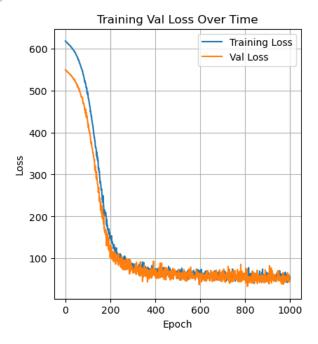
This Boston Housing dataset model has practical applications in real estate:

- Automated property valuation for agents, banks, and appraisers
- Investment decision support for real estate investors and developers
- Market analysis to identify price trends and key value drivers
- · Risk assessment for mortgage lending and insurance
- Integration into real estate websites and apps for instant estimates
- The model offers data-driven, scalable property assessments, reducing bias and saving time.

```
In [3]: import pandas as pd
         import torch
         boston_df = pd.read_csv('/Users/vbaderdi/Downloads/Boston.csv')
         dataset_df = pd.read_csv('/Users/vbaderdi/Downloads/dataset.csv')
 In [4]: boston_df.isna().sum()
Out[4]: Unnamed: 0
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In [18]: boston_df.head()
Out[18]:
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                                                                                   17.8 392.83 4.03
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                                                                                   18.7 394.63 2.94
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                                                                       3 222
                                                                                  18.7 396.90 5.33
                                                                                                    36.2
 In [5]: y = boston_df.iloc[:,-1]
         x = boston_df.iloc[:,:-1]
 In [6]: from sklearn.model_selection import train_test_split
In [7]: x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.25,shuffle=True)
 In [8]: from sklearn.preprocessing import StandardScaler
         scaler = StandardScaler()
         x_train_scaled = scaler.fit_transform(x_train)
         x_test_scaled = scaler.fit_transform(x_test)
 In [9]: # Define the model
         import torch
          import torch.nn as nn
          class RegressionNet(nn.Module): # 'Module' not 'module'
              def __init__(self, input_dim=14):
                  super(RegressionNet, self).__init__()
                  self.layer_1 = nn.Linear(14, 28)
                  self.bn1 = nn.BatchNorm1d(28)
                  # Layer 2
                  self.layer_2 = nn.Linear(28, 14)
                  self.bn2 = nn.BatchNorm1d(14)
                  # Layer 3
                 self.layer_3 = nn.Linear(14, 1)
                  self.relu = nn.ReLU()
                  self.dropout = nn.Dropout(0.2)
```

```
def forward(self,x):
                  x = self.dropout(self.relu(self.layer_1(x)))
                  x = self.dropout(self.relu(self.layer_2(x)))
                  x = self.layer_3(x)
In [10]: # Data prep for training
         x_train_scaled = torch.FloatTensor(x_train_scaled)
         x_test_scaled = torch.FloatTensor(x_test_scaled)
         y_train = torch.FloatTensor(y_train.tolist()).reshape(-1,1)
         y_test = torch.FloatTensor(y_test.tolist()).reshape(-1,1)
In [11]: # Model training
         model = RegressionNet()
         criterion = nn.MSELoss()
         optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
         num_epoch = 1000
         train_loss_plot = []
          loss_test = []
          for epoch in range(num_epoch):
              model.train()
              outputs = model(x_train_scaled)
              loss = criterion(outputs,y_train)
              optimizer.zero_grad()
              loss.backward()
             optimizer.step()
             # Test accuracy
              train_loss_plot.append(loss.item())
              loss_test.append(criterion(model(x_test_scaled),y_test).item())
In [12]: # Model evaluate
         import matplotlib.pyplot as plt
         plt.figure(figsize=(10, 5))
         plt.subplot(1, 2, 1)
         plt.plot(train_loss_plot, label='Training Loss')
plt.plot(loss_test, label='Val Loss')
         plt.title('Training Val Loss Over Time')
         plt.xlabel('Epoch')
         plt.ylabel('Loss')
         plt.grid(True)
         plt.legend(loc='upper right') # Specify location
Out[12]: <matplotlib.legend.Legend at 0x19c86ac50>
```



```
In [13]: # Example of how to evaluate on unseen test data
         model.eval()
         with torch.no_grad():
             test_predictions = model(x_test_scaled)
```

```
mse = criterion(test_predictions, y_test)
print(f'Test MSE: {mse.item():.4f}')
```

Test MSE: 12.8748

```
In [17]: # Example of how to scatter plots of prediction vs ground truth price from unseen test data
plt.figure(figsize=(5, 6))
plt.scatter(y_test.squeeze().tolist(),test_predictions, alpha=0.5, label='Data Points')
plt.xlabel('Ground Truth Price')
plt.ylabel('Predicted Price')
plt.title('Model Performance on unseen data')
plt.legend()
plt.grid(True)
plt.show()
```

Model Performance on unseen data 50 Data Points 40 20

In []:

10

10

20

30

Ground Truth Price

40

50