# Assignment

1. change the `encoding_dim` through various values ( `range(2,18,2)` and store or keep track of the best loss you can get. Plot the 8 pairs of dimensions vs loss on a scatter plot

In [1]:
```
# Import Packages
from keras.callbacks import TensorBoard
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import mnist
import numpy as np

(xtrain, ytrain), (xtest, ytest) = mnist.load_data()

xtrain = xtrain.astype('float32') / 255.
xtest = xtest.astype('float32') / 255.
xtrain = xtrain.reshape((len(xtrain), np.prod(xtrain.shape[1:])))
xtest = xtest.reshape((len(xtest), np.prod(xtest.shape[1:])))
xtrain.shape, xtest.shape
```

Out[1]:
```
((60000, 784), (10000, 784))
```

In [2]:
```
## Creating a Function

def auto_encoding(encoding_dim, xtrain, xtest):
    # Making Encoder, Decoder global variables for later use
    global encoder, decoder
    # this is the size of our encoded representations
    # encoding_dim = 4  # 32 floats -> compression of factor 24.5, assuming the input

    # this is our input placeholder
    x = input_img = Input(shape=(784,))
    # "encoded" is the encoded representation of the input
    x = Dense(256, activation='relu')(x)
    x = Dense(128, activation='relu')(x)
    encoded = Dense(encoding_dim, activation='relu')(x)


    # "decoded" is the lossy reconstruction of the input
    x = Dense(128, activation='relu')(encoded)
    x = Dense(256, activation='relu')(x)
    decoded = Dense(784, activation='sigmoid')(x)

    # this model maps an input to its reconstruction
    autoencoder = Model(input_img, decoded)

    encoder = Model(input_img, encoded)

    # create a placeholder for an encoded (32-dimensional) input
    encoded_input = Input(shape=(encoding_dim,))
    # retrieve the last layer of the autoencoder model
    dcd1 = autoencoder.layers[-1]
    dcd2 = autoencoder.layers[-2]
    dcd3 = autoencoder.layers[-3]
```

```
    # create the decoder model
    decoder = Model(encoded_input, dcd1(dcd2(dcd3(encoded_input))))

    # Compile
    autoencoder.compile(optimizer='adam', loss='binary_crossentropy')

    # Fit
    fitting = autoencoder.fit(xtrain, xtrain,
                epochs=50,
                batch_size=256,
                shuffle=True,
                validation_data=(xtest, xtest),
                callbacks=[TensorBoard(log_dir='/tmp/autoencoder')])
    # Capture Loss

    loss = fitting.history['loss']

    # Append

    losses_for_all_models.append(loss[-1])

    # Return Encoder, Decoder
    encoder = Model(input_img, encoded)
    decoder = Model(encoded_input, dcd1(dcd2(dcd3(encoded_input))))
    return encoder, decoder
```

In [3]:

```
# Loopable
r = range(2,18,2)
list(r)
```

Out[3]:

```
[2, 4, 6, 8, 10, 12, 14, 16]
```

In [4]:

```
%%capture
losses_for_all_models = []
for encoding_dim in r:
    auto_encoding(encoding_dim, xtrain, xtest)
```

In [5]:

```
losses_for_all_models
```

Out[5]:

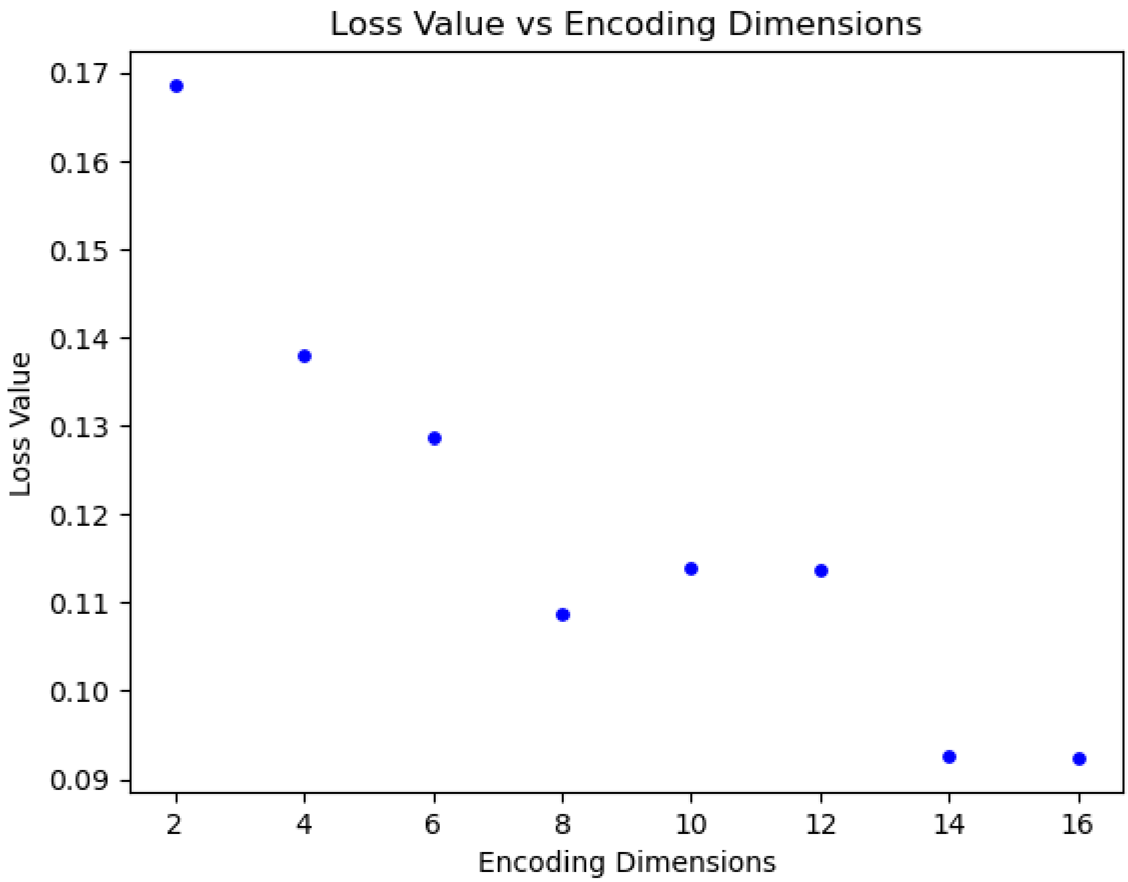
```
[0.16860432922840118,
 0.138000950217247,
 0.1286267191171646,
 0.10880253463983536,
 0.1139471456408500 7,
 0.11375362426042557,
 0.0926068052649498,
 0.09242004156112671]
```

In [6]:

```
import matplotlib.pyplot as plt
plt.scatter(r, losses_for_all_models, s=15, c='blue')
plt.xlabel('Encoding Dimensions')
plt.ylabel('Loss Value')
plt.title('Loss Value vs Encoding Dimensions')
```

Out[6]:

```
Text(0.5, 1.0, 'Loss Value vs Encoding Dimensions')
```




As the scatterplot shows, there is a negative correlation between the number of encoding dimensions and the final loss value; with more encoding dimensions, there is a lower resulting loss value.

1. ***After*** training an autoencoder with `encoding_dim=8`, apply noise (like the previous assignment) to *only* the input of the trained autoencoder (not the output). The output images should be without noise.

Print a few noisy images along with the output images to show they don't have noise.

