House Price AI, Revisited

This project is adapted from a prior project, linked here, where Scikit-Learn was used on a house price dataset[1] to perform regression to predict the house price value.

I wish to revisit this project using Tensorflow instead of Scikit-Learn so I have more control over the AI itself. Additionally, the old model had an r^2 value of `0.999996824199374`, but that included house location data. I seek to create a model that does not rely on location data.

In [2]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import tensorflow as tf
```

```
2023-07-12 17:16:27.220727: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
```

We read the data into a Pandas DataFrame[1].

In [3]:
```
df = pd.read_csv('data.csv')
```

In [4]:
```
df.dtypes
```

Out[4]:
```
date              object
price            float64
bedrooms         float64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront         int64
view               int64
condition          int64
sqft_above         int64
sqft_basement      int64
yr_built           int64
yr_renovated       int64
street            object
city              object
statezip          object
country           object
dtype: object
```

We see that the only columns that aren't numbers are the data, street, city, statezip, and country columns. Since we don't wish to use location data, and since the date isn't important for our price regression, we can drop all of those columns. In the other model, we enumerated the location data instead. We then manually assert that there are no other columns that aren't `float64` or `int64`.

In [5]:
```
df = df.drop(['date', 'street', 'city', 'statezip', 'country'], axis=1)
```

In [6]:
```
df.dtypes
```

Out[6]:
```
price            float64
bedrooms         float64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront         int64
view               int64
condition          int64
sqft_above         int64
sqft_basement      int64
yr_built           int64
yr_renovated       int64
dtype: object
```

In [7]:
```
df.head()
```

Out[7]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
0	313000.0	3.0	1.50	1340	7912	1.5	0	0	3
1	2384000.0	5.0	2.50	3650	9050	2.0	0	4	5
2	342000.0	3.0	2.00	1930	11947	1.0	0	0	4
3	420000.0	3.0	2.25	2000	8030	1.0	0	0	4
4	550000.0	4.0	2.50	1940	10500	1.0	0	0	4

We then check for any null values. We see that there are none, but we attempt to drop those values anyway (just in case).

In [8]:
```
df.isna().sum()
```

Out[8]:
```
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
dtype: int64
```

In [9]:
```
df = df.dropna()
```

We then split the data into train and test sets, with 80% bein in the training set.

In [10]:
```
train_df = df.sample(frac=0.8, random_state=0)
test_df = df.drop(train_df.index)
```

We can describe the training dataset with different metrics like the mean, std, and other values.

In [11]:
```
train_df.describe().transpose()
```

Out[11]:

	count	mean	std	min	25%	50%	75%
price	3680.0	552674.649108	593696.508031	0.0	322875.00	465000.00	657025.0
bedrooms	3680.0	3.396467	0.911488	0.0	3.00	3.00	4.0
bathrooms	3680.0	2.162840	0.784678	0.0	1.75	2.25	2.5
sqft_living	3680.0	2142.219837	966.077603	380.0	1460.00	1980.00	2620.0
sqft_lot	3680.0	15220.664402	37480.055461	638.0	5004.50	7700.00	11235.5
floors	3680.0	1.515353	0.534456	1.0	1.00	1.50	2.0
waterfront	3680.0	0.007880	0.088433	0.0	0.00	0.00	0.0
view	3680.0	0.235326	0.768751	0.0	0.00	0.00	0.0
condition	3680.0	3.447554	0.671697	1.0	3.00	3.00	4.0
sqft_above	3680.0	1836.182065	869.016072	380.0	1190.00	1600.00	2320.0
sqft_basement	3680.0	306.037772	461.328536	0.0	0.00	0.00	600.0
yr_built	3680.0	1971.001902	29.667987	1900.0	1951.00	1976.00	1997.0
yr_renovated	3680.0	800.618478	978.006312	0.0	0.00	0.00	1999.0

We then split the train and test datasets into the features and the labels, where the labels is the price column (what we wish to predict).

In [12]:
```
train_features = train_df.copy()
test_features = test_df.copy()
train_labels = train_df.pop('price')
test_labels = test_df.pop('price')
```

In [13]:
```
train_df.describe().transpose()[['mean', 'std']]
```

Out[13]:

	mean	std
bedrooms	3.396467	0.911488
bathrooms	2.162840	0.784678
sqft_living	2142.219837	966.077603
sqft_lot	15220.664402	37480.055461
floors	1.515353	0.534456
waterfront	0.007880	0.088433
view	0.235326	0.768751
condition	3.447554	0.671697
sqft_above	1836.182065	869.016072
sqft_basement	306.037772	461.328536
yr_built	1971.001902	29.667987
yr_renovated	800.618478	978.006312

In order to get better results, we should normalize the data. With Tensorflow, we don't need to do this beforehand. We can have the model do it during training using a Normalization layer, adapted to the training features.

In [14]:
```
normalizer = tf.keras.layers.Normalization(axis=-1)
```

In [15]:
```
normalizer.adapt(np.array(train_features))
```

We can see how this normalizer works with examples:

In [16]:
```
print(normalizer.mean.numpy())
```

