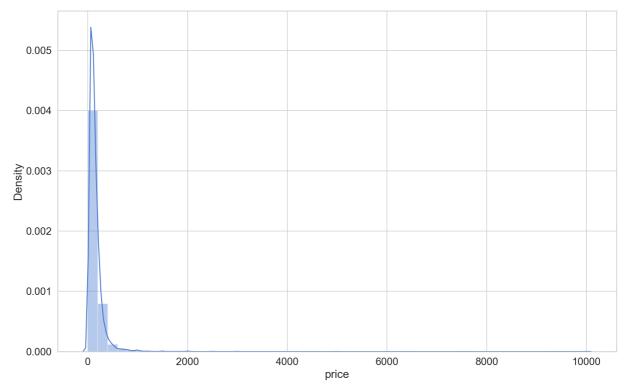
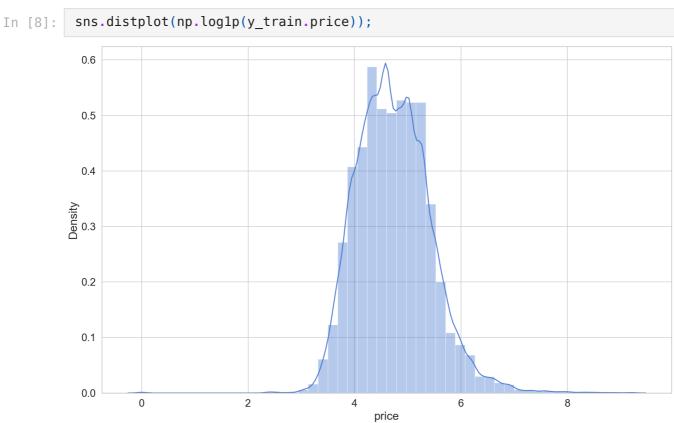
```
In [1]:
         import numpy as np
         import tensorflow as tf
         from tensorflow import keras
         import pandas as pd
         import seaborn as sns
         from pylab import rcParams
         import matplotlib.pyplot as plt
         from matplotlib import rc
         from sklearn.model selection import train test split
         import joblib
         %matplotlib inline
         %config InlineBackend.figure format='retina'
         sns.set(style='whitegrid', palette='muted', font scale=1.5)
         rcParams['figure.figsize'] = 16, 10
         RANDOM SEED = 60
         np.random.seed(RANDOM SEED)
         tf.random.set seed(RANDOM SEED)
In [2]:
        X_test = pd.read_csv('data/X_test.csv')
         X_train = pd.read_csv('data/X_train.csv')
         y train = pd.read csv('data/y train.csv')
```

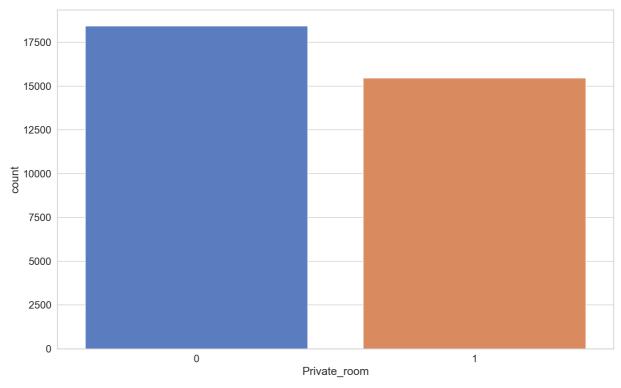
Exploration

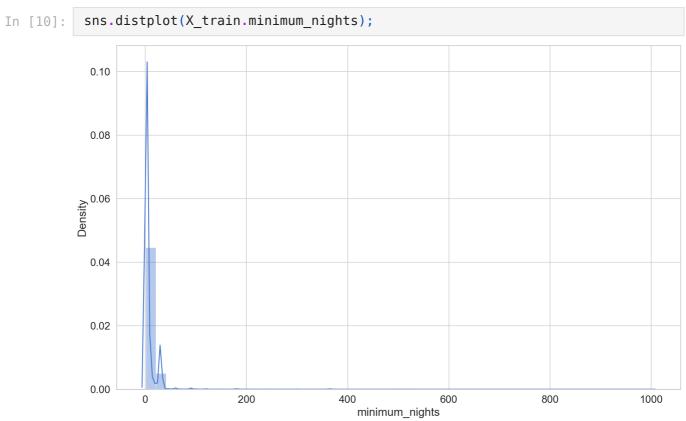
```
print(f"Shape x test {X test.shape}")
In [3]:
          print(f"Shape x train {X train.shape}")
          print(f"Shape y train {y train.shape}")
          Shape x test (3765, 10)
          Shape x train (33884, 10)
          Shape y train (33884, 2)
In [4]:
          X test.columns
Out[4]: Index(['id', 'latitude', 'longitude', 'minimum_nights', 'number_of_reviews',
                  'reviews_per_month', 'calculated_host_listings_count', 'availability_365', 'Private_room', 'Entire_home/apt'],
                 dtype='object')
          X_train.columns
In [5]:
Out[5]: Index(['id', 'latitude', 'longitude', 'minimum_nights', 'number_of_reviews',
                  'reviews_per_month', 'calculated_host_listings_count',
'availability_365', 'Private_room', 'Entire_home/apt'],
                 dtype='object')
In [6]:
          y_train.columns
Out[6]: Index(['id', 'price'], dtype='object')
          sns.distplot(y_train.price);
In [7]:
```



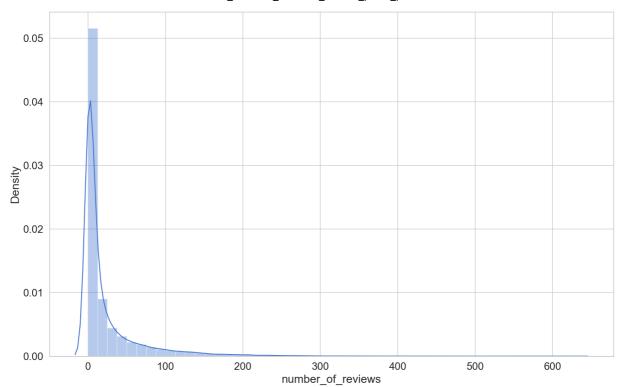


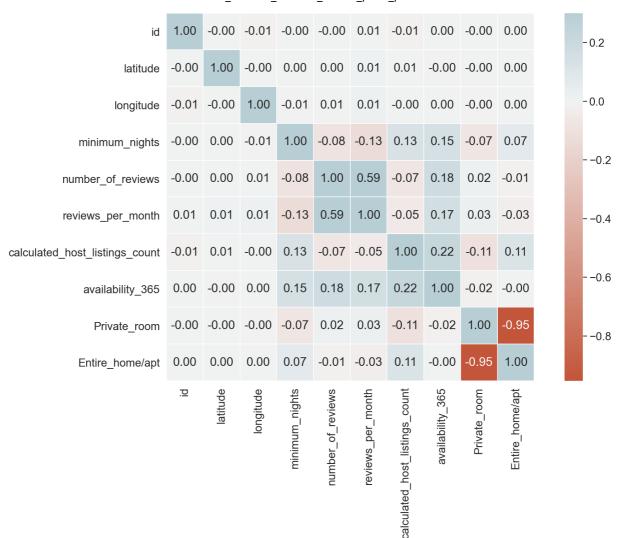
In [9]: sns.countplot(x='Private_room', data=X_train);





In [11]: sns.distplot(X_train.number_of_reviews);





Preprocessing

Missing data?

```
In [15]: missing = X_train.isnull().sum()
   missing[missing > 0].sort_values(ascending=False)

Out[15]: Series([], dtype: int64)

In [16]: missing_y = y_train.isnull().sum()
   missing_y[missing_y > 0].sort_values(ascending=False)

Out[16]: Series([], dtype: int64)
```

Remove unused columns!

```
In [17]: X_train = X_train.drop('id', axis=1)
    X_test = X_test.drop('id', axis=1)
    y_train = y_train.drop('id', axis=1)

In [18]: missing = X_train.isnull().sum()
    missing[missing > 0].sort_values(ascending=False)

Out[18]: Series([], dtype: int64)
```

```
In [19]: X_train.columns
          Index(['latitude', 'longitude', 'minimum_nights', 'number_of_reviews',
Out[19]:
                  'reviews_per_month', 'calculated_host_listings_count'
                  'availability_365', 'Private_room', 'Entire_home/apt'],
                 dtype='object')
           X train.head()
In [20]:
                 latitude
                        longitude
                                   minimum_nights number_of_reviews reviews_per_month calculated_hc
Out[20]:
          0
                40.71239
                        -73.95271
                                                                  2
                                                4
                                                                                 0.19
             40696.00000 -73.91303
                                                                                 0.66
          1
                                                4
                                                                 17
          2
                40.62707 -74.02817
                                                3
                                                                  1
                                                                                 0.04
                                                                                 0.08
          3
                40.77910 -73.98565
                                                1
          4
                40.75777 -73.93509
                                                1
                                                                  0
                                                                                 0.00
```

