Yinan Kang Assignment 2

CSCI 89

In [46]:
```
!pwd
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

```
/Users/yinankang/Downloads
```

In [13]:
```
import os
import numpy as np
import gensim
# Get the interactive Tools for Matplotlib
%matplotlib notebook
import matplotlib.pyplot as plt
plt.style.use('ggplot')
from sklearn.decomposition import PCA
from gensim.test.utils import datapath, get_tmpfile
from gensim.models import KeyedVectors
from gensim.scripts.glove2word2vec import glove2word2vec
```

Setting up from where the lecture example Jupyter notebook began...

Problem 1

In [20]:
```
# Getting '100 dimension' glove in there
glove_file = datapath('glove.6B.100d.txt')
word2vec_glove_file = get_tmpfile("glove.6B.100d.word2vec.txt")
glove2word2vec(glove_file, word2vec_glove_file)
```

```
/anaconda3/lib/python3.7/site-packages/smart_open/smart_open_lib.py:39
8: UserWarning: This function is deprecated, use smart_open.open instea
d. See the migration notes for details: https://github.com/RaRe-Technol
ogies/smart_open/blob/master/README.rst#migrating-to-the-new-open-funct
ion
  'See the migration notes for details: %s' % _MIGRATION_NOTES_URL
```

Out[20]:
```
(400000, 100)
```

In [21]:
```
model = KeyedVectors.load_word2vec_format(word2vec_glove_file)
```

```
/anaconda3/lib/python3.7/site-packages/smart_open/smart_open_lib.py:398: UserWarning: This function is deprecated, use smart_open.open instead. See the migration notes for details: https://github.com/RaRe-Technologies/smart_open/blob/master/README.rst#migrating-to-the-new-open-function
  'See the migration notes for details: %s' % _MIGRATION_NOTES_URL
```

In [26]:
```
def analogy(x1, x2, y1):
        result = model.most_similar(positive=[y1, x2], negative=[x1])
        return result[0][0]
```

In [37]:
```
def display_pca_scatterplot(model, words=None, sample=0):
        if words == None:
                if sample > 0:
                        words = np.random.choice(list(model.vocab.keys()), sample)
                else:
                        words = [ word for word in model.vocab ]
        word_vectors = np.array([model[w] for w in words])
        twodim = PCA().fit_transform(word_vectors)[:,:2]
        plt.figure(figsize=(6,6))
        plt.scatter(twodim[:,0], twodim[:,1], edgecolors='k', c='r')
        for word, (x,y) in zip(words, twodim):
                plt.text(x+0.05, y+0.05, word)
```

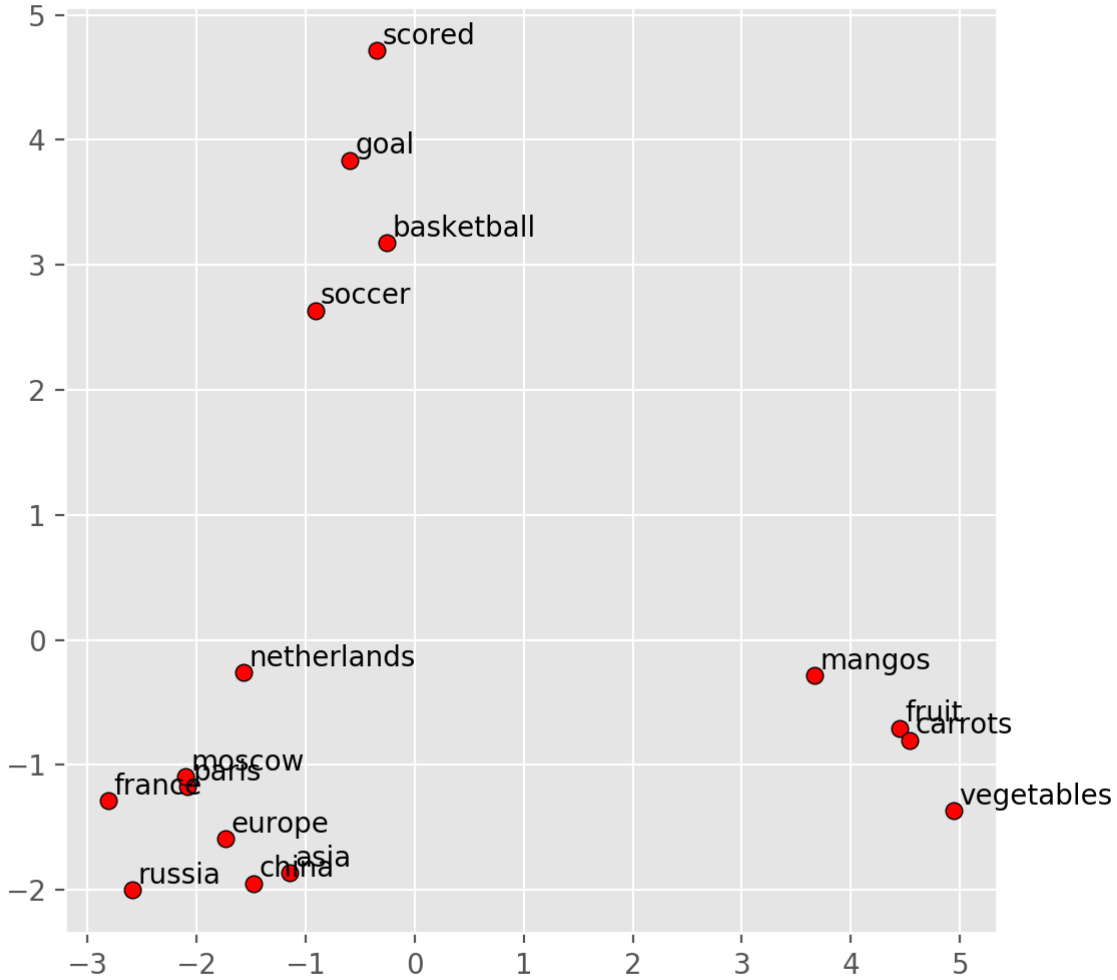
In [55]:
```
# Chose the following analogies:
analogy('france','paris','russia')
analogy('mangos','fruit','carrots')
analogy('soccer','goal','basketball')
analogy('china','asia','netherlands')

