547
Epoch 1025/1500
6 - mse: 76345.7734 - val loss: 82701.1875 - val mse: 82483.8203
Epoch 1026/1500
0 - mse: 76109.4375 - val loss: 82745.9766 - val mse: 82528.5938
Epoch 1027/1500
4 - mse: 76037.5391 - val loss: 82380.7891 - val mse: 82163.3281
Epoch 1028/1500
8 - mse: 75937.9375 - val loss: 82463.0938 - val mse: 82245.6016
Epoch 1029/1500
0 - mse: 75783.3984 - val loss: 82436.4453 - val mse: 82218.8594
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Epoch 1030/1500
3 - mse: 75593.8984 - val loss: 82362.2656 - val mse: 82144.6484
Epoch 1031/1500
6 - mse: 75464.2891 - val_loss: 82303.6641 - val_mse: 82086.0078
Epoch 1032/1500
8 - mse: 75335.5703 - val loss: 82415.8594 - val mse: 82198.1016
Epoch 1033/1500
8 - mse: 75203.2891 - val_loss: 82449.5625 - val_mse: 82231.7734
Epoch 1034/1500
1 - mse: 75149.7969 - val loss: 82359.9688 - val mse: 82142.1328
Epoch 1035/1500
5 - mse: 74971.5078 - val loss: 82434.6562 - val mse: 82216.7656
Epoch 1036/1500
3 - mse: 74885.9531 - val loss: 82414.2578 - val mse: 82196.3203
Epoch 1037/1500
9 - mse: 74749.4375 - val_loss: 82372.5000 - val_mse: 82154.5000
Epoch 1038/1500
6 - mse: 74627.8750 - val loss: 82288.1172 - val mse: 82070.0469
Epoch 1039/1500
4 - mse: 74471.1094 - val loss: 82334.5547 - val mse: 82116.4297
Epoch 1040/1500
1 - mse: 74311.7422 - val loss: 82256.9219 - val mse: 82038.7656
Epoch 1041/1500
6 - mse: 74240.1172 - val loss: 82204.7891 - val mse: 81986.5703
Epoch 1042/1500
1 - mse: 74092.7344 - val loss: 82048.5625 - val mse: 81830.2812
Epoch 1043/1500
8 - mse: 74006.4688 - val loss: 82065.4688 - val mse: 81847.1406
Epoch 1044/1500
70/70 [============================] - 0s 2ms/step - loss: 74088.242
2 - mse: 73869.9375 - val loss: 82031.6016 - val mse: 81813.2188
Epoch 1045/1500
2 - mse: 73798.2188 - val loss: 81957.4688 - val mse: 81739.0469
Epoch 1046/1500
70/70 [============================] - 0s 2ms/step - loss: 73829.812
5 - mse: 73611.4219 - val loss: 81619.3281 - val mse: 81400.8438
Epoch 1047/1500
0 - mse: 73460.6797 - val loss: 81797.4531 - val mse: 81578.9453
Epoch 1048/1500
6 - mse: 73426.0859 - val loss: 81530.1172 - val mse: 81311.5391
```

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Epoch 1049/1500
1 - mse: 73301.8438 - val_loss: 81638.3516 - val_mse: 81419.7109
Epoch 1050/1500
1 - mse: 73108.1875 - val_loss: 81536.2109 - val_mse: 81317.5156
Epoch 1051/1500
1 - mse: 73028.3906 - val loss: 81391.2109 - val mse: 81172.4609
Epoch 1052/1500
9 - mse: 72868.5469 - val_loss: 81267.6875 - val_mse: 81048.8672
Epoch 1053/1500
3 - mse: 72802.7344 - val loss: 81185.0703 - val mse: 80966.2031
Epoch 1054/1500
9 - mse: 72754.4219 - val loss: 80984.1953 - val mse: 80765.2500
Epoch 1055/1500
3 - mse: 72501.2578 - val loss: 80797.9844 - val mse: 80579.0000
Epoch 1056/1500
1 - mse: 72409.3594 - val_loss: 80734.0234 - val_mse: 80514.9531
Epoch 1057/1500
7 - mse: 72232.6094 - val loss: 80681.7188 - val mse: 80462.5859
Epoch 1058/1500
1 - mse: 72150.2109 - val loss: 80492.6719 - val mse: 80273.4844
Epoch 1059/1500
0 - mse: 72022.3203 - val loss: 80463.6172 - val mse: 80244.3672
Epoch 1060/1500
9 - mse: 71922.9297 - val loss: 80399.9688 - val mse: 80180.6875
Epoch 1061/1500
8 - mse: 71732.5938 - val loss: 80215.7031 - val mse: 79996.3516
Epoch 1062/1500
1 - mse: 71687.1875 - val loss: 80179.7891 - val mse: 79960.3828
Epoch 1063/1500
0 - mse: 71545.8594 - val loss: 80127.5547 - val mse: 79908.0703
Epoch 1064/1500
7 - mse: 71357.5781 - val loss: 79883.6719 - val mse: 79664.1406
Epoch 1065/1500
8 - mse: 71355.4453 - val loss: 79772.0469 - val mse: 79552.4531
Epoch 1066/1500
9 - mse: 71146.0938 - val loss: 79704.6719 - val mse: 79485.0391
Epoch 1067/1500
7 - mse: 71077.9062 - val loss: 79580.5938 - val mse: 79360.8594
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Epoch 1068/1500
1 - mse: 70959.1797 - val loss: 79524.2578 - val mse: 79304.4453
Epoch 1069/1500
9 - mse: 70797.5234 - val loss: 79475.3828 - val mse: 79255.4844
Epoch 1070/1500
3 - mse: 70727.0469 - val loss: 79444.9375 - val mse: 79224.9922
Epoch 1071/1500
1 - mse: 70532.8906 - val_loss: 79488.3516 - val_mse: 79268.3203
Epoch 1072/1500
4 - mse: 70431.3359 - val loss: 79131.0625 - val mse: 78910.9609
Epoch 1073/1500
9 - mse: 70338.0703 - val loss: 79084.4531 - val mse: 78864.2656
Epoch 1074/1500
0 - mse: 70154.0703 - val loss: 78933.2578 - val mse: 78712.9844
Epoch 1075/1500
8 - mse: 70078.9844 - val_loss: 78741.8516 - val_mse: 78521.5000
Epoch 1076/1500
6 - mse: 69918.5469 - val loss: 78609.7422 - val mse: 78389.3125
Epoch 1077/1500
4 - mse: 69881.4688 - val loss: 78318.9688 - val mse: 78098.4922
Epoch 1078/1500
8 - mse: 69627.5391 - val loss: 78271.0859 - val mse: 78050.5156
Epoch 1079/1500
6 - mse: 69588.9141 - val loss: 78177.9453 - val mse: 77957.2969
Epoch 1080/1500
9 - mse: 69420.7891 - val loss: 78007.8984 - val mse: 77787.2109
Epoch 1081/1500
8 - mse: 69295.4062 - val loss: 77453.8516 - val mse: 77233.0703
Epoch 1082/1500
6 - mse: 69156.6094 - val loss: 77234.3125 - val mse: 77013.4766
Epoch 1083/1500
4 - mse: 69021.0156 - val loss: 77056.2031 - val mse: 76835.2969
Epoch 1084/1500
6 - mse: 68814.6172 - val loss: 76827.4219 - val mse: 76606.4375
Epoch 1085/1500
6 - mse: 68764.6719 - val loss: 76710.3828 - val mse: 76489.3281
Epoch 1086/1500
8 - mse: 68496.9141 - val loss: 76348.3047 - val mse: 76127.1953
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Epoch 1087/1500
4 - mse: 68425.3047 - val_loss: 76185.8203 - val_mse: 75964.6406
Epoch 1088/1500
8 - mse: 68196.3125 - val loss: 75940.3672 - val mse: 75719.1250
Epoch 1089/1500