Predict log1p

```
In [21]: X = X_train
y = np.log1p(y_train.price.values)
```

Feature scaling

```
In [22]:
           from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
           from sklearn.compose import make column transformer
           transformer = make column transformer(
                (MinMaxScaler(), X train.columns))
           transformer.fit(X)
In [23]:
          ColumnTransformer(transformers=[('minmaxscaler', MinMaxScaler(),
Out[23]:
                                                Index(['latitude', 'longitude', 'minimum nig
          hts', 'number_of_reviews',
                  'reviews_per_month', 'calculated_host_listings_count',
'availability_365', 'Private_room', 'Entire_home/apt'],
                 dtype='object'))])
In [24]:
           # scaling
           X = transformer.transform(X)
```

Split the training and test data

```
In [25]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rand
In [26]: X_train.shape
Out[26]: (27107, 9)
```

Neural Network Model (3-layers)

```
In [27]: def plot_mse(history):
    hist = pd.DataFrame(history.history)
```

```
In [28]:
          model1 = keras.Sequential()
          model1.add(keras.layers.Dense(units=32, activation="relu", input shape=[X tra
          model1.add(keras.layers.Dense(units=64, activation="relu"))
          model1.add(keras.layers.Dense(units=128, activation='relu'))
          model1.add(keras.layers.Dense(1, activation="linear"))
          model1.compile(
              optimizer=keras.optimizers.Adam(0.0001),
              loss = 'mse',
              metrics = ['mse'])
          BATCH SIZE = 32
          early stop = keras.callbacks.EarlyStopping(
            monitor='val mse',
            mode="min",
            patience=10
          history = model1.fit(
            x=X train,
            y=y train,
            shuffle=True,
            epochs=100,
            validation split=0.2,
            batch size=BATCH SIZE
          )
          plot mse(history)
```

```
Epoch 1/100
4.7365 - val loss: 0.3555 - val mse: 0.3555
Epoch 2/100
0.3431 - val_loss: 0.3226 - val mse: 0.3226
Epoch 3/100
0.3165 - val loss: 0.3055 - val mse: 0.3055
Epoch 4/100
0.3030 - val_loss: 0.2958 - val mse: 0.2958
Epoch 5/100
0.2980 - val_loss: 0.2933 - val mse: 0.2933
Epoch 6/100
0.2960 - val loss: 0.2914 - val mse: 0.2914
Epoch 7/100
0.2947 - val loss: 0.2896 - val mse: 0.2896
Epoch 8/100
```

```
0.2934 - val_loss: 0.2890 - val_mse: 0.2890
Epoch 9/100
       678/678 [===
0.2930 - val_loss: 0.2893 - val_mse: 0.2893
Epoch 10/100
0.2926 - val loss: 0.2875 - val mse: 0.2875
Epoch 11/100
0.2918 - val loss: 0.2885 - val mse: 0.2885
Epoch 12/100
0.2907 - val loss: 0.2882 - val mse: 0.2882
Epoch 13/100
0.2908 - val loss: 0.2884 - val mse: 0.2884
Epoch 14/100
0.2902 - val loss: 0.2872 - val mse: 0.2872
Epoch 15/100
0.2905 - val loss: 0.2926 - val mse: 0.2926
Epoch 16/100
0.2895 - val loss: 0.2863 - val mse: 0.2863
Epoch 17/100
0.2900 - val loss: 0.2896 - val mse: 0.2896
Epoch 18/100
0.2895 - val loss: 0.2867 - val mse: 0.2867
Epoch 19/100
0.2887 - val loss: 0.2858 - val mse: 0.2858
Epoch 20/100
0.2892 - val loss: 0.2868 - val mse: 0.2868
Epoch 21/100
0.2887 - val loss: 0.2858 - val mse: 0.2858
Epoch 22/100
0.2883 - val loss: 0.2895 - val mse: 0.2895
Epoch 23/100
0.2883 - val loss: 0.2852 - val mse: 0.2852
Epoch 24/100
0.2879 - val loss: 0.2841 - val mse: 0.2841
Epoch 25/100
0.2880 - val loss: 0.2839 - val mse: 0.2839
Epoch 26/100
0.2878 - val loss: 0.2862 - val mse: 0.2862
Epoch 27/100
0.2881 - val_loss: 0.2888 - val mse: 0.2888
Epoch 28/100
0.2878 - val loss: 0.2859 - val mse: 0.2859
Epoch 29/100
0.2877 - val loss: 0.2856 - val mse: 0.2856
Epoch 30/100
0.2872 - val loss: 0.2846 - val mse: 0.2846
Epoch 31/100
```

```
0.2877 - val_loss: 0.2835 - val_mse: 0.2835
Epoch 32/100
       678/678 [====
0.2869 - val_loss: 0.2827 - val_mse: 0.2827
Epoch 33/100
0.2871 - val loss: 0.2842 - val mse: 0.2842
Epoch 34/100
0.2868 - val loss: 0.2834 - val mse: 0.2834
Epoch 35/100
0.2868 - val loss: 0.2828 - val mse: 0.2828
Epoch 36/100
0.2866 - val loss: 0.2826 - val mse: 0.2826
Epoch 37/100
0.2865 - val loss: 0.2825 - val mse: 0.2825
Epoch 38/100
0.2863 - val loss: 0.2818 - val mse: 0.2818
Epoch 39/100
0.2862 - val loss: 0.2871 - val mse: 0.2871
Epoch 40/100
0.2862 - val loss: 0.2827 - val mse: 0.2827
Epoch 41/100
0.2864 - val loss: 0.2826 - val mse: 0.2826
Epoch 42/100
0.2861 - val loss: 0.2823 - val mse: 0.2823
Epoch 43/100
0.2860 - val loss: 0.2869 - val mse: 0.2869
Epoch 44/100
0.2861 - val loss: 0.2812 - val mse: 0.2812
Epoch 45/100
0.2859 - val loss: 0.2815 - val mse: 0.2815
Epoch 46/100
0.2859 - val loss: 0.2815 - val mse: 0.2815
Epoch 47/100
0.2856 - val loss: 0.2820 - val mse: 0.2820
Epoch 48/100
0.2856 - val loss: 0.2819 - val mse: 0.2819
Epoch 49/100
0.2853 - val loss: 0.2829 - val mse: 0.2829
Epoch 50/100
0.2849 - val_loss: 0.2807 - val mse: 0.2807
Epoch 51/100
0.2849 - val loss: 0.2814 - val mse: 0.2814
Epoch 52/100
0.2856 - val loss: 0.2819 - val mse: 0.2819
Epoch 53/100
0.2852 - val loss: 0.2812 - val mse: 0.2812
Epoch 54/100
```

```
0.2853 - val_loss: 0.2803 - val_mse: 0.2803
Epoch 55/100
       678/678 [====
0.2849 - val_loss: 0.2831 - val_mse: 0.2831
Epoch 56/100
0.2847 - val loss: 0.2801 - val mse: 0.2801
Epoch 57/100
0.2854 - val loss: 0.2801 - val mse: 0.2801
Epoch 58/100
0.2851 - val loss: 0.2800 - val mse: 0.2800
Epoch 59/100
0.2848 - val loss: 0.2806 - val mse: 0.2806
Epoch 60/100
0.2848 - val loss: 0.2857 - val mse: 0.2857
Epoch 61/100
0.2844 - val loss: 0.2801 - val mse: 0.2801
Epoch 62/100
0.2843 - val loss: 0.2834 - val mse: 0.2834
Epoch 63/100
0.2841 - val loss: 0.2839 - val mse: 0.2839
Epoch 64/100
0.2846 - val loss: 0.2792 - val mse: 0.2792
Epoch 65/100
0.2844 - val loss: 0.2797 - val mse: 0.2797
Epoch 66/100
0.2844 - val loss: 0.2793 - val mse: 0.2793
Epoch 67/100
0.2842 - val loss: 0.2809 - val mse: 0.2809
Epoch 68/100
0.2843 - val loss: 0.2810 - val mse: 0.2810
Epoch 69/100
0.2837 - val loss: 0.2807 - val mse: 0.2807
Epoch 70/100
0.2836 - val loss: 0.2805 - val mse: 0.2805
Epoch 71/100
0.2833 - val loss: 0.2791 - val mse: 0.2791
Epoch 72/100
0.2841 - val loss: 0.2796 - val mse: 0.2796
Epoch 73/100
0.2837 - val loss: 0.2791 - val mse: 0.2791
Epoch 74/100
0.2836 - val loss: 0.2796 - val mse: 0.2796
Epoch 75/100
0.2834 - val loss: 0.2798 - val mse: 0.2798
Epoch 76/100
0.2836 - val loss: 0.2788 - val mse: 0.2788
Epoch 77/100
```

```
0.2833 - val_loss: 0.2797 - val_mse: 0.2797
Epoch 78/100
       678/678 [====
0.2836 - val_loss: 0.2781 - val_mse: 0.2781
Epoch 79/100
0.2830 - val loss: 0.2781 - val mse: 0.2781
Epoch 80/100
0.2828 - val loss: 0.2786 - val mse: 0.2786
Epoch 81/100
0.2824 - val loss: 0.2783 - val mse: 0.2783
Epoch 82/100
0.2831 - val loss: 0.2792 - val mse: 0.2792
Epoch 83/100
0.2824 - val loss: 0.2784 - val mse: 0.2784
Epoch 84/100
0.2824 - val loss: 0.2801 - val mse: 0.2801
Epoch 85/100
0.2826 - val loss: 0.2795 - val mse: 0.2795
Epoch 86/100
0.2828 - val loss: 0.2778 - val mse: 0.2778
Epoch 87/100
0.2824 - val loss: 0.2774 - val mse: 0.2774
Epoch 88/100
0.2825 - val loss: 0.2774 - val mse: 0.2774
Epoch 89/100
0.2822 - val loss: 0.2776 - val mse: 0.2776
Epoch 90/100
0.2815 - val loss: 0.2790 - val mse: 0.2790
Epoch 91/100
0.2820 - val loss: 0.2781 - val mse: 0.2781
Epoch 92/100
0.2818 - val loss: 0.2779 - val mse: 0.2779
Epoch 93/100
0.2815 - val loss: 0.2790 - val mse: 0.2790
Epoch 94/100
0.2818 - val loss: 0.2817 - val mse: 0.2817
Epoch 95/100
0.2815 - val loss: 0.2776 - val mse: 0.2776
Epoch 96/100
0.2814 - val loss: 0.2765 - val mse: 0.2765
Epoch 97/100
0.2815 - val loss: 0.2767 - val mse: 0.2767
Epoch 98/100
0.2808 - val loss: 0.2780 - val mse: 0.2780
Epoch 99/100
0.2811 - val loss: 0.2768 - val mse: 0.2768
Epoch 100/100
```