# Plot
display_pca_scatterplot(model,['france','paris','russia','moscow','mangos','fruit','carrots','vegetables','soccer','goal','basketball'
```

Out[55]: 'moscow'

Out[55]: 'vegetables'

Out[55]: 'scored'

Out[55]: 'europe'



Problem 3

Using 300 dimensional

In [56]:
```
glove_file = datapath('glove.6B.300d.txt')
word2vec_glove_file = get_tmpfile("glove.6B.300d.word2vec.txt")
glove2word2vec(glove_file, word2vec_glove_file)
```

```
/anaconda3/lib/python3.7/site-packages/smart_open/smart_open_lib.py:39
8: UserWarning: This function is deprecated, use smart_open.open instea
d. See the migration notes for details: https://github.com/RaRe-Technol
ogies/smart_open/blob/master/README.rst#migrating-to-the-new-open-funct
ion
  'See the migration notes for details: %s' % _MIGRATION_NOTES_URL
```

Out[56]:
```
(400000, 300)
```

In [59]:
```
model = KeyedVectors.load_word2vec_format(word2vec_glove_file)
def analogy(x1, x2, y1):
        result = model.most_similar(positive=[y1, x2], negative=[x1])
        return result[0][0]
def display_pca_scatterplot(model, words=None, sample=0):
        if words == None:
                if sample > 0:
                        words = np.random.choice(list(model.vocab.keys
()), sample)
                else:
                        words = [ word for word in model.vocab ]
        word_vectors = np.array([model[w] for w in words])
        twodim = PCA().fit_transform(word_vectors)[:,:2]
        plt.figure(figsize=(6,6))
        plt.scatter(twodim[:,0], twodim[:,1], edgecolors='k', c='r')
        for word, (x,y) in zip(words, twodim):
                plt.text(x+0.05, y+0.05, word)
```