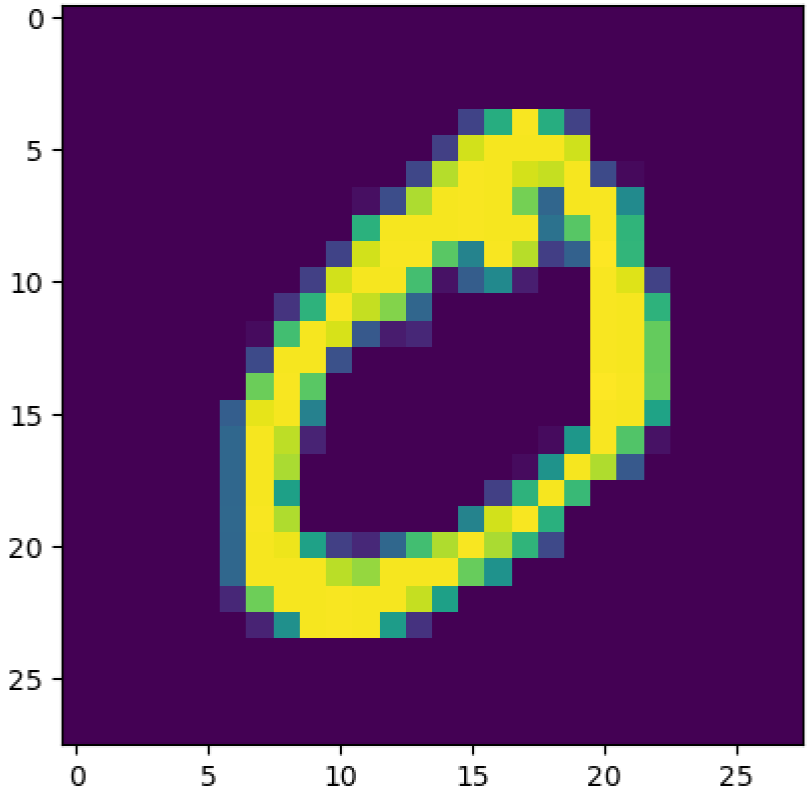
In [7]:
```
## Noise

# Variables
loc = 0
scale_values = 1.00

# Generate random noise with the same shape as the image
x_train_noise = np.random.normal(loc, scale_values, xtrain.shape)
x_test_noise = np.random.normal(loc, scale_values, xtest.shape)

# Add noise
xtrain_noise_added = xtrain + x_train_noise
xtest_noise_added  = xtest  + x_test_noise
```

In [8]:
```
%%capture
encoding_dim = 8
```

```
auto_encoding(encoding_dim, xtrain, xtest)
```

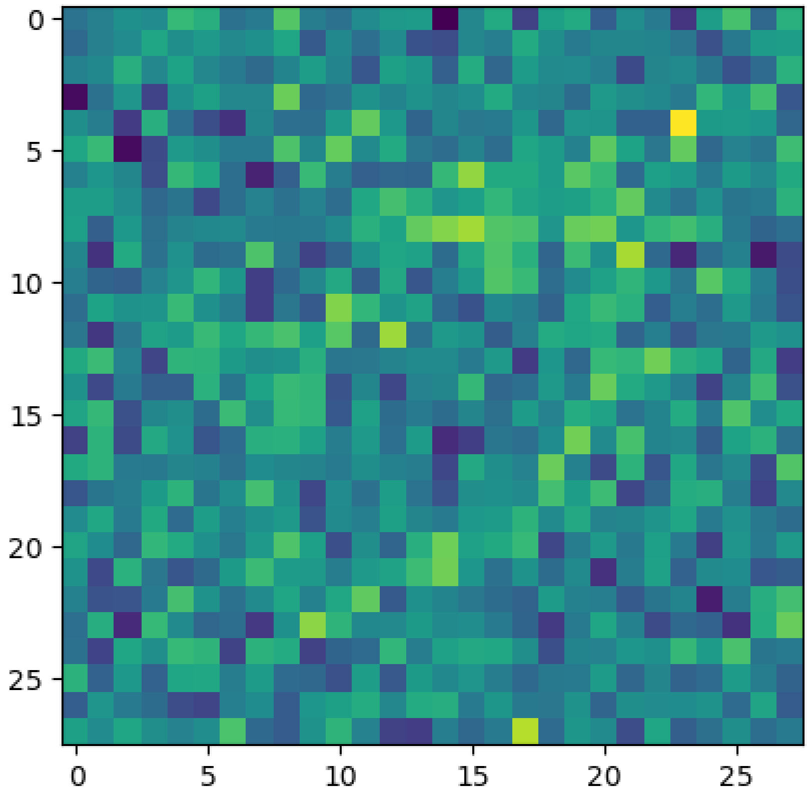
In [9]:
```
# Without Noise
plt.imshow(xtrain[1].reshape(28,28))
```