Four-layer neural network and more epochs model

40

Epoch

60

80

100

20

```
model2 = keras.Sequential()
In [29]:
         model2.add(keras.layers.Dense(units=64, activation="relu", input shape=[X tra
         model2.add(keras.layers.Dense(units=128, activation="sigmoid"))
         model2.add(keras.layers.Dense(units=256, activation="sigmoid"))
         model2.add(keras.layers.Dense(units=512, activation="relu"))
         model2.add(keras.layers.Dense(1, activation='linear'))
         model2.compile(
             optimizer=keras.optimizers.Adam(0.0001),
            loss = 'mse',
            metrics = ['mse'])
         BATCH SIZE = 64
         early_stop = keras.callbacks.EarlyStopping(
           monitor='val mse',
           mode="min",
           patience=10
         history = model2.fit(
           x=X_train,
           y=y_train,
           shuffle=True,
           epochs=150,
           validation split=0.2,
           batch size=BATCH SIZE
         plot mse(history)
        0.4299 - val_loss: 0.3759 - val_mse: 0.3759
```

Epoch 3/150

```
0.3298 - val loss: 0.3110 - val mse: 0.3110
Epoch 4/150
0.3101 - val_loss: 0.3053 - val_mse: 0.3053
Epoch 5/150
0.3070 - val loss: 0.3026 - val mse: 0.3026
Epoch 6/150
0.3058 - val loss: 0.3049 - val mse: 0.3049
Epoch 7/150
0.3040 - val loss: 0.2987 - val mse: 0.2987
Epoch 8/150
0.3018 - val loss: 0.2972 - val mse: 0.2972
Epoch 9/150
0.3007 - val loss: 0.2965 - val mse: 0.2965
Epoch 10/150
0.2998 - val loss: 0.2947 - val mse: 0.2947
Epoch 11/150
0.2978 - val loss: 0.2953 - val mse: 0.2953
Epoch 12/150
0.2960 - val loss: 0.2935 - val mse: 0.2935
Epoch 13/150
0.2967 - val loss: 0.2946 - val mse: 0.2946
Epoch 14/150
0.2958 - val loss: 0.2982 - val mse: 0.2982
Epoch 15/150
0.2968 - val loss: 0.2984 - val mse: 0.2984
Epoch 16/150
0.2942 - val loss: 0.2908 - val mse: 0.2908
Epoch 17/150
0.2963 - val loss: 0.2970 - val mse: 0.2970
Epoch 18/150
0.2961 - val loss: 0.2925 - val mse: 0.2925
Epoch 19/150
0.2935 - val loss: 0.2902 - val mse: 0.2902
Epoch 20/150
0.2958 - val loss: 0.2972 - val mse: 0.2972
Epoch 21/150
0.2947 - val_loss: 0.2907 - val mse: 0.2907
Epoch 22/150
0.2932 - val loss: 0.2932 - val mse: 0.2932
Epoch 23/150
0.2942 - val loss: 0.2970 - val mse: 0.2970
Epoch 24/150
0.2929 - val loss: 0.2902 - val mse: 0.2902
Epoch 25/150
0.2933 - val loss: 0.2896 - val mse: 0.2896
Epoch 26/150
```

```
0.2933 - val_loss: 0.2922 - val_mse: 0.2922
Epoch 27/150
0.2946 - val_loss: 0.3020 - val_mse: 0.3020
Epoch 28/150
0.2938 - val loss: 0.2897 - val mse: 0.2897
Epoch 29/150
0.2936 - val loss: 0.2923 - val mse: 0.2923
Epoch 30/150
0.2931 - val loss: 0.2944 - val mse: 0.2944
Epoch 31/150
0.2942 - val loss: 0.2920 - val mse: 0.2920
Epoch 32/150
0.2931 - val loss: 0.2890 - val mse: 0.2890
Epoch 33/150
0.2933 - val loss: 0.2886 - val mse: 0.2886
Epoch 34/150
0.2925 - val loss: 0.2912 - val mse: 0.2912
Epoch 35/150
0.2929 - val loss: 0.2900 - val mse: 0.2900
Epoch 36/150
0.2921 - val loss: 0.2885 - val mse: 0.2885
Epoch 37/150
0.2922 - val loss: 0.2885 - val mse: 0.2885
Epoch 38/150
0.2921 - val loss: 0.2901 - val mse: 0.2901
Epoch 39/150
0.2923 - val loss: 0.2971 - val mse: 0.2971
Epoch 40/150
0.2921 - val loss: 0.2883 - val mse: 0.2883
Epoch 41/150
0.2938 - val loss: 0.2883 - val mse: 0.2883
Epoch 42/150
0.2922 - val loss: 0.2922 - val mse: 0.2922
Epoch 43/150
0.2925 - val loss: 0.2977 - val mse: 0.2977
Epoch 44/150
0.2928 - val loss: 0.2894 - val mse: 0.2894
Epoch 45/150
0.2917 - val loss: 0.2878 - val mse: 0.2878
Epoch 46/150
0.2919 - val loss: 0.2878 - val mse: 0.2878
Epoch 47/150
0.2923 - val loss: 0.2894 - val mse: 0.2894
Epoch 48/150
0.2920 - val loss: 0.2879 - val mse: 0.2879
Epoch 49/150
```

```
0.2919 - val_loss: 0.2881 - val_mse: 0.2881
Epoch 50/150
0.2913 - val_loss: 0.2873 - val_mse: 0.2873
Epoch 51/150
0.2911 - val loss: 0.2873 - val mse: 0.2873
Epoch 52/150
0.2927 - val loss: 0.2883 - val mse: 0.2883
Epoch 53/150
0.2922 - val loss: 0.2873 - val mse: 0.2873
Epoch 54/150
0.2917 - val loss: 0.2889 - val mse: 0.2889
Epoch 55/150
0.2912 - val loss: 0.2930 - val mse: 0.2930
Epoch 56/150
0.2912 - val loss: 0.2878 - val mse: 0.2878
Epoch 57/150
0.2925 - val loss: 0.2876 - val mse: 0.2876
Epoch 58/150
0.2919 - val loss: 0.2896 - val mse: 0.2896
Epoch 59/150
0.2920 - val loss: 0.2927 - val mse: 0.2927
Epoch 60/150
0.2920 - val loss: 0.2961 - val mse: 0.2961
Epoch 61/150
0.2907 - val loss: 0.2867 - val mse: 0.2867
Epoch 62/150
0.2910 - val loss: 0.2918 - val mse: 0.2918
Epoch 63/150
0.2902 - val loss: 0.2890 - val mse: 0.2890
Epoch 64/150
0.2911 - val loss: 0.2864 - val mse: 0.2864
Epoch 65/150
0.2907 - val loss: 0.2865 - val mse: 0.2865
Epoch 66/150
0.2911 - val loss: 0.2868 - val mse: 0.2868
Epoch 67/150
0.2907 - val loss: 0.2877 - val mse: 0.2877
Epoch 68/150
0.2912 - val loss: 0.2865 - val mse: 0.2865
Epoch 69/150
0.2900 - val loss: 0.2894 - val mse: 0.2894
Epoch 70/150
0.2910 - val loss: 0.2878 - val mse: 0.2878
Epoch 71/150
0.2896 - val loss: 0.2859 - val mse: 0.2859
Epoch 72/150
```

```
0.2909 - val_loss: 0.2896 - val_mse: 0.2896
Epoch 73/150
0.2900 - val_loss: 0.2867 - val_mse: 0.2867
Epoch 74/150
0.2909 - val loss: 0.2865 - val mse: 0.2865
Epoch 75/150
0.2901 - val loss: 0.2886 - val mse: 0.2886
Epoch 76/150
0.2907 - val loss: 0.2867 - val mse: 0.2867
Epoch 77/150
0.2905 - val loss: 0.2879 - val mse: 0.2879
Epoch 78/150
0.2908 - val loss: 0.2857 - val mse: 0.2857
Epoch 79/150
0.2894 - val loss: 0.2856 - val mse: 0.2856
Epoch 80/150
0.2895 - val loss: 0.2857 - val mse: 0.2857
Epoch 81/150
0.2892 - val loss: 0.2854 - val mse: 0.2854
Epoch 82/150
0.2902 - val loss: 0.2874 - val mse: 0.2874
Epoch 83/150
0.2891 - val loss: 0.2872 - val mse: 0.2872
Epoch 84/150
0.2895 - val loss: 0.2874 - val mse: 0.2874
Epoch 85/150
0.2894 - val loss: 0.2867 - val mse: 0.2867
Epoch 86/150
0.2907 - val loss: 0.2851 - val mse: 0.2851
Epoch 87/150
0.2895 - val loss: 0.2855 - val mse: 0.2855
Epoch 88/150
0.2894 - val loss: 0.2854 - val mse: 0.2854
Epoch 89/150
0.2891 - val loss: 0.2850 - val mse: 0.2850
Epoch 90/150
0.2883 - val_loss: 0.2866 - val mse: 0.2866
Epoch 91/150
0.2894 - val loss: 0.2848 - val mse: 0.2848
Epoch 92/150
0.2890 - val loss: 0.2860 - val mse: 0.2860
Epoch 93/150
0.2890 - val loss: 0.2853 - val mse: 0.2853
Epoch 94/150
0.2896 - val loss: 0.2925 - val mse: 0.2925
Epoch 95/150
```

```
0.2891 - val_loss: 0.2847 - val_mse: 0.2847
Epoch 96/150
0.2893 - val_loss: 0.2849 - val_mse: 0.2849
Epoch 97/150
0.2887 - val loss: 0.2844 - val mse: 0.2844
Epoch 98/150
0.2881 - val loss: 0.2854 - val mse: 0.2854
Epoch 99/150
0.2884 - val loss: 0.2851 - val mse: 0.2851
Epoch 100/150
0.2882 - val loss: 0.2862 - val mse: 0.2862
Epoch 101/150
0.2885 - val loss: 0.2843 - val mse: 0.2843
Epoch 102/150
0.2878 - val loss: 0.2862 - val mse: 0.2862
Epoch 103/150
0.2885 - val loss: 0.2951 - val mse: 0.2951
Epoch 104/150
0.2889 - val loss: 0.2851 - val mse: 0.2851
Epoch 105/150
0.2887 - val loss: 0.2847 - val mse: 0.2847
Epoch 106/150
0.2881 - val loss: 0.2842 - val mse: 0.2842
Epoch 107/150
0.2879 - val loss: 0.2872 - val mse: 0.2872
Epoch 108/150
0.2885 - val loss: 0.2840 - val mse: 0.2840
Epoch 109/150
0.2879 - val loss: 0.2837 - val mse: 0.2837
Epoch 110/150
0.2883 - val loss: 0.2902 - val mse: 0.2902
Epoch 111/150
0.2877 - val loss: 0.2859 - val mse: 0.2859
Epoch 112/15\overline{0}
0.2890 - val loss: 0.2836 - val mse: 0.2836
Epoch 113/150
0.2884 - val loss: 0.2949 - val mse: 0.2949
Epoch 114/150
0.2877 - val loss: 0.2832 - val_mse: 0.2832
Epoch 115/150
0.2883 - val loss: 0.2926 - val mse: 0.2926
Epoch 116/150
0.2872 - val loss: 0.2836 - val mse: 0.2836
Epoch 117/150
0.2878 - val loss: 0.2837 - val mse: 0.2837
Epoch 118/150
```

```
0.2878 - val_loss: 0.2863 - val_mse: 0.2863
Epoch 119/150
339/339 [======
       0.2889 - val_loss: 0.2829 - val_mse: 0.2829
Epoch 120/150
0.2877 - val loss: 0.2865 - val mse: 0.2865
Epoch 121/150
0.2879 - val loss: 0.2827 - val mse: 0.2827
Epoch 122/150
0.2874 - val loss: 0.2831 - val mse: 0.2831
Epoch 123/150
0.2869 - val loss: 0.2826 - val mse: 0.2826
Epoch 124/150
0.2873 - val loss: 0.2825 - val mse: 0.2825
Epoch 125/150
0.2874 - val loss: 0.2824 - val mse: 0.2824
Epoch 126/150
0.2868 - val loss: 0.2882 - val mse: 0.2882
Epoch 127/150
0.2877 - val loss: 0.2824 - val mse: 0.2824
Epoch 128/150
0.2873 - val loss: 0.2833 - val mse: 0.2833
Epoch 129/150
0.2868 - val loss: 0.2911 - val mse: 0.2911
Epoch 130/150
0.2863 - val loss: 0.2821 - val mse: 0.2821
Epoch 131/150
0.2867 - val loss: 0.2823 - val mse: 0.2823
Epoch 132/150
0.2862 - val loss: 0.2821 - val mse: 0.2821
Epoch 133/150
0.2869 - val loss: 0.2834 - val mse: 0.2834
Epoch 134/150
0.2867 - val loss: 0.2840 - val mse: 0.2840
Epoch 135/150
0.2870 - val loss: 0.2846 - val mse: 0.2846
Epoch 136/150
0.2861 - val loss: 0.2830 - val mse: 0.2830
Epoch 137/150
0.2863 - val loss: 0.2813 - val mse: 0.2813
Epoch 138/150
0.2862 - val loss: 0.2859 - val mse: 0.2859
Epoch 139/150
0.2856 - val loss: 0.2826 - val mse: 0.2826
Epoch 140/150
0.2860 - val loss: 0.2815 - val mse: 0.2815
Epoch 141/15\overline{0}
```

```
======] - 2s 7ms/step - loss: 0.2868 - mse:
0.2868 - val_loss: 0.2822 - val_mse: 0.2822
Epoch 142/150
339/339 [=====
             ========== ] - 2s 7ms/step - loss: 0.2867 - mse:
0.2867 - val_loss: 0.2824 - val_mse: 0.2824
Epoch 143/150
0.2859 - val loss: 0.2868 - val mse: 0.2868
Epoch 144/150
0.2858 - val loss: 0.2811 - val mse: 0.2811
Epoch 145/150
0.2856 - val loss: 0.2813 - val mse: 0.2813
Epoch 146/150
0.2863 - val loss: 0.2808 - val mse: 0.2808
Epoch 147/150
0.2852 - val loss: 0.2824 - val mse: 0.2824
Epoch 148/150
0.2854 - val loss: 0.2840 - val mse: 0.2840
Epoch 149/150
0.2857 - val loss: 0.2809 - val mse: 0.2809
Epoch 150/150
0.2856 - val loss: 0.2806 - val_mse: 0.2806
                                      Train MSE
 1.2

    Val MSE

 1.0
8.0
WSE
 0.6
 0.4
                                 120
                                      140
```