```
/anaconda3/lib/python3.7/site-packages/smart_open/smart_open_lib.py:39
8: UserWarning: This function is deprecated, use smart_open.open instea
d. See the migration notes for details: https://github.com/RaRe-Technol
ogies/smart_open/blob/master/README.rst#migrating-to-the-new-open-funct
ion
  'See the migration notes for details: %s' % _MIGRATION_NOTES_URL
```

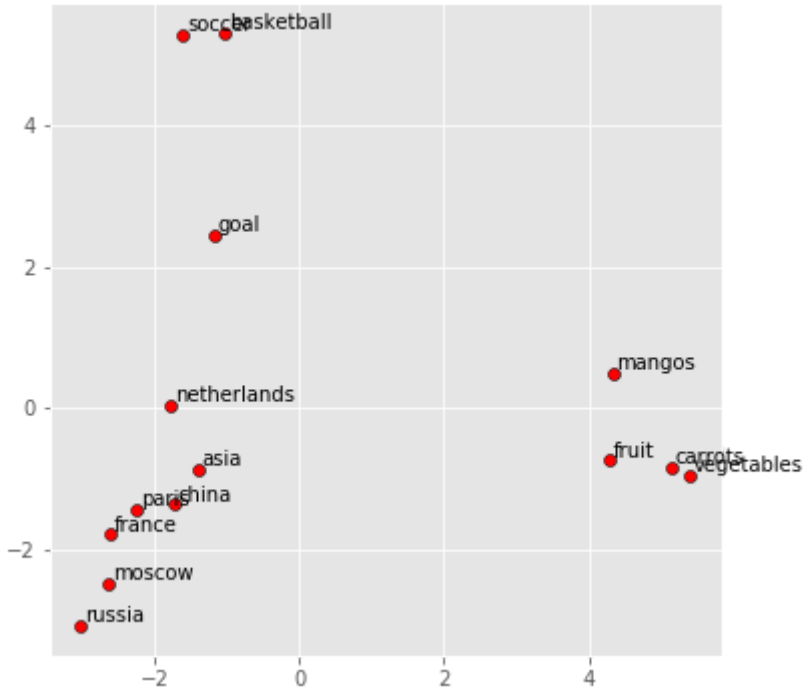
In [110]:
```
analogy('france','paris','russia')
analogy('mangos','fruit','carrots')
analogy('soccer','goal','basketball')
analogy('china','asia','netherlands')

# Plot
display_pca_scatterplot(model,['france','paris','russia','moscow','mangos','fruit','carrots','vegetables','soccer','goal','basketball'
                               ,'china','asia','netherlands'])
```

Out[110]: 'moscow'

Out[110]: 'vegetables'

Out[110]: 'goals'

Out[110]: 'europe'



We see that with '300 dimensional', the spatial difference between like terms grows larger.

Problem 3

Using T-SNE

In [111]:
```
## Problem 4
### Using Scikit-Learn TSNE

from sklearn.manifold import TSNE
import matplotlib.pyplot as plt

tsne = TSNE(
    perplexity = 30, n_components=2, init='pca', n_iter=5000, method =
'exact')
plot_only = 500
low_dim_embs = tsne.fit_transform(final_embeddings[:plot_only, :])
labels = [reverse_dictionary[i] for i in xrange(plot_only)]
plot_with_labels(low_dim_embs, labels, os.path.join(gettempdir(), 'tsne.
png'))
```