0 - mse: 67949.6562 - val_loss: 75988.5312 - val mse: 75767.1953
Epoch 1090/1500
1 - mse: 67716.4844 - val_loss: 75765.0938 - val_mse: 75543.7109
Epoch 1091/1500
4 - mse: 67614.9922 - val loss: 75535.5781 - val mse: 75314.1172
Epoch 1092/1500
2 - mse: 67289.5547 - val loss: 75586.5312 - val mse: 75364.9688
Epoch 1093/1500
8 - mse: 67198.1641 - val loss: 75475.9297 - val mse: 75254.3125
Epoch 1094/1500
6 - mse: 67061.6250 - val_loss: 75552.5312 - val_mse: 75330.8516
Epoch 1095/1500
7 - mse: 66919.9766 - val loss: 75344.7656 - val mse: 75123.0078
Epoch 1096/1500
4 - mse: 66754.4688 - val loss: 75248.3984 - val mse: 75026.5625
Epoch 1097/1500
9 - mse: 66588.5781 - val loss: 75100.6719 - val mse: 74878.7656
Epoch 1098/1500
6 - mse: 66359.5703 - val loss: 75012.8594 - val mse: 74790.8594
Epoch 1099/1500
1 - mse: 66265.3828 - val loss: 74932.2656 - val mse: 74710.2188
Epoch 1100/1500
6 - mse: 66161.6953 - val loss: 74784.4375 - val mse: 74562.3281
Epoch 1101/1500
4 - mse: 65997.5547 - val loss: 74751.7344 - val mse: 74529.5938
Epoch 1102/1500
9 - mse: 65831.0547 - val loss: 74678.8984 - val mse: 74456.7031
Epoch 1103/1500
3 - mse: 65670.1328 - val loss: 74621.5156 - val mse: 74399.2656
Epoch 1104/1500
0 - mse: 65640.6250 - val loss: 74581.9609 - val mse: 74359.6328
Epoch 1105/1500
0 - mse: 65478.0469 - val loss: 74622.0312 - val mse: 74399.6484
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Epoch 1106/1500
9 - mse: 65431.2734 - val_loss: 74513.3594 - val_mse: 74290.9062
Epoch 1107/1500
8 - mse: 65255.5273 - val_loss: 74554.6484 - val_mse: 74332.1172
Epoch 1108/1500
7 - mse: 65251.9805 - val loss: 74238.0625 - val mse: 74015.4609
Epoch 1109/1500
8 - mse: 65034.6758 - val_loss: 74443.8828 - val_mse: 74221.2344
Epoch 1110/1500
5 - mse: 65013.1016 - val loss: 74230.8281 - val mse: 74008.1172
Epoch 1111/1500
8 - mse: 64935.0977 - val loss: 74438.5781 - val mse: 74215.8359
Epoch 1112/1500
9 - mse: 64903.0859 - val loss: 74142.3984 - val mse: 73919.5625
Epoch 1113/1500
6 - mse: 64656.4375 - val_loss: 74272.4531 - val_mse: 74049.5781
Epoch 1114/1500
5 - mse: 64629.7930 - val loss: 74364.4688 - val mse: 74141.5469
Epoch 1115/1500
0 - mse: 64680.3516 - val loss: 74022.3750 - val mse: 73799.3750
Epoch 1116/1500
6 - mse: 64510.7969 - val loss: 74398.3594 - val mse: 74175.2734
Epoch 1117/1500
0 - mse: 64356.8867 - val loss: 74213.6484 - val mse: 73990.5312
Epoch 1118/1500
3 - mse: 64424.6172 - val loss: 74009.0781 - val mse: 73785.8828
Epoch 1119/1500
3 - mse: 64217.2461 - val loss: 74143.8984 - val mse: 73920.6328
Epoch 1120/1500
7 - mse: 64101.7383 - val loss: 74339.1875 - val mse: 74115.8828
Epoch 1121/1500
5 - mse: 64023.3711 - val loss: 74160.2891 - val mse: 73936.8984
Epoch 1122/1500
70/70 [============================] - 0s 3ms/step - loss: 64226.375
0 - mse: 64003.0078 - val loss: 74022.9844 - val mse: 73799.5234
Epoch 1123/1500
3 - mse: 63916.8047 - val loss: 74082.5156 - val mse: 73859.0000
Epoch 1124/1500
9 - mse: 63710.9727 - val loss: 74181.8125 - val mse: 73958.2422
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Epoch 1125/1500
1 - mse: 63734.2148 - val_loss: 74114.0078 - val_mse: 73890.3594
Epoch 1126/1500
1 - mse: 63618.7461 - val_loss: 73939.5547 - val_mse: 73715.8828
Epoch 1127/1500
4 - mse: 63598.1992 - val loss: 73923.4219 - val mse: 73699.6484
Epoch 1128/1500
5 - mse: 63442.2070 - val_loss: 74032.7656 - val_mse: 73808.9375
Epoch 1129/1500
8 - mse: 63470.1367 - val loss: 74002.5625 - val mse: 73778.6719
Epoch 1130/1500
7 - mse: 63300.2266 - val loss: 74053.5781 - val mse: 73829.6172
Epoch 1131/1500
6 - mse: 63227.2500 - val loss: 74017.1875 - val mse: 73793.1406
Epoch 1132/1500
6 - mse: 63117.6406 - val_loss: 73964.9219 - val_mse: 73740.8281
Epoch 1133/1500
2 - mse: 63099.5664 - val loss: 73984.8516 - val mse: 73760.7188
Epoch 1134/1500
5 - mse: 62916.9609 - val loss: 73952.9922 - val mse: 73728.7812
Epoch 1135/1500
2 - mse: 62919.5859 - val loss: 73931.8828 - val mse: 73707.5859
Epoch 1136/1500
9 - mse: 62860.9375 - val loss: 73807.1484 - val mse: 73582.7891
Epoch 1137/1500
1 - mse: 62785.8125 - val loss: 73620.8516 - val mse: 73396.4297
Epoch 1138/1500
3 - mse: 62918.5820 - val loss: 73565.8750 - val mse: 73341.3828
Epoch 1139/1500
5 - mse: 62658.5820 - val loss: 73747.6484 - val mse: 73523.0859
Epoch 1140/1500
6 - mse: 62727.1211 - val loss: 73707.3047 - val mse: 73482.6562
Epoch 1141/1500
3 - mse: 62567.0977 - val loss: 73657.9219 - val mse: 73433.2031
Epoch 1142/1500
8 - mse: 62487.4414 - val loss: 73618.5156 - val mse: 73393.7266
Epoch 1143/1500
8 - mse: 62476.2930 - val loss: 73332.5000 - val mse: 73107.6641
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Epoch 1144/1500
6 - mse: 62422.2461 - val_loss: 73607.4922 - val_mse: 73382.5547
Epoch 1145/1500
0 - mse: 62405.6406 - val_loss: 73447.5000 - val_mse: 73222.5000
Epoch 1146/1500
8 - mse: 62299.3203 - val loss: 73315.1172 - val mse: 73090.0312
Epoch 1147/1500
4 - mse: 62317.3281 - val_loss: 73254.9766 - val_mse: 73029.8438
Epoch 1148/1500
2 - mse: 62148.8750 - val loss: 73326.5703 - val mse: 73101.3516
Epoch 1149/1500
8 - mse: 62191.9844 - val loss: 73327.7734 - val mse: 73102.4609
Epoch 1150/1500
9 - mse: 62053.2109 - val loss: 73321.3750 - val mse: 73095.9922
Epoch 1151/1500
5 - mse: 62040.2500 - val_loss: 73013.2812 - val_mse: 72787.8438
Epoch 1152/1500
1 - mse: 61990.0352 - val loss: 73100.0781 - val mse: 72874.5547
Epoch 1153/1500
8 - mse: 61988.2578 - val loss: 73209.2031 - val mse: 72983.6250
Epoch 1154/1500
3 - mse: 61821.0859 - val loss: 73164.6250 - val mse: 72938.9766
Epoch 1155/1500