Neural Network with SDG optimizer

```
In [30]: model3 = keras.Sequential()
  model3.add(keras.layers.Dense(units=64, activation="relu", input_shape=[X_tramodel3.add(keras.layers.Dense(units=128, activation="selu"))
  model3.add(keras.layers.Dense(units=256, activation="selu"))
  model3.add(keras.layers.Dense(units=512, activation="relu"))
  model3.add(keras.layers.Dense(1, activation='linear'))

model3.compile(
    optimizer='SGD',
    loss = 'mse',
```

Epoch

```
metrics = ['mse'])

BATCH_SIZE = 64

early_stop = keras.callbacks.EarlyStopping(
    monitor='val_mse',
    mode="min",
    patience=10
)

history = model3.fit(
    x=X_train,
    y=y_train,
    shuffle=True,
    epochs=150,
    validation_split=0.2,
    batch_size=BATCH_SIZE
)

plot_mse(history)
```

```
0.3291 - val loss: 0.3709 - val mse: 0.3709
Epoch 3/150
0.3131 - val loss: 0.2965 - val mse: 0.2965
Epoch 4/150
0.3112 - val loss: 0.3099 - val mse: 0.3099
Epoch 5/150
0.3018 - val loss: 0.2891 - val mse: 0.2891
Epoch 6/150
0.3080 - val loss: 0.2889 - val mse: 0.2889
Epoch 7/150
0.3045 - val loss: 0.2896 - val mse: 0.2896
Epoch 8/150
0.3023 - val loss: 0.2905 - val mse: 0.2905
Epoch 9/150
0.2993 - val loss: 0.2886 - val mse: 0.2886
Epoch 10/150
0.3029 - val loss: 0.2901 - val mse: 0.2901
Epoch 11/150
339/339 [=====
                 =======] - 2s 7ms/step - loss: 0.3024 - mse:
0.3024 - val loss: 0.2959 - val mse: 0.2959
Epoch 12/150
339/339 [======
            0.3020 - val loss: 0.3693 - val mse: 0.3693
Epoch 13/150
339/339 [=====
                  ======] - 2s 7ms/step - loss: 0.3025 - mse:
0.3025 - val loss: 0.2945 - val mse: 0.2945
Epoch 14/150
339/339 [======
            0.3002 - val loss: 0.2885 - val mse: 0.2885
Epoch 15/150
339/339 [===
                   ======] - 2s 7ms/step - loss: 0.2999 - mse:
0.2999 - val loss: 0.2955 - val mse: 0.2955
Epoch 16/150
             ========== ] - 2s 6ms/step - loss: 0.2988 - mse:
339/339 [====
0.2988 - val_loss: 0.2948 - val_mse: 0.2948
Epoch 17/150
              ========= ] - 2s 7ms/step - loss: 0.3003 - mse:
339/339 [=====
```

```
0.3003 - val_loss: 0.2916 - val_mse: 0.2916
Epoch 18/150
       339/339 [====
0.2978 - val_loss: 0.3066 - val_mse: 0.3066
Epoch 19/150
0.2968 - val loss: 0.2870 - val mse: 0.2870
Epoch 20/150
0.3001 - val loss: 0.2903 - val mse: 0.2903
Epoch 21/150
0.2962 - val loss: 0.2901 - val mse: 0.2901
Epoch 22/150
0.2975 - val loss: 0.2951 - val mse: 0.2951
Epoch 23/150
0.2975 - val loss: 0.2924 - val mse: 0.2924
Epoch 24/150
0.2981 - val loss: 0.2882 - val mse: 0.2882
Epoch 25/150
0.2964 - val loss: 0.3064 - val mse: 0.3064
Epoch 26/150
0.2958 - val loss: 0.2948 - val mse: 0.2948
Epoch 27/150
0.2973 - val loss: 0.2893 - val mse: 0.2893
Epoch 28/150
0.2982 - val loss: 0.2879 - val mse: 0.2879
Epoch 29/150
0.2958 - val loss: 0.2870 - val mse: 0.2870
Epoch 30/150
0.2958 - val loss: 0.3361 - val mse: 0.3361
Epoch 31/150
0.2962 - val loss: 0.2860 - val mse: 0.2860
Epoch 32/150
0.2961 - val loss: 0.2978 - val mse: 0.2978
Epoch 33/150
0.2962 - val loss: 0.2973 - val mse: 0.2973
Epoch 34/150
0.2955 - val loss: 0.2957 - val mse: 0.2957
Epoch 35/150
0.2952 - val loss: 0.2862 - val mse: 0.2862
Epoch 36/150
0.2966 - val_loss: 0.2863 - val mse: 0.2863
Epoch 37/150
0.2958 - val loss: 0.2900 - val mse: 0.2900
Epoch 38/150
0.2954 - val loss: 0.2852 - val mse: 0.2852
Epoch 39/150
0.2954 - val loss: 0.2858 - val mse: 0.2858
Epoch 40/150
```

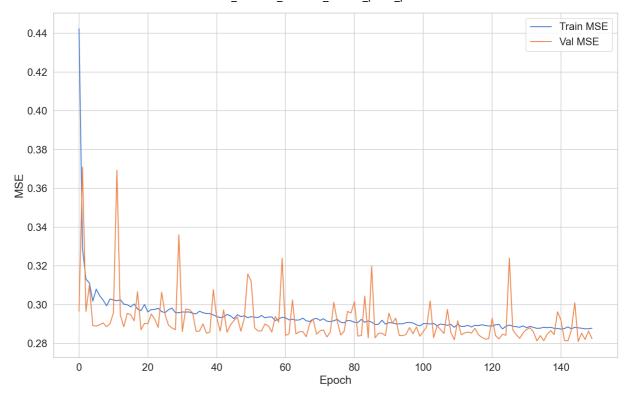
```
0.2947 - val_loss: 0.3077 - val_mse: 0.3077
Epoch 41/150
       339/339 [====
0.2938 - val_loss: 0.2931 - val_mse: 0.2931
Epoch 42/150
0.2933 - val loss: 0.2863 - val mse: 0.2863
Epoch 43/150
0.2936 - val loss: 0.2973 - val mse: 0.2973
Epoch 44/150
0.2949 - val loss: 0.2857 - val mse: 0.2857
Epoch 45/150
0.2942 - val loss: 0.2895 - val mse: 0.2895
Epoch 46/150
0.2927 - val loss: 0.2918 - val mse: 0.2918
Epoch 47/150
0.2948 - val loss: 0.2935 - val mse: 0.2935
Epoch 48/150
0.2937 - val loss: 0.2863 - val mse: 0.2863
Epoch 49/150
0.2943 - val loss: 0.2928 - val mse: 0.2928
Epoch 50/150
0.2932 - val loss: 0.3158 - val mse: 0.3158
Epoch 51/150
0.2938 - val loss: 0.3121 - val mse: 0.3121
Epoch 52/150
0.2935 - val loss: 0.2880 - val mse: 0.2880
Epoch 53/150
0.2933 - val loss: 0.2864 - val mse: 0.2864
Epoch 54/150
0.2944 - val loss: 0.2864 - val mse: 0.2864
Epoch 55/150
0.2932 - val loss: 0.2900 - val mse: 0.2900
Epoch 56/150
0.2936 - val loss: 0.2890 - val mse: 0.2890
Epoch 57/150
0.2936 - val loss: 0.2858 - val mse: 0.2858
Epoch 58/150
0.2917 - val loss: 0.2938 - val mse: 0.2938
Epoch 59/150
0.2926 - val loss: 0.2910 - val mse: 0.2910
Epoch 60/150
0.2935 - val loss: 0.3239 - val mse: 0.3239
Epoch 61/150
0.2932 - val loss: 0.2840 - val mse: 0.2840
Epoch 62/150
0.2921 - val loss: 0.2850 - val mse: 0.2850
Epoch 63/150
```

```
0.2925 - val_loss: 0.3024 - val_mse: 0.3024
Epoch 64/150
       339/339 [=====
0.2920 - val_loss: 0.2849 - val_mse: 0.2849
Epoch 65/150
0.2921 - val loss: 0.2860 - val mse: 0.2860
Epoch 66/150
0.2930 - val loss: 0.2860 - val mse: 0.2860