```
[[5.5267475e+05 3.3964672e+00 2.1628401e+00 2.1422190e+03 1.5220662e+04
  1.5153531e+00 7.8804353e-03 2.3532604e-01 3.4475543e+00 1.8361820e+03
  3.0603769e+02 1.9710018e+03 8.0061859e+02]]
```

In [17]:
```
first = np.array(train_features[:1])

with np.printoptions(precision=2, suppress=True):
  print('First example:', first)
  print()
  print('Normalized:', normalizer(first).numpy())
```

```
First example: [[289000.       3.       2.5    2090.     4700.       2.       0.
0.
       3.    2090.       0.    2002.       0. ]]

Normalized: [[-0.44 -0.44  0.43 -0.05 -0.28  0.91 -0.09 -0.31 -0.67  0.29 -0.66  1.04
  -0.82]]
```

Now we can define the Sequential model. We first put the normalizer so that way the training data is normalized. We then have four Dense layers with 512 filters, ReLU activated, with L2 Regularization (to help overfitting issues I encountered earlier). We then add a standard Dense layer with one filter to finish off the model.

In [18]:
```
model = tf.keras.Sequential([
    normalizer,
    tf.keras.layers.Dense(512, activation='relu', kernel_regularizer=tf.keras.regular
    tf.keras.layers.Dense(512, activation='relu', kernel_regularizer=tf.keras.regular
    tf.keras.layers.Dense(512, activation='relu', kernel_regularizer=tf.keras.regular
    tf.keras.layers.Dense(512, activation='relu', kernel_regularizer=tf.keras.regular
    tf.keras.layers.Dense(1)
])
```

We compile the model with the Adam optimizer of learning rate 0.001. The loss funciton we are using is mean absolute error, since it is more resistant to outliers compared to mean square error (MSE).

In [19]:
```
model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
    loss='mean_absolute_error'
)
```

In [20]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 normalization (Normalizatio  (None, 13)               27
 n)

 dense (Dense)               (None, 512)               7168

 dense_1 (Dense)             (None, 512)               262656

 dense_2 (Dense)             (None, 512)               262656

 dense_3 (Dense)             (None, 512)               262656

 dense_4 (Dense)             (None, 1)                 513

=================================================================
Total params: 795,676
Trainable params: 795,649
Non-trainable params: 27
_________________________________________________________________
```

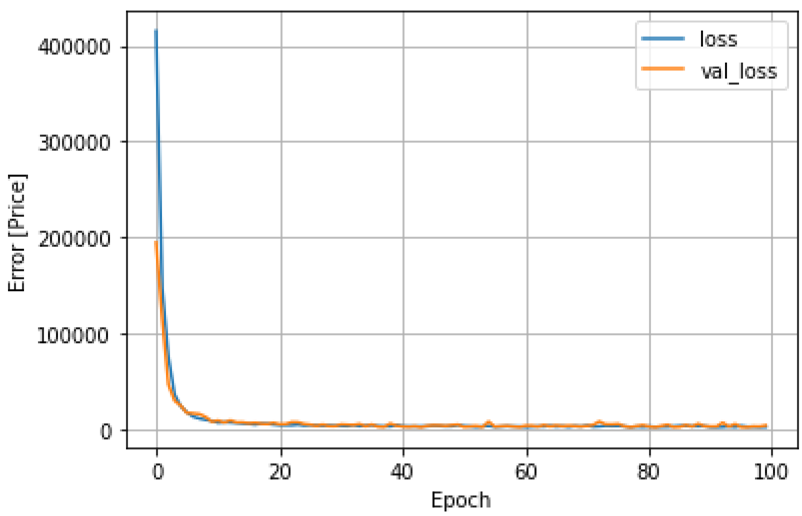
Fit the model to the training features and labels, with a 20% validation split over 100 epochs.