9 - mse: 61861.5000 - val loss: 73146.6406 - val mse: 72920.9297
Epoch 1156/1500
2 - mse: 61645.7266 - val loss: 73127.8594 - val mse: 72902.0938
Epoch 1157/1500
0 - mse: 61615.0938 - val loss: 73097.5781 - val mse: 72871.7578
Epoch 1158/1500
1 - mse: 61519.9531 - val loss: 72863.6641 - val mse: 72637.7500
Epoch 1159/1500
8 - mse: 61566.5078 - val loss: 72704.5391 - val mse: 72478.5781
Epoch 1160/1500
70/70 [============================] - 0s 2ms/step - loss: 61589.847
7 - mse: 61363.8594 - val loss: 72929.6719 - val mse: 72703.6328
Epoch 1161/1500
0 - mse: 61284.3555 - val loss: 72797.9375 - val mse: 72571.8281
Epoch 1162/1500
4 - mse: 61150.8008 - val loss: 72811.1484 - val mse: 72584.9609
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Epoch 1163/1500
2 - mse: 61097.9297 - val loss: 72698.1328 - val mse: 72471.9141
Epoch 1164/1500
9 - mse: 61009.2734 - val loss: 72471.0938 - val mse: 72244.7969
Epoch 1165/1500
0 - mse: 60993.7344 - val loss: 72410.6406 - val mse: 72184.2656
Epoch 1166/1500
9 - mse: 60912.2812 - val_loss: 72278.0234 - val_mse: 72051.5859
Epoch 1167/1500
0 - mse: 60870.2305 - val loss: 72214.3672 - val mse: 71987.8516
Epoch 1168/1500
4 - mse: 60756.5273 - val loss: 72346.0234 - val mse: 72119.4531
Epoch 1169/1500
4 - mse: 60685.3906 - val loss: 72179.1406 - val mse: 71952.5000
Epoch 1170/1500
4 - mse: 60595.1562 - val_loss: 71866.3203 - val_mse: 71639.6016
Epoch 1171/1500
47 - mse: 60505.0625 - val loss: 71825.0312 - val mse: 71598.2344
Epoch 1172/1500
84 - mse: 60287.5859 - val loss: 71782.9531 - val mse: 71556.0859
Epoch 1173/1500
28 - mse: 60304.5117 - val loss: 71684.7188 - val mse: 71457.7891
Epoch 1174/1500
1 - mse: 60105.9688 - val loss: 71386.7969 - val mse: 71159.7891
Epoch 1175/1500
3 - mse: 60015.3906 - val loss: 71232.1094 - val mse: 71005.0469
Epoch 1176/1500
39 - mse: 59886.4336 - val loss: 71019.0938 - val mse: 70791.9531
Epoch 1177/1500
11 - mse: 59734.4766 - val loss: 70890.3359 - val mse: 70663.1406
Epoch 1178/1500
59 - mse: 59647.8633 - val loss: 70915.6016 - val mse: 70688.3281
Epoch 1179/1500
42 - mse: 59530.3086 - val loss: 70867.9453 - val mse: 70640.6172
Epoch 1180/1500
30 - mse: 59445.1875 - val loss: 70698.6094 - val mse: 70471.1953
Epoch 1181/1500
06 - mse: 59391.9609 - val loss: 70591.6484 - val mse: 70364.1719
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Epoch 1182/1500
44 - mse: 59263.7656 - val_loss: 70499.9453 - val_mse: 70272.3906
Epoch 1183/1500
5 - mse: 59244.5859 - val loss: 70349.7344 - val mse: 70122.1016
Epoch 1184/1500
4 - mse: 59066.5781 - val loss: 70349.2031 - val mse: 70121.5078
Epoch 1185/1500
2 - mse: 59035.3203 - val_loss: 70231.3828 - val_mse: 70003.6016
Epoch 1186/1500
6 - mse: 58957.8711 - val loss: 70151.0625 - val mse: 69923.2266
Epoch 1187/1500
17 - mse: 58763.4062 - val loss: 70088.9062 - val mse: 69861.0000
Epoch 1188/1500
80 - mse: 58759.4922 - val loss: 70034.6250 - val mse: 69806.6406
Epoch 1189/1500
22 - mse: 58674.7773 - val_loss: 69890.0703 - val_mse: 69662.0391
Epoch 1190/1500
09 - mse: 58596.3828 - val loss: 69829.3047 - val mse: 69601.1875
Epoch 1191/1500
61 - mse: 58558.8594 - val loss: 69684.0312 - val_mse: 69455.8359
Epoch 1192/1500
12 - mse: 58390.8398 - val loss: 69487.3438 - val mse: 69259.1094
Epoch 1193/1500
22 - mse: 58368.9883 - val loss: 69534.8750 - val mse: 69306.5703
Epoch 1194/1500
80 - mse: 58221.8711 - val loss: 69404.0703 - val mse: 69175.7188
Epoch 1195/1500
22 - mse: 58210.1211 - val loss: 69252.7109 - val mse: 69024.3047
Epoch 1196/1500
41 - mse: 58090.7344 - val loss: 69219.5938 - val mse: 68991.1094
Epoch 1197/1500
98 - mse: 57972.8516 - val loss: 69103.7422 - val mse: 68875.1875
Epoch 1198/1500
16 - mse: 57957.0273 - val loss: 68975.2031 - val mse: 68746.6016
Epoch 1199/1500
91 - mse: 57900.4258 - val loss: 68915.7344 - val mse: 68687.0547
Epoch 1200/1500
86 - mse: 57502.6172 - val loss: 68706.3750 - val mse: 68477.6484
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Epoch 1201/1500
23 - mse: 57482.1602 - val_loss: 68479.6875 - val_mse: 68250.8984
Epoch 1202/1500
3 - mse: 57309.4375 - val_loss: 68232.7812 - val_mse: 68003.9453
Epoch 1203/1500
3 - mse: 57198.9492 - val loss: 68167.1719 - val mse: 67938.2578
Epoch 1204/1500
48 - mse: 57080.0156 - val_loss: 68027.5469 - val_mse: 67798.5469
Epoch 1205/1500
88 - mse: 57003.9609 - val loss: 67922.1953 - val mse: 67693.1484
Epoch 1206/1500
00 - mse: 56807.1758 - val loss: 67737.1797 - val mse: 67508.0703
Epoch 1207/1500
80 - mse: 56804.5156 - val loss: 67670.2578 - val mse: 67441.0469
Epoch 1208/1500
00 - mse: 56671.5312 - val_loss: 67592.6328 - val_mse: 67363.3750
Epoch 1209/1500
66 - mse: 56533.9766 - val loss: 67448.4531 - val mse: 67219.1484
Epoch 1210/1500
00 - mse: 56507.6523 - val loss: 67324.8984 - val_mse: 67095.5234
Epoch 1211/1500
50 - mse: 56343.2734 - val loss: 67246.6719 - val mse: 67017.2578
Epoch 1212/1500
31 - mse: 56335.2383 - val loss: 67146.7891 - val mse: 66917.2891
Epoch 1213/1500
52 - mse: 56211.5273 - val loss: 67043.6875 - val mse: 66814.1172
Epoch 1214/1500
30 - mse: 56044.7344 - val loss: 66993.4141 - val mse: 66763.7891
Epoch 1215/1500
7 - mse: 56091.4297 - val loss: 66885.0859 - val mse: 66655.3984
Epoch 1216/1500
0 - mse: 55887.8398 - val loss: 66832.1719 - val mse: 66602.4297
Epoch 1217/1500
70/70 [============================] - 1s 8ms/step - loss: 56075.687
5 - mse: 55845.9219 - val loss: 66709.8984 - val mse: 66480.0859
Epoch 1218/1500
1 - mse: 55808.5039 - val loss: 66710.5234 - val mse: 66480.6406
Epoch 1219/1500
8 - mse: 55623.5781 - val loss: 66579.6719 - val mse: 66349.7422
```