Epoch 67/150
0.2916 - val loss: 0.2834 - val mse: 0.2834
Epoch 68/150
0.2913 - val loss: 0.2903 - val mse: 0.2903
Epoch 69/150
0.2925 - val loss: 0.2925 - val mse: 0.2925
Epoch 70/150
0.2929 - val loss: 0.2847 - val mse: 0.2847
Epoch 71/150
0.2918 - val loss: 0.2864 - val mse: 0.2864
Epoch 72/150
0.2927 - val_loss: 0.2869 - val mse: 0.2869
Epoch 73/150
0.2914 - val loss: 0.2832 - val mse: 0.2832
Epoch 74/150
0.2912 - val loss: 0.2859 - val mse: 0.2859
Epoch 75/150
0.2916 - val loss: 0.3011 - val mse: 0.3011
Epoch 76/150
0.2924 - val loss: 0.2915 - val mse: 0.2915
Epoch 77/150
0.2909 - val loss: 0.2843 - val mse: 0.2843
Epoch 78/150
0.2905 - val loss: 0.2863 - val mse: 0.2863
Epoch 79/150
0.2918 - val loss: 0.2964 - val mse: 0.2964
Epoch 80/150
0.2916 - val loss: 0.2957 - val mse: 0.2957
Epoch 81/150
0.2909 - val loss: 0.3015 - val mse: 0.3015
Epoch 82/150
0.2908 - val_loss: 0.2838 - val mse: 0.2838
Epoch 83/150
0.2923 - val loss: 0.2840 - val mse: 0.2840
Epoch 84/150
0.2909 - val loss: 0.3044 - val mse: 0.3044
Epoch 85/150
0.2915 - val loss: 0.2828 - val mse: 0.2828
Epoch 86/150
```

```
0.2910 - val_loss: 0.3198 - val_mse: 0.3198
Epoch 87/150
       339/339 [====
0.2897 - val_loss: 0.2828 - val_mse: 0.2828
Epoch 88/150
0.2899 - val loss: 0.2852 - val mse: 0.2852
Epoch 89/150
0.2919 - val loss: 0.2852 - val mse: 0.2852
Epoch 90/150
0.2899 - val loss: 0.2839 - val mse: 0.2839
Epoch 91/150
0.2906 - val loss: 0.2956 - val mse: 0.2956
Epoch 92/150
0.2906 - val loss: 0.2903 - val mse: 0.2903
Epoch 93/150
0.2900 - val loss: 0.2930 - val mse: 0.2930
Epoch 94/150
0.2901 - val loss: 0.2841 - val mse: 0.2841
Epoch 95/150
0.2901 - val loss: 0.2839 - val mse: 0.2839
Epoch 96/150
0.2907 - val loss: 0.2846 - val mse: 0.2846
Epoch 97/150
0.2908 - val loss: 0.2882 - val mse: 0.2882
Epoch 98/150
0.2905 - val loss: 0.2849 - val mse: 0.2849
Epoch 99/150
0.2896 - val loss: 0.2885 - val mse: 0.2885
Epoch 100/150
0.2890 - val loss: 0.2837 - val mse: 0.2837
Epoch 101/150
0.2902 - val loss: 0.2860 - val mse: 0.2860
Epoch 102/15\overline{0}
0.2902 - val loss: 0.2886 - val mse: 0.2886
Epoch 103/150
0.2900 - val loss: 0.3019 - val mse: 0.3019
Epoch 104/150
0.2903 - val loss: 0.2829 - val_mse: 0.2829
Epoch 105/150
0.2891 - val loss: 0.2891 - val mse: 0.2891
Epoch 106/150
0.2899 - val loss: 0.2872 - val_mse: 0.2872
Epoch 107/150
0.2896 - val loss: 0.2850 - val mse: 0.2850
Epoch 108/150
0.2893 - val loss: 0.2975 - val mse: 0.2975
Epoch 109/150
```

```
0.2898 - val_loss: 0.2856 - val_mse: 0.2856
Epoch 110/150
       339/339 [=====
0.2883 - val_loss: 0.2819 - val_mse: 0.2819
Epoch 111/150
0.2898 - val loss: 0.2917 - val mse: 0.2917
Epoch 112/150
0.2887 - val loss: 0.2845 - val mse: 0.2845
Epoch 113/15\overline{0}
0.2888 - val loss: 0.2853 - val mse: 0.2853
Epoch 114/150
0.2893 - val loss: 0.2858 - val mse: 0.2858
Epoch 115/150
0.2884 - val loss: 0.2853 - val mse: 0.2853
Epoch 116/150
0.2893 - val loss: 0.2878 - val mse: 0.2878
Epoch 117/150
0.2891 - val loss: 0.2844 - val mse: 0.2844
Epoch 118/150
0.2896 - val loss: 0.2831 - val mse: 0.2831
Epoch 119/150
0.2892 - val loss: 0.2822 - val mse: 0.2822
Epoch 120/150
0.2889 - val loss: 0.2823 - val mse: 0.2823
Epoch 121/150
0.2890 - val loss: 0.2929 - val mse: 0.2929
Epoch 122/150
0.2896 - val loss: 0.2840 - val mse: 0.2840
Epoch 123/150
0.2897 - val loss: 0.2823 - val mse: 0.2823
Epoch 124/150
0.2874 - val loss: 0.2847 - val mse: 0.2847
Epoch 125/15\overline{0}
0.2888 - val loss: 0.2842 - val mse: 0.2842
Epoch 126/150
0.2895 - val loss: 0.3240 - val mse: 0.3240
Epoch 127/150
0.2888 - val loss: 0.2869 - val mse: 0.2869
Epoch 128/150
0.2886 - val loss: 0.2845 - val mse: 0.2845
Epoch 129/150
0.2883 - val loss: 0.2826 - val_mse: 0.2826
Epoch 130/150
0.2890 - val loss: 0.2854 - val mse: 0.2854
Epoch 131/150
0.2881 - val loss: 0.2871 - val mse: 0.2871
Epoch 132/15\overline{0}
```

```
0.2887 - val_loss: 0.2880 - val_mse: 0.2880
Epoch 133/150
       339/339 [=====
0.2882 - val_loss: 0.2859 - val_mse: 0.2859
Epoch 134/150
0.2877 - val loss: 0.2813 - val mse: 0.2813
Epoch 135/150
0.2878 - val loss: 0.2840 - val mse: 0.2840
Epoch 136/15\overline{0}
0.2883 - val loss: 0.2813 - val mse: 0.2813
Epoch 137/15\overline{0}
0.2881 - val loss: 0.2847 - val mse: 0.2847
Epoch 138/150
0.2883 - val loss: 0.2866 - val mse: 0.2866
Epoch 139/150
0.2878 - val loss: 0.2845 - val mse: 0.2845
Epoch 140/150
0.2876 - val loss: 0.2963 - val mse: 0.2963
Epoch 141/150
0.2874 - val loss: 0.2920 - val mse: 0.2920
Epoch 142/150
0.2876 - val loss: 0.2815 - val mse: 0.2815
Epoch 143/150
0.2885 - val loss: 0.2812 - val mse: 0.2812
Epoch 144/150
0.2875 - val loss: 0.2867 - val mse: 0.2867
Epoch 145/150
0.2883 - val loss: 0.3010 - val mse: 0.3010
Epoch 146/150
0.2880 - val loss: 0.2809 - val mse: 0.2809
Epoch 147/150
0.2878 - val loss: 0.2852 - val mse: 0.2852
Epoch 148/15\overline{0}
0.2875 - val loss: 0.2820 - val mse: 0.2820
Epoch 149/150
0.2875 - val loss: 0.2864 - val mse: 0.2864
Epoch 150/150
0.2878 - val loss: 0.2824 - val mse: 0.2824
```