Out[9]: <matplotlib.image.AxesImage at 0x22b3d136d40>




In [10]:
```
# With Noise
plt.imshow(xtrain_noise_added[1].reshape(28,28))
```

Out[10]: <matplotlib.image.AxesImage at 0x22b0ab117b0>

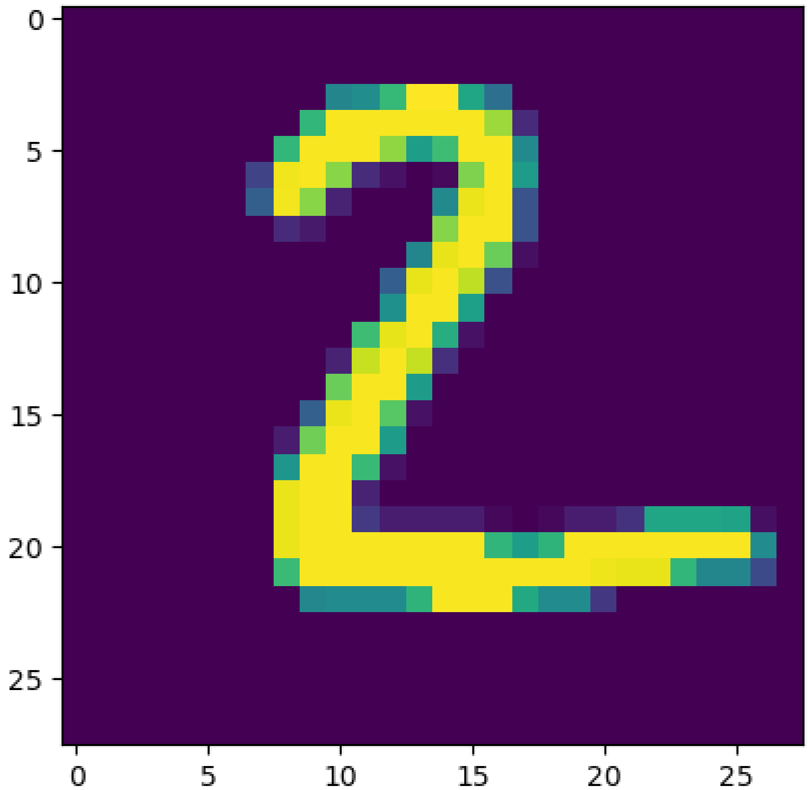



In [11]:
```
# Encoding
encoded_imgs = encoder.predict(xtest)
# Decoding
decoded_imgs = decoder.predict(encoded_imgs)
```

```
313/313 [==============================] - 0s 1ms/step
313/313 [==============================] - 0s 868us/step
```

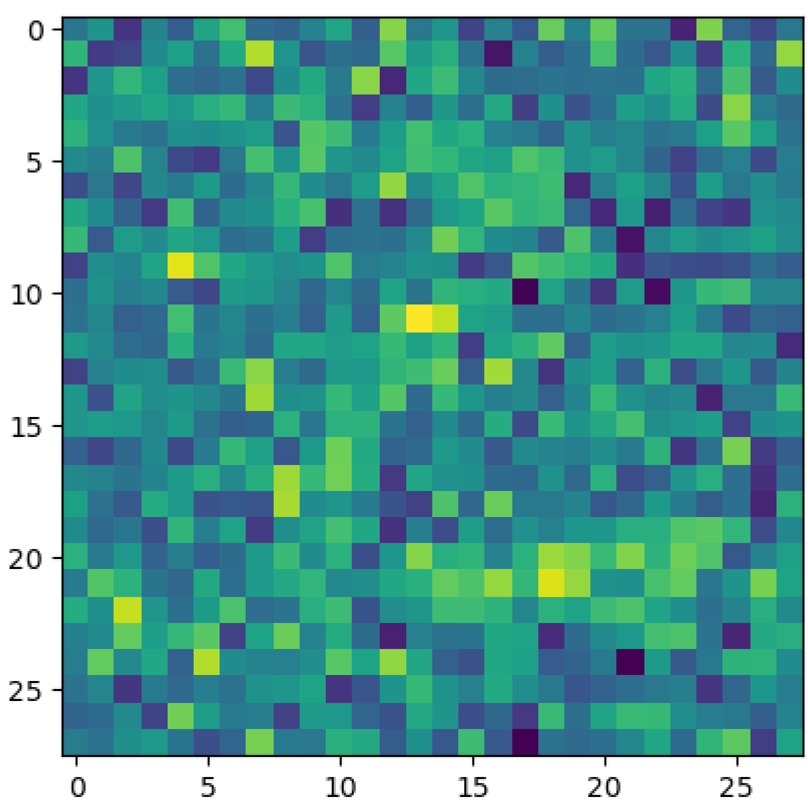
In [12]:
```
# Original Test Image
plt.imshow(xtest[1].reshape(28, 28))
```