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Epoch 1220/1500
7 - mse: 55622.2344 - val loss: 66519.1094 - val mse: 66289.1250
Epoch 1221/1500
2 - mse: 55484.4375 - val_loss: 66422.4766 - val_mse: 66192.4453
Epoch 1222/1500
7 - mse: 55478.6133 - val loss: 66314.7188 - val mse: 66084.6094
Epoch 1223/1500
6 - mse: 55349.6289 - val_loss: 66221.3750 - val_mse: 65991.2422
Epoch 1224/1500
2 - mse: 55287.3906 - val loss: 66100.2266 - val mse: 65870.0234
Epoch 1225/1500
1 - mse: 55142.5625 - val loss: 66085.2109 - val mse: 65854.9531
Epoch 1226/1500
0 - mse: 55016.9023 - val loss: 66003.7656 - val mse: 65773.4688
Epoch 1227/1500
3 - mse: 54939.2031 - val_loss: 65962.6641 - val_mse: 65732.2812
Epoch 1228/1500
3 - mse: 54897.0859 - val loss: 65856.9609 - val mse: 65626.5391
Epoch 1229/1500
4 - mse: 54732.7773 - val loss: 65785.7422 - val mse: 65555.2422
Epoch 1230/1500
2 - mse: 54681.3984 - val loss: 65741.1406 - val mse: 65510.5938
Epoch 1231/1500
7 - mse: 54555.4844 - val loss: 65673.4062 - val mse: 65442.7969
Epoch 1232/1500
7 - mse: 54476.8086 - val loss: 65606.0938 - val mse: 65375.3984
Epoch 1233/1500
8 - mse: 54454.2227 - val loss: 65511.9141 - val mse: 65281.1719
Epoch 1234/1500
0 - mse: 54317.8906 - val loss: 65516.0586 - val mse: 65285.2383
Epoch 1235/1500
6 - mse: 54176.4883 - val loss: 65448.4688 - val mse: 65217.5586
Epoch 1236/1500
1 - mse: 54172.5625 - val loss: 65347.3438 - val mse: 65116.3945
Epoch 1237/1500
6 - mse: 54039.8867 - val loss: 65322.1406 - val mse: 65091.1172
Epoch 1238/1500
5 - mse: 53910.3320 - val loss: 65263.7344 - val mse: 65032.6641
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Epoch 1239/1500
5 - mse: 53819.9688 - val loss: 65142.7031 - val mse: 64911.5586
Epoch 1240/1500
9 - mse: 53787.0938 - val loss: 65128.1758 - val mse: 64896.9688
Epoch 1241/1500
3 - mse: 53589.6836 - val loss: 65091.8984 - val mse: 64860.6406
Epoch 1242/1500
1 - mse: 53403.7656 - val_loss: 65056.0859 - val_mse: 64824.7500
Epoch 1243/1500
7 - mse: 53284.4180 - val loss: 65010.2930 - val mse: 64778.8945
Epoch 1244/1500
4 - mse: 53210.9648 - val loss: 64901.8516 - val mse: 64670.3828
Epoch 1245/1500
4 - mse: 53324.3008 - val loss: 65415.9258 - val mse: 65184.4062
Epoch 1246/1500
5 - mse: 52830.2578 - val_loss: 64811.7656 - val_mse: 64580.1523
Epoch 1247/1500
9 - mse: 52910.8359 - val loss: 64744.3008 - val mse: 64512.6367
Epoch 1248/1500
1 - mse: 53076.0156 - val loss: 65234.0273 - val mse: 65002.3125
Epoch 1249/1500
1 - mse: 52634.3711 - val loss: 64599.3633 - val mse: 64367.5391
Epoch 1250/1500
9 - mse: 52966.9492 - val loss: 65076.0469 - val mse: 64844.1680
Epoch 1251/1500
1 - mse: 52687.8906 - val loss: 65007.3359 - val mse: 64775.3984
Epoch 1252/1500
1 - mse: 52670.3320 - val loss: 64404.2461 - val mse: 64172.2266
Epoch 1253/1500
1 - mse: 52401.8711 - val loss: 64352.7305 - val mse: 64120.6641
Epoch 1254/1500
4 - mse: 52699.4180 - val loss: 64828.6211 - val mse: 64596.4883
Epoch 1255/1500
70/70 [============================] - 0s 6ms/step - loss: 52478.972
7 - mse: 52246.7852 - val loss: 64192.3945 - val mse: 63960.1523
Epoch 1256/1500
0 - mse: 52537.2891 - val loss: 64754.3945 - val mse: 64522.1016
Epoch 1257/1500
6 - mse: 52316.7891 - val loss: 64861.9336 - val mse: 64629.5938
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Epoch 1258/1500
0 - mse: 52223.2422 - val loss: 64608.2227 - val mse: 64375.8008
Epoch 1259/1500
5 - mse: 52018.4570 - val loss: 64030.7031 - val mse: 63798.2148
Epoch 1260/1500
9 - mse: 52274.8281 - val loss: 64461.4531 - val mse: 64228.9102
Epoch 1261/1500
3 - mse: 52179.5039 - val_loss: 64406.6016 - val_mse: 64174.0117
Epoch 1262/1500
6 - mse: 51928.5977 - val loss: 64307.4297 - val mse: 64074.7617
Epoch 1263/1500
4 - mse: 51814.3047 - val loss: 63778.3359 - val mse: 63545.5859
Epoch 1264/1500
0 - mse: 52038.7734 - val loss: 64145.8516 - val mse: 63913.0352
Epoch 1265/1500
4 - mse: 51687.2695 - val_loss: 63710.5938 - val_mse: 63477.6992
Epoch 1266/1500
3 - mse: 51899.6758 - val loss: 64041.1055 - val mse: 63808.1484
Epoch 1267/1500
9 - mse: 51552.1875 - val loss: 63592.1992 - val mse: 63359.1758
Epoch 1268/1500
5 - mse: 51785.7930 - val loss: 63959.8242 - val mse: 63726.7500
Epoch 1269/1500
8 - mse: 51434.9844 - val loss: 63514.8711 - val mse: 63281.7266
Epoch 1270/1500
8 - mse: 51695.5469 - val loss: 63837.6133 - val mse: 63604.4062
Epoch 1271/1500
8 - mse: 51305.4102 - val loss: 63449.6641 - val mse: 63216.3828
Epoch 1272/1500
5 - mse: 51611.0508 - val loss: 63739.4844 - val mse: 63506.1328
Epoch 1273/1500
6 - mse: 51128.9766 - val loss: 63310.6367 - val mse: 63077.2188
Epoch 1274/1500
9 - mse: 51536.3672 - val loss: 63640.0117 - val mse: 63406.5273
Epoch 1275/1500
9 - mse: 51276.4219 - val loss: 63767.0586 - val mse: 63533.5234
Epoch 1276/1500
84 - mse: 51120.5859 - val loss: 63195.2578 - val mse: 62961.6641
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Epoch 1277/1500
4 - mse: 51306.8086 - val_loss: 63552.3203 - val_mse: 63318.6484
Epoch 1278/1500
36 - mse: 51161.5000 - val_loss: 63634.1211 - val mse: 63400.3945
Epoch 1279/1500
9 - mse: 51100.8438 - val loss: 63553.5391 - val mse: 63319.7539
Epoch 1280/1500
95 - mse: 51013.9531 - val_loss: 63550.3008 - val_mse: 63316.4336
Epoch 1281/1500
8 - mse: 51086.8164 - val loss: 63503.8203 - val mse: 63269.8945
Epoch 1282/1500
89 - mse: 50891.9336 - val loss: 63495.5859 - val mse: 63261.5938
Epoch 1283/1500
3 - mse: 50996.7617 - val loss: 63424.0664 - val mse: 63189.9922
Epoch 1284/1500
5 - mse: 50712.9766 - val_loss: 63473.3047 - val_mse: 63239.1719
Epoch 1285/1500
1 - mse: 50832.2539 - val loss: 63374.9102 - val mse: 63140.7109
Epoch 1286/1500
22 - mse: 50669.7734 - val loss: 63234.3203 - val_mse: 63000.0391
Epoch 1287/1500
05 - mse: 50692.1953 - val loss: 63348.3594 - val mse: 63114.0195
Epoch 1288/1500
02 - mse: 50601.7969 - val loss: 63383.4531 - val mse: 63149.0703
Epoch 1289/1500
8 - mse: 50594.9727 - val loss: 63409.4727 - val mse: 63175.0234
Epoch 1290/1500
2 - mse: 50532.4766 - val loss: 63318.4766 - val mse: 63083.9648
Epoch 1291/1500
4 - mse: 50525.6484 - val loss: 63571.5000 - val mse: 63336.9297
Epoch 1292/1500
78 - mse: 50398.4180 - val loss: 63670.2422 - val mse: 63435.6172
Epoch 1293/1500
11 - mse: 50388.4648 - val loss: 63649.1094 - val mse: 63414.4219
Epoch 1294/1500
8 - mse: 50435.1484 - val loss: 63714.3555 - val mse: 63479.6055
Epoch 1295/1500
0 - mse: 50209.7891 - val loss: 63654.9375 - val mse: 63420.1055