Neural Network with dropout regularization at 50%

```
model4 = keras.Sequential()
In [31]:
         model4.add(keras.layers.Dropout(0.5, input shape=(X train.shape[1],)))
         model4.add(keras.layers.Dense(units=128, activation="relu"))
         model4.add(keras.layers.Dropout(0.5))
         model4.add(keras.layers.Dense(units=256, activation="relu"))
         model4.add(keras.layers.Dropout(0.5))
         model4.add(keras.layers.Dense(units=512, activation="relu"))
         model4.add(keras.layers.Dropout(0.5))
         model4.add(keras.layers.Dense(1, activation='linear'))
         model4.compile(
             optimizer='adam',
             loss = 'mse',
             metrics = ['mse'])
         BATCH SIZE = 64
         early_stop = keras.callbacks.EarlyStopping(
           monitor='val_mse',
           mode="min",
           patience=15
         history = model4.fit(
           x=X_train,
           y=y_train,
           shuffle=True,
           epochs=150,
           validation_split=0.2,
           batch_size=BATCH_SIZE
         plot mse(history)
        50
        0.6588 - val_loss: 1.5405 - val_mse: 1.5405
```

Epoch 3/150

```
0.5837 - val loss: 0.7010 - val mse: 0.7010
Epoch 4/150
0.5447 - val_loss: 0.4953 - val_mse: 0.4953
Epoch 5/150
0.5092 - val loss: 0.4250 - val mse: 0.4250
Epoch 6/150
0.5002 - val loss: 0.4216 - val mse: 0.4216
Epoch 7/150
0.4918 - val loss: 0.3627 - val mse: 0.3627
Epoch 8/150
0.4842 - val loss: 0.3674 - val mse: 0.3674
Epoch 9/150
0.4817 - val loss: 0.3785 - val mse: 0.3785
Epoch 10/150
0.4828 - val loss: 0.3759 - val mse: 0.3759
Epoch 11/150
0.4763 - val loss: 0.3830 - val mse: 0.3830
Epoch 12/150
0.4724 - val loss: 0.3468 - val mse: 0.3468
Epoch 13/150
0.4741 - val loss: 0.3618 - val mse: 0.3618
Epoch 14/150
0.4679 - val loss: 0.3486 - val mse: 0.3486
Epoch 15/150
0.4663 - val loss: 0.3529 - val mse: 0.3529
Epoch 16/150
0.4685 - val loss: 0.3367 - val mse: 0.3367
Epoch 17/150
0.4690 - val loss: 0.3568 - val mse: 0.3568
Epoch 18/150
0.4666 - val loss: 0.3368 - val mse: 0.3368
Epoch 19/150
0.4646 - val loss: 0.3456 - val mse: 0.3456
Epoch 20/150
0.4581 - val loss: 0.3372 - val_mse: 0.3372
Epoch 21/150
0.4556 - val loss: 0.3530 - val mse: 0.3530
Epoch 22/150
0.4518 - val loss: 0.3370 - val mse: 0.3370
Epoch 23/150
0.4539 - val loss: 0.3287 - val mse: 0.3287
Epoch 24/150
0.4538 - val loss: 0.3525 - val mse: 0.3525
Epoch 25/150
0.4490 - val loss: 0.3362 - val mse: 0.3362
Epoch 26/150
```

```
0.4486 - val_loss: 0.3364 - val_mse: 0.3364
Epoch 27/150
0.4513 - val_loss: 0.3668 - val_mse: 0.3668
Epoch 28/150
0.4446 - val loss: 0.3477 - val mse: 0.3477
Epoch 29/150
0.4501 - val loss: 0.3420 - val mse: 0.3420
Epoch 30/150
0.4473 - val loss: 0.3543 - val mse: 0.3543
Epoch 31/150
0.4454 - val loss: 0.3519 - val mse: 0.3519
Epoch 32/150
0.4418 - val loss: 0.3388 - val mse: 0.3388
Epoch 33/150
0.4399 - val loss: 0.3410 - val mse: 0.3410
Epoch 34/150
0.4444 - val loss: 0.3374 - val mse: 0.3374
Epoch 35/150
0.4378 - val loss: 0.3497 - val mse: 0.3497
Epoch 36/150
0.4381 - val loss: 0.3575 - val mse: 0.3575
Epoch 37/150
0.4383 - val loss: 0.3489 - val mse: 0.3489
Epoch 38/150
0.4384 - val loss: 0.3461 - val mse: 0.3461
Epoch 39/150
0.4322 - val loss: 0.3409 - val mse: 0.3409
Epoch 40/150
0.4381 - val loss: 0.3370 - val mse: 0.3370
Epoch 41/150
0.4324 - val loss: 0.3246 - val mse: 0.3246
Epoch 42/150
0.4316 - val loss: 0.3201 - val mse: 0.3201
Epoch 43/150
0.4382 - val loss: 0.3550 - val mse: 0.3550
Epoch 44/150
0.4327 - val_loss: 0.3398 - val mse: 0.3398
Epoch 45/150
0.4319 - val loss: 0.3202 - val mse: 0.3202
Epoch 46/150
0.4291 - val loss: 0.3507 - val mse: 0.3507
Epoch 47/150
0.4265 - val loss: 0.3475 - val mse: 0.3475
Epoch 48/150
0.4291 - val loss: 0.3266 - val mse: 0.3266
Epoch 49/150
```