Out[12]: <matplotlib.image.AxesImage at 0x22b07b77670>



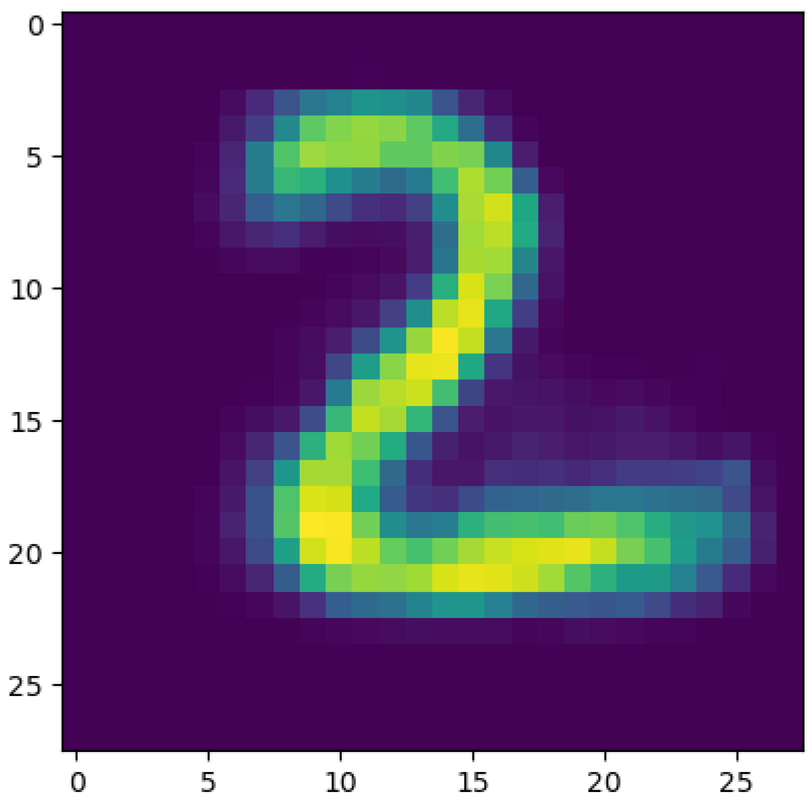
In [13]:
```
# Test image with noise added
plt.imshow(xtest_noise_added[1].reshape(28, 28))
```

Out[13]: <matplotlib.image.AxesImage at 0x22b07c1e920>

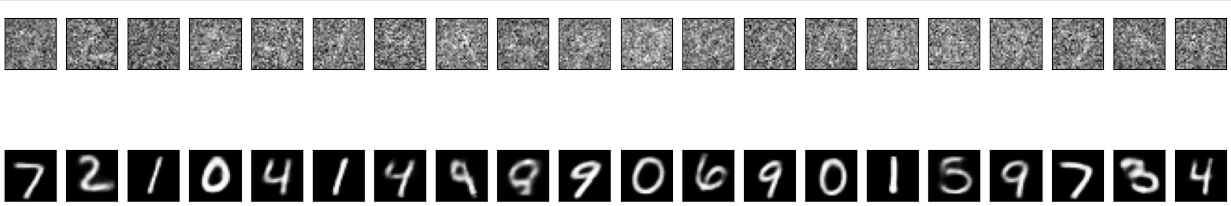


In [14]:
```
# Decoded image
plt.imshow(decoded_imgs[1].reshape(28,28))
```

Out[14]:
```
<matplotlib.image.AxesImage at 0x22b0ab32ef0>
```




In [15]:
```python
n = 20  # how many digits we will display
plt.figure(figsize=(20, 4))
for i in range(n):
    # display original
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(xtest_noise_added[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # display reconstruction
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(decoded_imgs[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()
```



Despite the noise added, the decoded images are legibile.