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Epoch 1296/1500
86 - mse: 50394.7109 - val_loss: 63834.1328 - val_mse: 63599.2578
Epoch 1297/1500
3 - mse: 50137.0625 - val loss: 63940.2539 - val mse: 63705.2969
Epoch 1298/1500
9 - mse: 50219.4727 - val loss: 63921.8516 - val mse: 63686.8477
Epoch 1299/1500
9 - mse: 50255.9609 - val_loss: 63944.3945 - val_mse: 63709.3516
Epoch 1300/1500
0 - mse: 50157.5859 - val loss: 64028.3477 - val mse: 63793.2305
Epoch 1301/1500
8 - mse: 50170.5430 - val loss: 63884.4336 - val mse: 63649.2500
Epoch 1302/1500
31 - mse: 50034.2305 - val loss: 64101.7773 - val mse: 63866.5352
Epoch 1303/1500
5 - mse: 50074.2578 - val_loss: 64103.5859 - val_mse: 63868.2812
Epoch 1304/1500
44 - mse: 49941.3984 - val loss: 64216.5078 - val mse: 63981.1445
Epoch 1305/1500
4 - mse: 50081.4102 - val loss: 64165.5938 - val mse: 63930.1953
Epoch 1306/1500
8 - mse: 49855.5938 - val loss: 64059.2305 - val mse: 63823.7539
Epoch 1307/1500
5 - mse: 49984.1328 - val loss: 64190.9961 - val mse: 63955.4570
Epoch 1308/1500
6 - mse: 50012.8438 - val loss: 64340.2539 - val mse: 64104.6562
Epoch 1309/1500
75 - mse: 49896.0430 - val loss: 64347.0625 - val mse: 64111.4062
Epoch 1310/1500
06 - mse: 49875.4297 - val loss: 64338.5273 - val mse: 64102.8008
Epoch 1311/1500
66 - mse: 49828.7031 - val loss: 64222.0859 - val mse: 63986.2930
Epoch 1312/1500
9 - mse: 49706.7578 - val loss: 64387.3594 - val mse: 64151.5039
Epoch 1313/1500
8 - mse: 49725.0625 - val loss: 64422.1602 - val mse: 64186.2539
Epoch 1314/1500
1 - mse: 49687.4922 - val loss: 64518.4336 - val mse: 64282.4531
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Epoch 1315/1500
33 - mse: 49794.1055 - val loss: 64478.0195 - val mse: 64242.0000
Epoch 1316/1500
52 - mse: 49682.9727 - val_loss: 64530.2422 - val_mse: 64294.1602
Epoch 1317/1500
0 - mse: 49604.6758 - val loss: 64296.9688 - val mse: 64060.8477
Epoch 1318/1500
2 - mse: 49558.4648 - val_loss: 64487.1836 - val_mse: 64250.9766
Epoch 1319/1500
8 - mse: 49505.5078 - val loss: 64499.6992 - val mse: 64263.4297
Epoch 1320/1500
7 - mse: 49581.6016 - val loss: 64478.0547 - val mse: 64241.7383
Epoch 1321/1500
1 - mse: 49458.4102 - val loss: 64538.4336 - val mse: 64302.0273
Epoch 1322/1500
2 - mse: 49566.9609 - val_loss: 64511.7188 - val_mse: 64275.2500
Epoch 1323/1500
6 - mse: 49399.7852 - val loss: 64468.2812 - val mse: 64231.7461
Epoch 1324/1500
8 - mse: 49394.3242 - val loss: 64506.6367 - val mse: 64270.0469
Epoch 1325/1500
6 - mse: 49406.7305 - val loss: 64501.5781 - val mse: 64264.9297
Epoch 1326/1500
8 - mse: 49336.4844 - val loss: 64578.1211 - val mse: 64341.4062
Epoch 1327/1500
8 - mse: 49327.6602 - val loss: 64602.3594 - val mse: 64365.5781
Epoch 1328/1500
8 - mse: 49268.8867 - val loss: 64630.9297 - val mse: 64394.1055
Epoch 1329/1500
7 - mse: 49308.0000 - val loss: 64653.9453 - val mse: 64417.0508
Epoch 1330/1500
6 - mse: 49170.6172 - val loss: 64682.9883 - val mse: 64446.0469
Epoch 1331/1500
70/70 [===========================] - 0s 6ms/step - loss: 49440.609
4 - mse: 49203.5977 - val loss: 64710.4062 - val mse: 64473.4062
Epoch 1332/1500
8 - mse: 49225.2891 - val loss: 64700.9219 - val mse: 64463.8672
Epoch 1333/1500
8 - mse: 49017.5000 - val loss: 64779.3828 - val mse: 64542.2617
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Epoch 1334/1500
8 - mse: 49051.4180 - val loss: 64808.6289 - val mse: 64571.4453
Epoch 1335/1500
7 - mse: 49120.4023 - val_loss: 64792.2656 - val_mse: 64555.0156
Epoch 1336/1500
8 - mse: 48965.1328 - val loss: 64902.7617 - val mse: 64665.4570
Epoch 1337/1500
2 - mse: 48962.8359 - val_loss: 64874.9375 - val_mse: 64637.5703
Epoch 1338/1500
8 - mse: 48971.0938 - val loss: 64934.8477 - val mse: 64697.4297
Epoch 1339/1500
2 - mse: 48938.2305 - val loss: 64916.9102 - val mse: 64679.4297
Epoch 1340/1500
4 - mse: 48926.7773 - val loss: 64980.5938 - val mse: 64743.0234
Epoch 1341/1500
7 - mse: 48892.3984 - val_loss: 64986.7344 - val_mse: 64749.1094
Epoch 1342/1500
0 - mse: 48936.9961 - val loss: 64935.0430 - val mse: 64697.3516
Epoch 1343/1500
4 - mse: 48764.3125 - val loss: 64938.2070 - val mse: 64700.4766
Epoch 1344/1500
2 - mse: 48737.2344 - val loss: 64955.9883 - val mse: 64718.1953
Epoch 1345/1500
7 - mse: 48770.0898 - val loss: 64937.7188 - val mse: 64699.8711
Epoch 1346/1500
7 - mse: 48691.9414 - val loss: 64910.8086 - val mse: 64672.8828
Epoch 1347/1500
4 - mse: 48778.0117 - val loss: 64895.0352 - val mse: 64657.0703
Epoch 1348/1500
7 - mse: 48608.9531 - val loss: 64904.1758 - val mse: 64666.1289
Epoch 1349/1500
5 - mse: 48535.8320 - val loss: 64878.6953 - val mse: 64640.5938
Epoch 1350/1500
6 - mse: 48570.6953 - val loss: 64848.8438 - val mse: 64610.6836
Epoch 1351/1500
3 - mse: 48587.4492 - val loss: 64920.2070 - val mse: 64681.9609
Epoch 1352/1500
8 - mse: 48611.9258 - val loss: 64841.3828 - val mse: 64603.0820
```

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Epoch 1353/1500
6 - mse: 48509.7070 - val loss: 64870.4297 - val mse: 64632.0664
Epoch 1354/1500
3 - mse: 48499.6641 - val_loss: 64840.7227 - val_mse: 64602.2891
Epoch 1355/1500
1 - mse: 48463.6914 - val loss: 64859.1172 - val mse: 64620.6406
Epoch 1356/1500
8 - mse: 48440.8359 - val_loss: 64856.8477 - val_mse: 64618.3086
Epoch 1357/1500
8 - mse: 48333.2812 - val loss: 64793.7539 - val mse: 64555.1445
Epoch 1358/1500
0 - mse: 48417.3438 - val loss: 64803.1094 - val mse: 64564.4297
Epoch 1359/1500
7 - mse: 48286.2734 - val loss: 64780.9961 - val mse: 64542.2617
Epoch 1360/1500
6 - mse: 48306.9648 - val_loss: 64786.7031 - val_mse: 64547.9141
Epoch 1361/1500
1 - mse: 48244.0625 - val loss: 64791.1172 - val mse: 64552.2656
Epoch 1362/1500
5 - mse: 48270.1523 - val loss: 64754.2422 - val mse: 64515.3047
Epoch 1363/1500
2 - mse: 48230.1719 - val loss: 64756.7305 - val mse: 64517.7539
Epoch 1364/1500
5 - mse: 48203.8594 - val loss: 64758.2461 - val mse: 64519.2031
Epoch 1365/1500
8 - mse: 48183.7461 - val loss: 64705.9414 - val mse: 64466.8555
Epoch 1366/1500
00 - mse: 48203.0781 - val loss: 64735.9141 - val mse: 64496.7422
Epoch 1367/1500
3 - mse: 48080.7852 - val loss: 64689.5391 - val mse: 64450.2930
Epoch 1368/1500
5 - mse: 48072.8789 - val loss: 64705.6797 - val mse: 64466.3750
Epoch 1369/1500
5 - mse: 48047.7461 - val loss: 64664.0859 - val mse: 64424.7305
Epoch 1370/1500
52 - mse: 48045.1328 - val loss: 64684.8359 - val mse: 64445.4453
Epoch 1371/1500
1 - mse: 48015.3672 - val loss: 64684.1992 - val mse: 64444.7422
```