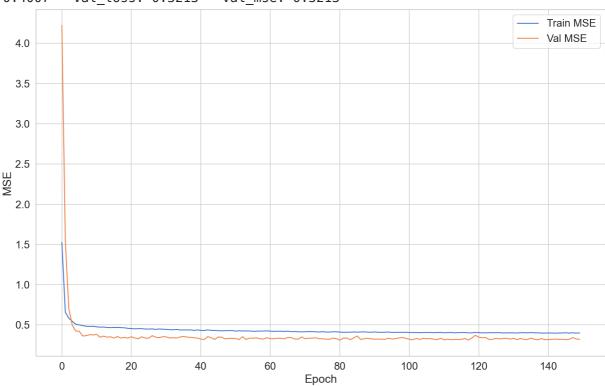
```
0.4299 - val_loss: 0.3334 - val_mse: 0.3334
Epoch 50/150
0.4304 - val_loss: 0.3333 - val_mse: 0.3333
Epoch 51/150
0.4236 - val loss: 0.3310 - val mse: 0.3310
Epoch 52/150
0.4271 - val loss: 0.3191 - val mse: 0.3191
Epoch 53/150
0.4256 - val loss: 0.3541 - val mse: 0.3541
Epoch 54/150
0.4255 - val loss: 0.3192 - val mse: 0.3192
Epoch 55/150
0.4250 - val loss: 0.3356 - val mse: 0.3356
Epoch 56/150
0.4213 - val loss: 0.3345 - val mse: 0.3345
Epoch 57/150
0.4221 - val loss: 0.3409 - val mse: 0.3409
Epoch 58/150
0.4243 - val loss: 0.3280 - val mse: 0.3280
Epoch 59/150
0.4236 - val loss: 0.3243 - val mse: 0.3243
Epoch 60/150
0.4267 - val loss: 0.3419 - val mse: 0.3419
Epoch 61/150
0.4232 - val loss: 0.3283 - val mse: 0.3283
Epoch 62/150
0.4203 - val loss: 0.3287 - val mse: 0.3287
Epoch 63/150
0.4220 - val loss: 0.3359 - val mse: 0.3359
Epoch 64/150
0.4226 - val loss: 0.3336 - val mse: 0.3336
Epoch 65/150
0.4195 - val loss: 0.3279 - val mse: 0.3279
Epoch 66/150
0.4231 - val loss: 0.3445 - val mse: 0.3445
Epoch 67/150
0.4170 - val loss: 0.3419 - val mse: 0.3419
Epoch 68/150
0.4177 - val loss: 0.3253 - val mse: 0.3253
Epoch 69/150
0.4153 - val loss: 0.3230 - val mse: 0.3230
Epoch 70/150
0.4144 - val loss: 0.3508 - val mse: 0.3508
Epoch 71/150
0.4154 - val loss: 0.3284 - val mse: 0.3284
Epoch 72/150
```

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0.4178 - val_loss: 0.3356 - val_mse: 0.3356
Epoch 73/150
0.4168 - val_loss: 0.3351 - val_mse: 0.3351
Epoch 74/150
0.4153 - val loss: 0.3411 - val mse: 0.3411
Epoch 75/150
0.4118 - val loss: 0.3292 - val mse: 0.3292
Epoch 76/150
0.4163 - val loss: 0.3280 - val mse: 0.3280
Epoch 77/150
0.4118 - val loss: 0.3237 - val mse: 0.3237
Epoch 78/150
0.4114 - val loss: 0.3220 - val mse: 0.3220
Epoch 79/150
0.4154 - val loss: 0.3369 - val mse: 0.3369
Epoch 80/150
0.4144 - val loss: 0.3300 - val mse: 0.3300
Epoch 81/150
0.4121 - val loss: 0.3107 - val mse: 0.3107
Epoch 82/150
0.4079 - val loss: 0.3376 - val mse: 0.3376
Epoch 83/150
0.4096 - val loss: 0.3372 - val mse: 0.3372
Epoch 84/150
0.4098 - val loss: 0.3169 - val mse: 0.3169
Epoch 85/150
0.4128 - val loss: 0.3386 - val mse: 0.3386
Epoch 86/150
0.4107 - val loss: 0.3634 - val mse: 0.3634
Epoch 87/150
0.4129 - val loss: 0.3195 - val mse: 0.3195
Epoch 88/150
0.4142 - val loss: 0.3286 - val mse: 0.3286
Epoch 89/150
0.4108 - val loss: 0.3345 - val mse: 0.3345
Epoch 90/150
0.4095 - val loss: 0.3277 - val mse: 0.3277
Epoch 91/150
0.4125 - val loss: 0.3234 - val mse: 0.3234
Epoch 92/150
0.4097 - val loss: 0.3243 - val mse: 0.3243
Epoch 93/150
0.4083 - val loss: 0.3231 - val mse: 0.3231
Epoch 94/150
0.4103 - val loss: 0.3221 - val mse: 0.3221
Epoch 95/150
```

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0.4115 - val_loss: 0.3359 - val_mse: 0.3359
Epoch 96/150
0.4065 - val_loss: 0.3247 - val_mse: 0.3247
Epoch 97/150
0.4082 - val loss: 0.3303 - val mse: 0.3303
Epoch 98/150
0.4082 - val loss: 0.3383 - val mse: 0.3383
Epoch 99/150
0.4080 - val loss: 0.3451 - val mse: 0.3451
Epoch 100/150
0.4093 - val loss: 0.3328 - val mse: 0.3328
Epoch 101/150
0.4057 - val loss: 0.3227 - val mse: 0.3227
Epoch 102/150
0.4060 - val loss: 0.3152 - val mse: 0.3152
Epoch 103/150
0.4060 - val loss: 0.3338 - val mse: 0.3338
Epoch 104/150
0.4037 - val loss: 0.3196 - val mse: 0.3196
Epoch 105/150
0.4049 - val loss: 0.3349 - val mse: 0.3349
Epoch 106/150
0.4063 - val loss: 0.3280 - val mse: 0.3280
Epoch 107/150
0.4062 - val loss: 0.3313 - val mse: 0.3313
Epoch 108/150
0.4034 - val loss: 0.3225 - val mse: 0.3225
Epoch 109/150
0.4055 - val loss: 0.3165 - val mse: 0.3165
Epoch 110/150
0.4075 - val loss: 0.3361 - val mse: 0.3361
Epoch 111/150
0.4031 - val loss: 0.3152 - val mse: 0.3152
Epoch 112/15\overline{0}
0.4042 - val loss: 0.3224 - val mse: 0.3224
Epoch 113/150
0.4066 - val loss: 0.3161 - val mse: 0.3161
Epoch 114/150
0.4022 - val loss: 0.3204 - val_mse: 0.3204
Epoch 115/150
0.4037 - val loss: 0.3186 - val mse: 0.3186
Epoch 116/150
0.4063 - val loss: 0.3206 - val mse: 0.3206
Epoch 117/150
0.4050 - val loss: 0.3319 - val mse: 0.3319
Epoch 118/150
```

```
0.4015 - val_loss: 0.3126 - val_mse: 0.3126
Epoch 119/150
0.4016 - val_loss: 0.3375 - val_mse: 0.3375
Epoch 120/150
0.4069 - val loss: 0.3715 - val mse: 0.3715
Epoch 121/150
0.4050 - val loss: 0.3475 - val mse: 0.3475
Epoch 122/150
0.4019 - val loss: 0.3412 - val mse: 0.3412
Epoch 123/150
0.4021 - val loss: 0.3425 - val mse: 0.3425
Epoch 124/150
0.4033 - val loss: 0.3176 - val mse: 0.3176
Epoch 125/150
0.4039 - val loss: 0.3227 - val mse: 0.3227
Epoch 126/150
0.4031 - val loss: 0.3336 - val mse: 0.3336
Epoch 127/150
0.4041 - val loss: 0.3266 - val mse: 0.3266
Epoch 128/150
0.4009 - val loss: 0.3317 - val mse: 0.3317
Epoch 129/150
0.4006 - val loss: 0.3346 - val mse: 0.3346
Epoch 130/150
0.4027 - val loss: 0.3243 - val mse: 0.3243
Epoch 131/150
0.4017 - val loss: 0.3347 - val mse: 0.3347
Epoch 132/150
0.4002 - val loss: 0.3171 - val mse: 0.3171
Epoch 133/150
0.4035 - val loss: 0.3334 - val mse: 0.3334
Epoch 134/150
0.4038 - val loss: 0.3199 - val mse: 0.3199
Epoch 135/150
0.4012 - val loss: 0.3194 - val mse: 0.3194
Epoch 136/150
0.4057 - val loss: 0.3374 - val mse: 0.3374
Epoch 137/150
0.4016 - val loss: 0.3224 - val_mse: 0.3224
Epoch 138/150
0.4013 - val loss: 0.3145 - val mse: 0.3145
Epoch 139/150
0.4000 - val loss: 0.3310 - val mse: 0.3310
Epoch 140/150
0.3983 - val loss: 0.3162 - val mse: 0.3162
Epoch 141/15\overline{0}
```

```
======] - 2s 5ms/step - loss: 0.4000 - mse:
0.4000 - val_loss: 0.3184 - val_mse: 0.3184
Epoch 142/150
               =======] - 2s 6ms/step - loss: 0.3997 - mse:
339/339 [=====
0.3997 - val_loss: 0.3210 - val_mse: 0.3210
Epoch 143/150
0.3977 - val loss: 0.3242 - val mse: 0.3242
Epoch 144/150
0.4000 - val loss: 0.3205 - val mse: 0.3205
Epoch 145/150
0.3997 - val loss: 0.3218 - val mse: 0.3218
Epoch 146/150
0.4031 - val loss: 0.3168 - val mse: 0.3168
Epoch 147/150
0.3982 - val loss: 0.3207 - val mse: 0.3207
Epoch 148/150
0.4029 - val loss: 0.3439 - val mse: 0.3439
Epoch 149/150
0.3991 - val loss: 0.3264 - val mse: 0.3264
Epoch 150/150
0.4007 - val loss: 0.3213 - val_mse: 0.3213
                                     Train MSE
                                     Val MSE
4.0
```



```
import time
In [32]:
          import xqboost as xqb
          from sklearn.metrics import mean squared error, r2 score
          xgb_reg_start = time.time()
          xgb_reg = xgb.XGBRegressor()
          xgb_reg.fit(X_train, y_train)
          training preds xgb reg = xgb reg.predict(X train)
          val_preds_xgb_reg = xgb_reg.predict(X_test)
          xgb reg end = time.time()
```

```
print(f"Time taken to run: {round((xgb_reg_end - xgb_reg_start)/60,1)} minute
print("\nTraining MSE:", round(mean_squared_error(y_train, training_preds_xgt
print("Validation MSE:", round(mean_squared_error(y_test, val_preds_xgb_reg),
print("\nTraining r2:", round(r2_score(y_train, training_preds_xgb_reg),4))
print("Validation r2:", round(r2 score(y test, val preds xgb reg),4))
```