```
---------------------------------------------------------------------------
----
NameError                                 Traceback (most recent call l
ast)
<ipython-input-111-8d029ecedf1f> in <module>()
      8     perplexity = 30, n_components=2, init='pca', n_iter=5000, m
ethod = 'exact')
      9 plot_only = 500
---> 10 low_dim_embs = tsne.fit_transform(final_embeddings[:plot_only,
:])
     11 labels = [reverse_dictionary[i] for i in xrange(plot_only)]
     12 plot_with_labels(low_dim_embs, labels, os.path.join(gettempdir(
), 'tsne.png'))

NameError: name 'final_embeddings' is not defined
```

Unsure how to go about this error. Also ran out of time b/c attending work conference :(

Problem 4

In [81]:
```
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import mnist
import numpy as np

encoding_dim = 64
input_img = Input(shape=(784,))
encoded = Dense(encoding_dim, activation = 'relu')(input_img)
decoded = Dense(784, activation = 'sigmoid')(encoded)
autoencoder = Model(input_img, decoded)

encoder = Model(input_img, encoded)

encoded_input = Input(shape=(encoding_dim,))
decoder_layer = autoencoder.layers[-1]
decoder = Model(encoded_input, decoder_layer(encoded_input))

autoencoder.compile(optimizer='adadelta',loss = 'binary_crossentropy')
```

In [82]:
```
# Only x data, as no labels are being included
(x_train,_), (x_test,_) = mnist.load_data()
x_train = x_train.astype('float64') / 255
x_train = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
```

In [115]:
```
print(x_train.shape)
history = autoencoder.fit(x_train, x_train, epochs=3, shuffle = True, ba
tch_size = 256
                          , validation_data=(x_test,x_test))

# Only doing 3 epochs b/c running locally
```

```
(60000, 28, 28, 1)
Train on 60000 samples, validate on 10000 samples
Epoch 1/3
60000/60000 [==============================] - 58s 961us/step - loss:
0.0857 - val_loss: 0.0845
Epoch 2/3
60000/60000 [==============================] - 55s 909us/step - loss:
0.0833 - val_loss: 0.0801
Epoch 3/3
60000/60000 [==============================] - 55s 912us/step - loss:
0.0814 - val_loss: 0.0816
```

In [93]:
```
# Plot Loss Function

history_dict = history.history
history_dict.keys()



import matplotlib.pyplot as plt
%matplotlib inline
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(loss) + 1)
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

Out[93]: dict_keys(['val_loss', 'loss'])

Out[93]: [<matplotlib.lines.Line2D at 0x1a2cbfc908>]

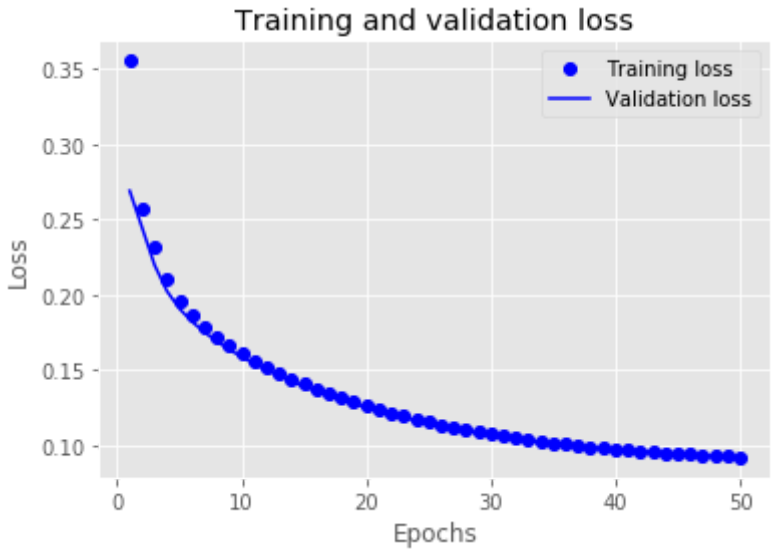
Out[93]: [<matplotlib.lines.Line2D at 0x1a15d5a3c8>]