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Epoch 1372/1500
0 - mse: 47982.5234 - val loss: 64683.4844 - val mse: 64443.9648
Epoch 1373/1500
19 - mse: 47888.5977 - val_loss: 64677.8320 - val_mse: 64438.2422
Epoch 1374/1500
61 - mse: 47825.3477 - val loss: 64665.8320 - val mse: 64426.1797
Epoch 1375/1500
5 - mse: 47930.9570 - val_loss: 64645.0117 - val_mse: 64405.2773
Epoch 1376/1500
8 - mse: 47776.1250 - val loss: 64657.8398 - val mse: 64418.0469
Epoch 1377/1500
3 - mse: 47861.3711 - val loss: 64644.4805 - val mse: 64404.6211
Epoch 1378/1500
4 - mse: 47770.6250 - val loss: 64648.1328 - val mse: 64408.2266
Epoch 1379/1500
1 - mse: 47779.4609 - val_loss: 64608.6289 - val_mse: 64368.6406
Epoch 1380/1500
2 - mse: 47726.3633 - val loss: 64633.4375 - val mse: 64393.3906
Epoch 1381/1500
45 - mse: 47756.2812 - val loss: 64629.9180 - val mse: 64389.8242
Epoch 1382/1500
95 - mse: 47715.5938 - val loss: 64626.6172 - val mse: 64386.4336
Epoch 1383/1500
9 - mse: 47633.6367 - val loss: 64618.1602 - val mse: 64377.9141
Epoch 1384/1500
2 - mse: 47642.9570 - val loss: 64595.4062 - val mse: 64355.1172
Epoch 1385/1500
8 - mse: 47625.4336 - val loss: 64739.0156 - val mse: 64498.6562
Epoch 1386/1500
5 - mse: 47597.1445 - val loss: 64762.5273 - val mse: 64522.0820
Epoch 1387/1500
5 - mse: 47660.0430 - val loss: 64877.2500 - val mse: 64636.7695
Epoch 1388/1500
1 - mse: 47539.7852 - val loss: 64950.6680 - val mse: 64710.1328
Epoch 1389/1500
9 - mse: 47589.8984 - val loss: 64997.3438 - val mse: 64756.7500
Epoch 1390/1500
70/70 [============================] - 0s 7ms/step - loss: 47789.039
1 - mse: 47548.3672 - val loss: 65051.5195 - val mse: 64810.8633
```

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Epoch 1391/1500
9 - mse: 47468.4961 - val loss: 65104.0664 - val mse: 64863.3516
Epoch 1392/1500
3 - mse: 47500.6680 - val_loss: 65171.0430 - val_mse: 64930.2734
Epoch 1393/1500
2 - mse: 47520.2734 - val loss: 65175.8672 - val mse: 64935.0312
Epoch 1394/1500
9 - mse: 47300.3984 - val_loss: 65198.4688 - val_mse: 64957.5703
Epoch 1395/1500
8 - mse: 47389.3320 - val loss: 65198.3281 - val mse: 64957.3633
Epoch 1396/1500
5 - mse: 47368.2344 - val loss: 65271.6797 - val mse: 65030.6406
Epoch 1397/1500
9 - mse: 47374.5078 - val loss: 65285.2227 - val mse: 65044.1484
Epoch 1398/1500
9 - mse: 47257.2383 - val_loss: 65265.2109 - val_mse: 65024.0820
Epoch 1399/1500
4 - mse: 47343.4102 - val loss: 65295.6445 - val mse: 65054.4492
Epoch 1400/1500
7 - mse: 47244.2852 - val loss: 65230.6094 - val mse: 64989.3516
Epoch 1401/1500
8 - mse: 47298.2656 - val loss: 65314.9688 - val mse: 65073.6602
Epoch 1402/1500
1 - mse: 47179.0703 - val loss: 65318.5469 - val mse: 65077.1836
Epoch 1403/1500
2 - mse: 47195.2227 - val loss: 65258.5078 - val mse: 65017.0898
Epoch 1404/1500
4 - mse: 47146.9961 - val loss: 65278.5469 - val mse: 65037.0703
Epoch 1405/1500
0 - mse: 47161.6953 - val loss: 65254.1953 - val mse: 65012.6641
Epoch 1406/1500
3 - mse: 47160.6406 - val loss: 65297.3711 - val mse: 65055.7734
Epoch 1407/1500
4 - mse: 47177.9062 - val loss: 65329.6992 - val mse: 65088.0391
Epoch 1408/1500
6 - mse: 46872.4883 - val loss: 65344.6875 - val mse: 65103.0156
Epoch 1409/1500
7 - mse: 47023.0234 - val loss: 65297.9531 - val mse: 65056.2227
```

```
Epoch 1410/1500
2 - mse: 46968.9961 - val loss: 65225.4453 - val mse: 64983.6719
Epoch 1411/1500
0 - mse: 47010.8281 - val_loss: 65290.2344 - val_mse: 65048.4219
Epoch 1412/1500
7 - mse: 46997.2812 - val_loss: 65273.1562 - val_mse: 65031.2891
Epoch 1413/1500
2 - mse: 46990.3242 - val_loss: 65290.6406 - val_mse: 65048.7305
Epoch 1414/1500
7 - mse: 46913.1797 - val loss: 65339.8398 - val mse: 65097.9062
Epoch 1415/1500
0 - mse: 46826.3359 - val loss: 65276.7695 - val mse: 65034.8164
Epoch 1416/1500
1 - mse: 46887.4219 - val loss: 65245.5195 - val mse: 65003.5195
Epoch 1417/1500
2 - mse: 46706.9102 - val_loss: 65209.3047 - val_mse: 64967.2383
Epoch 1418/1500
1 - mse: 46774.3008 - val loss: 65232.7812 - val mse: 64990.6641
Epoch 1419/1500
8 - mse: 46816.7383 - val loss: 65203.3633 - val mse: 64961.1758
Epoch 1420/1500
2 - mse: 46729.7539 - val loss: 65248.5430 - val mse: 65006.3086
Epoch 1421/1500
3 - mse: 46782.8867 - val loss: 65166.1016 - val mse: 64923.8125
Epoch 1422/1500
38 - mse: 46695.2305 - val loss: 65182.7969 - val mse: 64940.4414
Epoch 1423/1500
9 - mse: 46720.2539 - val loss: 65259.8477 - val mse: 65017.4375
Epoch 1424/1500
62 - mse: 46671.6797 - val loss: 65158.7227 - val mse: 64916.2539
Epoch 1425/1500
58 - mse: 46634.3906 - val loss: 65164.4336 - val mse: 64921.9141
Epoch 1426/1500
8 - mse: 46558.7188 - val loss: 65163.3594 - val mse: 64920.7891
Epoch 1427/1500
1 - mse: 46574.7578 - val loss: 65122.0859 - val mse: 64879.4453
Epoch 1428/1500
7 - mse: 46535.5859 - val loss: 65141.6641 - val mse: 64898.9648
```