In [21]:
```
%%time
history = model.fit(
    train_features, train_labels, validation_split=0.2, epochs=100, verbose=0
)
```

```
/Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-packages/keras/engine/data_adapter.py:1700: FutureWarning: The behavior of `series[i:j]` with an integer-dtype index is deprecated. In a future version, this will be treated as *label-based* indexing, consistent with e.g. `series[i]` lookups. To retain the old behavior, use `series.iloc[i:j]`. To get the future behavior, use `series.loc[i:j]`.
  return t[start:end]
CPU times: user 3min 30s, sys: 26.3 s, total: 3min 57s
Wall time: 56 s
```

Plot the loss vs epochs graph.

In [22]:
```
plt.plot(history.history['loss'], label='loss')
plt.plot(history.history['val_loss'], label='val_loss')
plt.xlabel('Epoch')
plt.ylabel('Error [Price]')
plt.legend()
plt.grid(True)
```



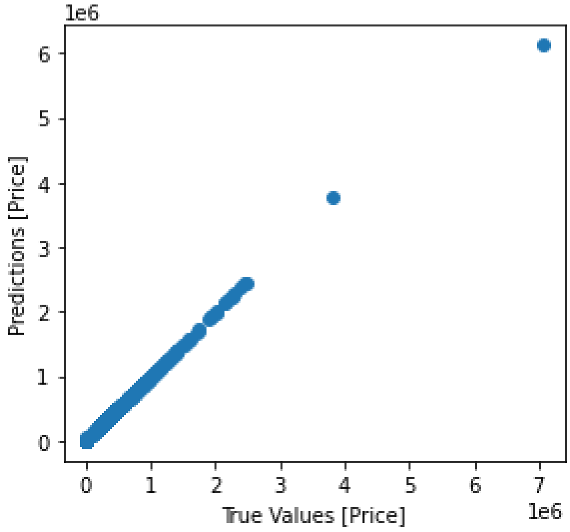
The loss graphs look good. In fact, 100 epochs may have been too much, and the model could likely perform well without needed so many epochs. We can now make predictions on the test features, and compare to the actual test labels.

In [23]:
```
test_predictions = model.predict(test_features).flatten()

a = plt.axes(aspect='equal')
plt.scatter(test_labels, test_predictions)
plt.xlabel('True Values [Price]')
plt.ylabel('Predictions [Price]')
```

```
29/29 [==============================] - 0s 2ms/step
```

Out[23]:
```
Text(0, 0.5, 'Predictions [Price]')
```



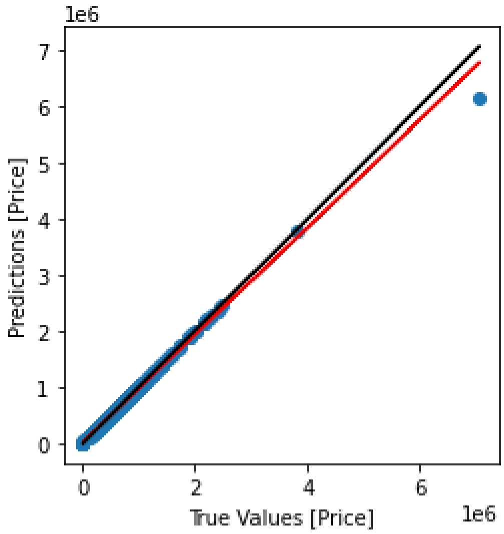
In [24]:
```
from sklearn.metrics import r2_score

r2_score(test_labels, test_predictions)
```

Out[24]:
```
0.9945587106393302
```

In [29]:
```
a = plt.axes(aspect='equal')
plt.scatter(test_labels, test_predictions)
plt.xlabel('True Values [Price]')
plt.ylabel('Predictions [Price]')
coef = np.polyfit(test_labels, test_predictions, 1)
fn = np.poly1d(coef)
plt.plot(test_labels, fn(test_labels), 'r')
plt.plot(test_labels, test_labels, 'k')
```

Out[29]:
```
[<matplotlib.lines.Line2D at 0x7f93fb4db130>]
```



With an r^2 value of `0.9946`, this model performs very well with no location data. It seems that the model does well with values under `4e6`, but the large outlier near `7e6` is not predicted super accurately. However, compared to the rest of the test data, this one data point being slightly inaccurate is fine. The black line is the correct prediction and the red line is closer to how our model predicts, which is not bad at all.

Acknowledgements

[1]Shree. (2018). House Price Prediction. Kaggle. https://www.kaggle.com/datasets/shree1992/housedata

Pandas: https://pandas.pydata.org/docs/ | Matplotlib: https://matplotlib.org | Numpy: https://numpy.org | Tensorflow: https://www.tensorflow.org/