Time taken to run: 0.0 minutes

Training MSE: 0.1296 Validation MSE: 0.2065

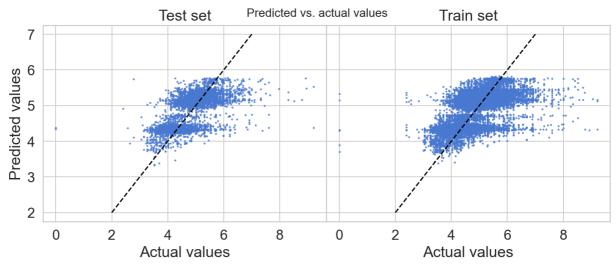
Training r2: 0.7326 Validation r2: 0.5828

```
Model Evaluation
In [331:
         from sklearn.metrics import mean squared error
          from sklearn.metrics import mean absolute error
          from math import sqrt
          from sklearn.metrics import r2 score
         f = open("Mirko Lantieri 858278 score1.txt", "a+")
In [34]:
          y pred = model1.predict(X test)
In [35]:
In [36]:
          print(f'MSE {mean squared error(y test, y pred)}')
          print(f'MAE {mean_absolute_error(y_test, y_pred)}')
          print(f'RMSE {np.sqrt(mean squared error(y test, y pred))}')
          print(f'R2 {r2 score(y test, y pred)}')
         MSE 0.2821209050290158
         MAE 0.3934433364372566
         RMSE 0.5311505483655419
         R2 0.4299887470821828
          f.write(f"{np.array2string(np.expml(y pred), separator=',')}\n")
In [37]:
Out[37]: 96
In [38]:
         y pred = model2.predict(X test)
          print(f'MSE {mean_squared_error(y_test, y_pred)}')
In [39]:
          print(f'MAE {mean absolute error(y test, y pred)}')
          print(f'RMSE {np.sqrt(mean squared error(y test, y pred))}')
          print(f'R2 {r2_score(y_test, y_pred)}')
         MSE 0.2852159162253565
         MAE 0.3893421514819327
         RMSE 0.534056098387947
         R2 0.42373543093873933
In [40]:
         f.write(f"{np.array2string(np.expm1(y_pred), separator=',')}\n")
Out[40]: 96
          y_pred = model3.predict(X test)
In [41]:
In [42]:
          print(f'MSE {mean_squared_error(y_test, y_pred)}')
          print(f'MAE {mean_absolute_error(y_test, y_pred)}')
          print(f'RMSE {np.sqrt(mean_squared_error(y_test, y_pred))}')
          print(f'R2 {r2_score(y_test, y_pred)}')
```

```
MSE 0.2863689202705159
          MAE 0.3954222547228138
          RMSE 0.5351344880219513
          R2 0.4214058436281747
          f.write(f"{np.array2string(np.expm1(y pred), separator=',')}\n")
In [43]:
Out[43]: 96
In [44]:
          y pred = model4.predict(X test)
          print(f'MSE {mean squared error(y test, y pred)}')
In [45]:
          print(f'MAE {mean absolute error(y test, y pred)}')
          print(f'RMSE {np.sqrt(mean_squared_error(y_test, y_pred))}')
          print(f'R2 {r2 score(y test, y pred)}')
          MSE 0.323951555103329
          MAE 0.424994437956569
          RMSE 0.5691674227354628
          R2 0.3454719997083088
In [46]:
          f.write(f"{np.array2string(np.expm1(y pred), separator=',')}\n")
          f.close()
          def nn model evaluation(model, skip epochs=0, X train=X train, X test=X test,
In [47]:
               For a given neural network model that has already been fit, prints for the
               values, a line graph of the loss in each epoch, and a scatterplot of pred
               representing where predicted = actual values. Optionally, a value for ski
               number of epochs in the line graph of losses (useful in cases where the l
               larger than subsequent epochs). Training and test sets can also optionall
               # MSE and r squared values
               y test pred = model.predict(X test)
               y train pred = model.predict(X train)
               print("Training MSE:", round(mean_squared_error(y_train, y_train_pred),4)
               print("Validation MSE:", round(mean_squared_error(y_test, y_test_pred),4)
print("\nTraining r2:", round(r2_score(y_train, y_train_pred),4))
print("Validation r2:", round(r2_score(y_test, y_test_pred),4))
               # Scatterplot of predicted vs. actual values
               fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))
               fig.suptitle('Predicted vs. actual values', fontsize=14, y=1)
               plt.subplots_adjust(top=0.93, wspace=0)
               ax1.scatter(y_test, y_test_pred, s=2, alpha=0.7)
               ax1.plot(list(range(2,8)), list(range(2,8)), color='black', linestyle='--
               ax1.set title('Test set')
               ax1.set xlabel('Actual values')
               ax1.set ylabel('Predicted values')
               ax2.scatter(y_train, y_train_pred, s=2, alpha=0.7)
               ax2.plot(list(range(2,8)), list(range(2,8)), color='black', linestyle='--
               ax2.set_title('Train set')
               ax2.set_xlabel('Actual values')
               ax2.set ylabel('')
               ax2.set yticklabels(labels='')
               plt.show()
In [48]:
          nn model evaluation(model1)
```

Training MSE: 0.281 Validation MSE: 0.2821

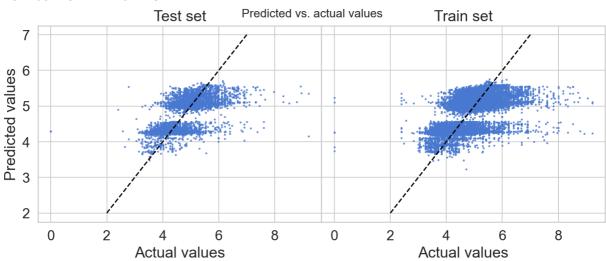
Training r2: 0.4203 Validation r2: 0.43



In [49]: nn_model_evaluation(model2)

Training MSE: 0.2829 Validation MSE: 0.2852

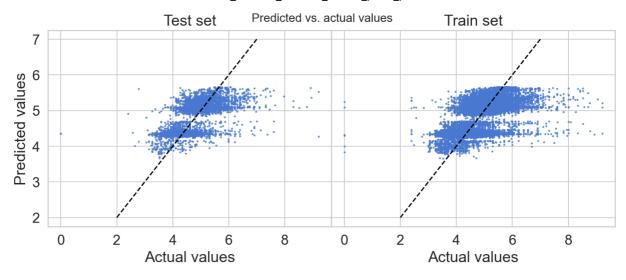
Training r2: 0.4164 Validation r2: 0.4237



In [50]: nn_model_evaluation(model3)

Training MSE: 0.2848 Validation MSE: 0.2864

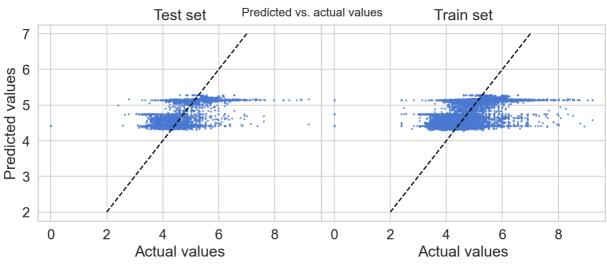
Training r2: 0.4126 Validation r2: 0.4214



In [51]: nn_model_evaluation(model4)

Training MSE: 0.3234 Validation MSE: 0.324

Training r2: 0.3329 Validation r2: 0.3455



In [52]: nn_model_evaluation(xgb_reg)

Training MSE: 0.1296 Validation MSE: 0.2065

Training r2: 0.7326 Validation r2: 0.5828