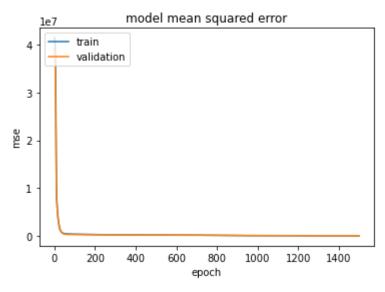
```
Epoch 1429/1500
02 - mse: 46550.1484 - val_loss: 65128.3086 - val_mse: 64885.5664
Epoch 1430/1500
38 - mse: 46535.5156 - val_loss: 65070.4141 - val_mse: 64827.6172
Epoch 1431/1500
16 - mse: 46493.7422 - val_loss: 65146.0586 - val mse: 64903.1992
Epoch 1432/1500
77 - mse: 46502.1719 - val_loss: 65101.8477 - val_mse: 64858.9297
Epoch 1433/1500
41 - mse: 46349.4180 - val loss: 65150.6680 - val mse: 64907.6797
Epoch 1434/1500
39 - mse: 46360.4492 - val loss: 65072.7344 - val mse: 64829.7070
Epoch 1435/1500
0 - mse: 46386.1758 - val loss: 65009.0039 - val mse: 64765.9141
Epoch 1436/1500
1 - mse: 46284.8750 - val_loss: 65052.4141 - val_mse: 64809.2695
Epoch 1437/1500
6 - mse: 46346.6055 - val loss: 64999.3125 - val mse: 64756.1289
Epoch 1438/1500
1 - mse: 46266.4492 - val loss: 64942.7539 - val mse: 64699.5039
Epoch 1439/1500
4 - mse: 46289.1406 - val loss: 64984.0547 - val mse: 64740.7500
Epoch 1440/1500
5 - mse: 46105.8008 - val loss: 64903.8047 - val mse: 64660.4336
Epoch 1441/1500
8 - mse: 46198.4141 - val loss: 64921.5664 - val mse: 64678.1406
Epoch 1442/1500
9 - mse: 46200.3008 - val loss: 64873.6172 - val mse: 64630.1523
Epoch 1443/1500
7 - mse: 46187.9688 - val loss: 64913.2227 - val mse: 64669.6719
Epoch 1444/1500
4 - mse: 46157.6445 - val loss: 64861.3164 - val mse: 64617.7344
Epoch 1445/1500
9 - mse: 46173.6875 - val loss: 64835.1055 - val mse: 64591.4297
Epoch 1446/1500
9 - mse: 46089.8594 - val loss: 64905.2773 - val mse: 64661.5508
Epoch 1447/1500
4 - mse: 45966.7461 - val loss: 64819.5859 - val mse: 64575.8203
```

```
Epoch 1448/1500
3 - mse: 46044.1953 - val loss: 64844.0391 - val mse: 64600.2070
Epoch 1449/1500
9 - mse: 46045.9336 - val_loss: 64820.6094 - val_mse: 64576.7305
Epoch 1450/1500
2 - mse: 45965.0898 - val loss: 64754.6875 - val mse: 64510.7539
Epoch 1451/1500
6 - mse: 46018.6289 - val_loss: 64777.8242 - val_mse: 64533.8242
Epoch 1452/1500
5 - mse: 45945.3281 - val loss: 64747.2461 - val mse: 64503.2031
Epoch 1453/1500
8 - mse: 45976.2266 - val loss: 64734.8633 - val mse: 64490.7344
Epoch 1454/1500
6 - mse: 45732.5039 - val loss: 64783.1289 - val mse: 64538.9570
Epoch 1455/1500
0 - mse: 45829.3945 - val_loss: 64707.0625 - val_mse: 64462.8359
Epoch 1456/1500
4 - mse: 45804.3594 - val loss: 64722.5703 - val mse: 64478.2891
Epoch 1457/1500
7 - mse: 45821.5039 - val loss: 64633.7188 - val mse: 64389.3789
Epoch 1458/1500
9 - mse: 45792.8906 - val loss: 64688.7891 - val mse: 64444.3867
Epoch 1459/1500
1 - mse: 45767.3203 - val loss: 64635.2656 - val mse: 64390.8281
Epoch 1460/1500
1 - mse: 45573.2695 - val loss: 64593.1562 - val mse: 64348.6289
Epoch 1461/1500
7 - mse: 45693.6797 - val loss: 64585.7930 - val mse: 64341.2461
Epoch 1462/1500
9 - mse: 45726.3008 - val loss: 64705.5586 - val mse: 64460.9375
Epoch 1463/1500
2 - mse: 45650.1055 - val loss: 64580.2812 - val mse: 64335.5977
Epoch 1464/1500
9 - mse: 45688.3008 - val loss: 64586.5078 - val mse: 64341.7656
Epoch 1465/1500
1 - mse: 45760.5508 - val loss: 64518.4805 - val mse: 64273.7109
Epoch 1466/1500
4 - mse: 45600.9844 - val loss: 64547.5117 - val mse: 64302.6836
```

```
Epoch 1467/1500
2 - mse: 45539.6367 - val loss: 64569.2305 - val mse: 64324.3477
Epoch 1468/1500
6 - mse: 45587.8164 - val_loss: 64472.3672 - val_mse: 64227.4180
Epoch 1469/1500
8 - mse: 45523.7500 - val loss: 64501.6406 - val mse: 64256.6289
Epoch 1470/1500
9 - mse: 45561.0977 - val_loss: 64456.1992 - val_mse: 64211.1289
Epoch 1471/1500
1 - mse: 45584.2305 - val loss: 64542.1953 - val mse: 64297.0586
Epoch 1472/1500
9 - mse: 45631.4883 - val loss: 64446.1758 - val mse: 64201.0117
Epoch 1473/1500
3 - mse: 45454.0898 - val loss: 64442.9297 - val mse: 64197.6992
Epoch 1474/1500
2 - mse: 45554.1055 - val_loss: 64462.6758 - val_mse: 64217.3906
Epoch 1475/1500
3 - mse: 45448.1016 - val loss: 64498.6016 - val mse: 64253.2461
Epoch 1476/1500
8 - mse: 45388.3125 - val loss: 64464.5547 - val mse: 64219.1523
Epoch 1477/1500
2 - mse: 45412.8047 - val loss: 64459.7188 - val mse: 64214.2539
Epoch 1478/1500
7 - mse: 45528.6875 - val loss: 64470.5273 - val mse: 64224.9844
Epoch 1479/1500
2 - mse: 45418.5625 - val loss: 64466.1055 - val mse: 64220.5352
Epoch 1480/1500
0 - mse: 45397.5312 - val loss: 64488.1484 - val mse: 64242.5273
Epoch 1481/1500
77 - mse: 45555.9023 - val loss: 64451.4102 - val mse: 64205.7461
Epoch 1482/1500
16 - mse: 45335.3672 - val loss: 64586.0000 - val mse: 64340.2617
Epoch 1483/1500
62 - mse: 45376.3438 - val loss: 64519.0820 - val mse: 64273.2969
Epoch 1484/1500
00 - mse: 45424.3945 - val loss: 64490.6289 - val mse: 64244.7812
Epoch 1485/1500
2 - mse: 45354.4453 - val loss: 64519.4922 - val mse: 64273.5781
```

```
Epoch 1486/1500
8 - mse: 45329.4883 - val loss: 64520.8906 - val mse: 64274.9180
Epoch 1487/1500
6 - mse: 45210.0586 - val loss: 64493.3164 - val mse: 64247.2891
Epoch 1488/1500
02 - mse: 45363.0703 - val loss: 64407.0312 - val mse: 64160.9375
Epoch 1489/1500
7 - mse: 45304.1250 - val_loss: 64550.6406 - val_mse: 64304.5000
Epoch 1490/1500
0 - mse: 45375.6445 - val loss: 64473.5391 - val mse: 64227.3516
Epoch 1491/1500
83 - mse: 45279.2305 - val loss: 64515.3984 - val mse: 64269.1562
Epoch 1492/1500
4 - mse: 45210.4219 - val loss: 64566.1328 - val mse: 64319.8320
Epoch 1493/1500
73 - mse: 45321.4180 - val_loss: 64464.2891 - val_mse: 64217.9531
Epoch 1494/1500
5 - mse: 45335.1836 - val loss: 64491.1055 - val mse: 64244.6953
Epoch 1495/1500
4 - mse: 45185.4844 - val loss: 64550.5820 - val mse: 64304.1328
Epoch 1496/1500
8 - mse: 45316.9492 - val loss: 64503.5312 - val mse: 64257.0156
Epoch 1497/1500
6 - mse: 45098.5547 - val loss: 64443.6055 - val mse: 64197.0430
Epoch 1498/1500
31 - mse: 45217.3164 - val loss: 64541.0156 - val mse: 64294.3828
Epoch 1499/1500
00 - mse: 45089.8086 - val loss: 64508.4609 - val mse: 64261.7773
Epoch 1500/1500
02 - mse: 45242.6562 - val loss: 64439.1914 - val_mse: 64192.4531
```

```
In [22]: # Plot the mse error over time
    plt.figure()
    plt.plot(history.history['mse'])
    plt.plot(history.history['val_mse'])
    plt.title('model mean squared error')
    plt.ylabel('mse')
    plt.xlabel('epoch')
    plt.legend(['train', 'validation'], loc='upper left')
    plt.show()
```



```
In [23]: # Make the prediction on the prediction dataset and write them to a cs
v file
pred = model.predict(pdf_df)
submit = {'country_id': index, 'next_week_hospitalizations':pred.astyp
e(int).flatten()}
sdf = pd.DataFrame(data = submit)
sdf.to_csv('submit_creative.csv',index = False)
```