Out[93]: Text(0.5,1,'Training and validation loss')

Out[93]: Text(0.5,0,'Epochs')

Out[93]: Text(0,0.5,'Loss')

Out[93]: <matplotlib.legend.Legend at 0x1a2cbfcda0>



Problem 5

In [105]:
```
# Getting data
from keras.datasets import mnist
import numpy as np
(x_train, _), (x_test, _) = mnist.load_data()
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
x_train = np.reshape(x_train, (len(x_train), 28, 28, 1))
# adapt this if using `channels_first` image data format
x_test = np.reshape(x_test, (len(x_test), 28, 28, 1))
# adapt this if using `channels_first` image data format
noise_factor = 0.5
x_train_noisy = x_train + noise_factor * np.random.normal(loc=0.0,
scale=1.0, size=x_train.shape)
x_test_noisy = x_test + noise_factor * np.random.normal(loc=0.0,
scale=1.0, size=x_test.shape)
x_train_noisy = np.clip(x_train_noisy, 0., 1.)
x_test_noisy = np.clip(x_test_noisy, 0., 1.)

# Seeing noisy digits
import matplotlib.pyplot as plt
%matplotlib inline
n = 10
plt.figure(figsize=(20, 2))
for i in range(1,n,1):
    ax = plt.subplot(1, n, i)
    plt.imshow(x_test_noisy[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()
```

Out[105]:
```
<Figure size 1440x144 with 0 Axes>
```

Out[105]:
```
<matplotlib.image.AxesImage at 0x1a1f77acf8>
```

Out[105]:
```
<matplotlib.image.AxesImage at 0x1a1f802b00>
```

Out[105]:
```
<matplotlib.image.AxesImage at 0x1a1f7d3940>
```

Out[105]:
```
<matplotlib.image.AxesImage at 0x1a1f863f60>
```

Out[105]:
```
<matplotlib.image.AxesImage at 0x1a1facbd30>
```

Out[105]:
```
<matplotlib.image.AxesImage at 0x1a1fa96b38>
```

Out[105]:
```
<matplotlib.image.AxesImage at 0x1a1fb84160>
```

Out[105]:
```
<matplotlib.image.AxesImage at 0x1a2cba3748>
```

Out[105]:
```
<matplotlib.image.AxesImage at 0x1a20025898>
```

In [99]:
```
# Using 32:
from keras.layers import Input, Dense, Conv2D, MaxPooling2D, UpSampling2
D
from keras.models import Model
from keras import backend as K
input_img = Input(shape=(28, 28, 1))
x = Conv2D(32, (3, 3), activation='relu', padding='same')(input_img)
x = MaxPooling2D((2, 2), padding='same')(x)
x = Conv2D(32, (3, 3), activation='relu', padding='same')(x)
encoded = MaxPooling2D((2, 2), padding='same')(x)
# at this point the representation is (7, 7, 32)
x = Conv2D(32, (3, 3), activation='relu', padding='same')(encoded)
x = UpSampling2D((2, 2))(x)
x = Conv2D(32, (3, 3), activation='relu', padding='same')(x)
x = UpSampling2D((2, 2))(x)
decoded = Conv2D(1, (3, 3), activation='sigmoid', padding='same')(x)
autoencoder = Model(input_img, decoded)
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')
```