## 3.2 Explanation in Words:

You need to answer the following questions in a markdown cell after this cell:

- 3.2.1 How much did you manage to improve performance on the test set? Did you reach the 150k MSE for the test in Kaggle? (Please include a screenshot of Kaggle Submission)
- 3.2.2 Please explain in detail how you achieved this and what you did specifically and why you tried this.

We decided to work with a Deep Neural network for the creative part of the problem because they can represent a wide variety of interesting functions when given appropriate weights and architecture. They have been historically known to work well in practice and Tensorflow 2.0 gives us a easy enough workflow to experiement with different architectures and hyperparameters.

## **Features**

The most important thing in getting a good model for us was choosing which features we wanted to use and in what way we wanted to tweak them to allow for better learning. We will describe what we did with each feature one by one:

- Country: Country should be an important feature because the rates at which the daily hospital occupancy changes majorly depends on how well a country did to keep COVID in check. Since, this was a categorical features, we decided to use one-hot encoding for this.
- Date: The number of COVID cases and hence next week's hospitalization numbers definitely have a temporal component to them, therefore, the date was certainly an important feature. To encode the date we decided to count the number of days elapsed till the current date since a fixed date. To choose this fixed date we found the earliest date in the training set and used that as an epoch. Note that the choice of this epoch doesn't really affect the final results because in the end we normalize all the numerical features.
- year-week: We decided to drop the feature year-week because it does a very similar job to Date and after
  converting the categorical feature into a week encoding we will end up with something very close to the Date
  encoding we described before.
- **Daily Hospital Occupancy**: Daily Hospital occupancy will certainly affect the hospital occupancy in the next week, so we decided to keep the feature.
- under\_15\_cases, over\_80\_cases, x-y\_cases: We decided to keep all the features of this form because it
  is possible that one age group is most susceptible to being hospitalized or spread COVID more than others.
  Thus, knowing the current number should allow the model to predict next week's hospitalization numbers
  better.
- **t\_values**: The t-values certainly look like something which would help the model predict better because it would allow the model to know the general trend (rise or fall) in the hospital numbers. To allow the model to learn this slightly better, rather than giving the t-values for a particular day directly, we decided to give the model the increase in number of hospitalizations from particular day. For example, value\_t-5 or the hospitalization numbers 5 days before are encoded as (Daily Hospital Occupancy value\_t-5) or the increase in hospitalization numbers since 5 days.

Finally, we normalized all the numerical features (everything except the country one-hot encoding) with sklearn.preprocessing.StandardScaler.

We weren't sure about how many t\_values to use for a model so we decided to keep that flexible and tried with different number of t\_values for learning a model. What we found was using too many t\_values was not improving the results but was in fact making them worse. Thus, at the end we decided to settle with using the first 7 t\_values or the increase in hospitalization number since the last 7 days.

## Model

We decided to use a RMSProp optimizer because of it adjust the learning rates automatically and allows for great performance even with saddle points. We choose an initial learning rate of 0.001 and stuck to it because we never had divergence issues. The main things we played with were the number of layers, number of neuron's

in each layer and the regularization. We used ReLU activation functions as they are computationally inexpensive and give better convergence in practice. The loss metric was the mean squared error (mse).

The dataset was again split into a training and validation set in a 70:30 ratio. The final model, or the configuration of the neural network was selected based on the overall performance on the validation mean squared error. We monitored the validation error and let the model train until the drop in the error started becoming less and less significant. The final model chosen for the neural network was again choosen based on the best validation error. We settled with a model with 3 hidden layers (each with 20 neurons) and an I1 regularization of 0.2 and I2 regularization of 0.01 for the neural net. This model gave a mean squared error of 77,897 on the public section of the kaggle dataset. The screenshot is attached below:



## Part 5: Resources and Literature Used

- RMSProp choice: <a href="https://towardsdatascience.com/understanding-rmsprop-faster-neural-network-learning-62e116fcf29a">https://towardsdatascience.com/understanding-rmsprop-faster-neural-network-learning-62e116fcf29a</a>)
- Stratified Kfold cross validation: <a href="https://machinelearningmastery.com/repeated-k-fold-cross-validation-with-python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20across\_(https://machinelearningmastery.com/repeated-k-fold-cross-validation-with-python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20across\_python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20across\_python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20across\_python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20across\_python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20across\_python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20across\_python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20across\_python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20across\_python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20across\_python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20across\_python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20across\_python/#:~:text=Different%20splits%20of%20the%20data%20may%20result%20in,mean%20result%20in,mean%20result%20in,mean%20result%20in,mean%20result%20in,mean%20result%20in,mean%20result%20in,mean%20in,m
- Tensorflow Classification: <a href="https://www.tensorflow.org/tutorials/structured\_data/feature\_columns">https://www.tensorflow.org/tutorials/structured\_data/feature\_columns</a>)
- Tensorflow Keras: <a href="https://machinelearningmastery.com/tensorflow-tutorial-deep-learning-with-tf-keras/">https://machinelearningmastery.com/tensorflow-tutorial-deep-learning-with-tf-keras/</a>)
- Activation functions: <a href="https://stats.stackexchange.com/questions/126238/what-are-the-advantages-of-relu-over-sigmoid-function-in-deep-neural-networks">https://stats.stackexchange.com/questions/126238/what-are-the-advantages-of-relu-over-sigmoid-function-in-deep-neural-networks</a>)

Tn [ ].	
TH [ ]:	