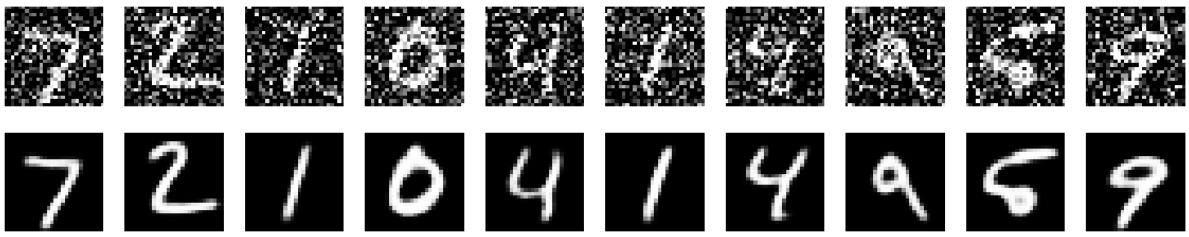
In [107]:
```
# Model train
autoencoder.fit(x_train_noisy, x_train,
    epochs=3, # Setting epochs low b/c running this locally
    batch_size=128,
    shuffle=True,
    validation_data=([x_test_noisy, x_test]))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/3
60000/60000 [==============================] - 103s 2ms/step - loss: 0.
1110 - val_loss: 0.1062
Epoch 2/3
60000/60000 [==============================] - 101s 2ms/step - loss: 0.
1075 - val_loss: 0.1057
Epoch 3/3
60000/60000 [==============================] - 98s 2ms/step - loss: 0.1
052 - val_loss: 0.1037
```

Out[107]:
```
<keras.callbacks.History at 0x1a28042c88>
```

In [108]:
```
# Seeing Results of '32'
decoded_imgs = autoencoder.predict(x_test)
import matplotlib.pyplot as plt
%matplotlib inline
n = 10 # how many digits we will display
plt.figure(figsize=(20, 4))
for i in range(n):
    # display original noisy images
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test_noisy[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()
```

```
Out[108]: <Figure size 1440x288 with 0 Axes>

Out[108]: <matplotlib.image.AxesImage at 0x1a286dc780>

Out[108]: <matplotlib.image.AxesImage at 0x1a288176d8>

Out[108]: <matplotlib.image.AxesImage at 0x1a288073c8>

Out[108]: <matplotlib.image.AxesImage at 0x1a288759e8>

Out[108]: <matplotlib.image.AxesImage at 0x1a15e1ef98>

Out[108]: <matplotlib.image.AxesImage at 0x312ab85c0>

Out[108]: <matplotlib.image.AxesImage at 0x312ae1ba8>

Out[108]: <matplotlib.image.AxesImage at 0x1a15fb41d0>

Out[108]: <matplotlib.image.AxesImage at 0x1a15f397b8>

Out[108]: <matplotlib.image.AxesImage at 0x1a15f67da0>

Out[108]: <matplotlib.image.AxesImage at 0x1a15dd03c8>

Out[108]: <matplotlib.image.AxesImage at 0x312bc89b0>

Out[108]: <matplotlib.image.AxesImage at 0x312bf2f98>

Out[108]: <matplotlib.image.AxesImage at 0x1a15e9e5c0>

Out[108]: <matplotlib.image.AxesImage at 0x1a16195ba8>

Out[108]: <matplotlib.image.AxesImage at 0x1a162ae1d0>

Out[108]: <matplotlib.image.AxesImage at 0x1a162da7b8>

Out[108]: <matplotlib.image.AxesImage at 0x1a16302da0>

Out[108]: <matplotlib.image.AxesImage at 0x1a163353c8>

Out[108]: <matplotlib.image.AxesImage at 0x1a163619b0>
```



Building and training '16' model:

In [109]:
```
input_img = Input(shape=(28, 28, 1))
x = Conv2D(16, (3, 3), activation='relu', padding='same')(input_img)
x = MaxPooling2D((2, 2), padding='same')(x)
x = Conv2D(16, (3, 3), activation='relu', padding='same')(x)
encoded = MaxPooling2D((2, 2), padding='same')(x)
# at this point the representation is (7, 7, 32)
x = Conv2D(16, (3, 3), activation='relu', padding='same')(encoded)
x = UpSampling2D((2, 2))(x)
x = Conv2D(16, (3, 3), activation='relu', padding='same')(x)
x = UpSampling2D((2, 2))(x)
decoded = Conv2D(1, (3, 3), activation='sigmoid', padding='same')(x)
autoencoder = Model(input_img, decoded)
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')

# Model train
autoencoder.fit(x_train_noisy, x_train,
    epochs=3, # Setting epochs low b/c running this locally
    batch_size=128,
    shuffle=True,
    validation_data=([x_test_noisy, x_test]))

# Seeing Results of '16'
decoded_imgs = autoencoder.predict(x_test)
import matplotlib.pyplot as plt
%matplotlib inline
n = 10 # how many digits we will display
plt.figure(figsize=(20, 4))
for i in range(n):
    # display original noisy images
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test_noisy[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()
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/3
60000/60000 [==============================] - 56s 940us/step - loss:
0.1887 - val_loss: 0.1307
Epoch 2/3
60000/60000 [==============================] - 56s 940us/step - loss:
0.1270 - val_loss: 0.1197
Epoch 3/3
60000/60000 [==============================] - 56s 935us/step - loss:
0.1186 - val_loss: 0.1173
```

Out[109]: <keras.callbacks.History at 0x1a16957518>

Out[109]: <Figure size 1440x288 with 0 Axes>

Out[109]: <matplotlib.image.AxesImage at 0x1a2fa03748>

Out[109]: <matplotlib.image.AxesImage at 0x1a2fa18d68>

Out[109]: <matplotlib.image.AxesImage at 0x1a2fa36390>

Out[109]: <matplotlib.image.AxesImage at 0x1a166f39b0>

Out[109]: <matplotlib.image.AxesImage at 0x1a1670af60>

Out[109]: <matplotlib.image.AxesImage at 0x1a167a9588>

Out[109]: <matplotlib.image.AxesImage at 0x1a167c6b70>

Out[109]: <matplotlib.image.AxesImage at 0x1a1674c198>

Out[109]: <matplotlib.image.AxesImage at 0x1a1676e780>

Out[109]: <matplotlib.image.AxesImage at 0x1a16c1dd68>

Out[109]: <matplotlib.image.AxesImage at 0x1a16c46390>

Out[109]: <matplotlib.image.AxesImage at 0x1a161db978>

Out[109]: <matplotlib.image.AxesImage at 0x1a16200f60>

Out[109]: <matplotlib.image.AxesImage at 0x1a16263588>

Out[109]: <matplotlib.image.AxesImage at 0x1a16690b70>

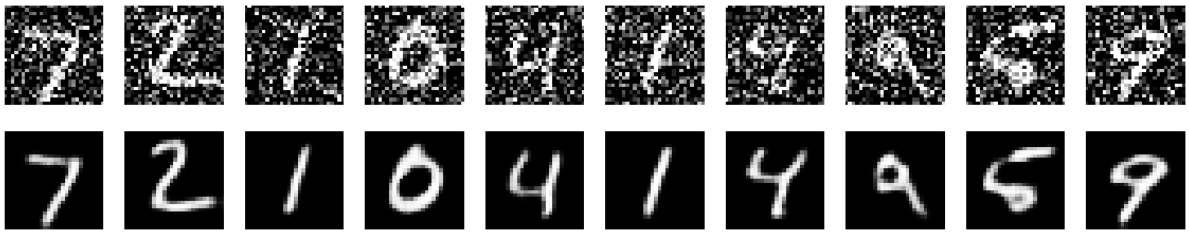
Out[109]: <matplotlib.image.AxesImage at 0x1a16b8b198>

Out[109]: <matplotlib.image.AxesImage at 0x1a16bb4780>

Out[109]: <matplotlib.image.AxesImage at 0x1a16bdfd68>

Out[109]: <matplotlib.image.AxesImage at 0x1a16c7f390>

Out[109]: <matplotlib.image.AxesImage at 0x1a16caa978>



The results are noticeably less clear with '16' channels vs '36'