

CI P4 – Neural Networks

March 31, 2017

1 Neural networks in Python using Scikit Learn

- We will be using an implementation of Multilayer Perceptron back-ported from the next version of scikit-learn
- Documentation: http://scikit-learn.org/dev/modules/neural_networks_supervised.html
- This implementation consists of two classes:
- `MLPRegressor` for regression
- `MLPClassifier` for classification

```
In [1]: from sklearn.neural_network import MLPRegressor, MLPClassifier
```

1.1 Regression with neural networks

```
In [2]: # In the assignment, the data loading function is provided
# Here, we use the example dataset that comes with scikit learn
from sklearn.datasets import load_boston
boston = load_boston()
print(boston.data.shape)
print(boston.target.shape)
```

```
(506, 13)
```

```
(506,)
```

```
In [3]: print(boston.DESCR)
```

```
Boston House Prices dataset
=====
```

```
Notes
```

```
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```

```
Data Set Characteristics:
```

```
:Number of Instances: 506
```

```
:Number of Attributes: 13 numeric/categorical predictive
```

```
:Median Value (attribute 14) is usually the target
```

:Attribute Information (in order):

- CRIM per capita crime rate by town
- ZN proportion of residential land zoned for lots over 25,000 sq.ft.
- INDUS proportion of non-retail business acres per town
- CHAS Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
- NOX nitric oxides concentration (parts per 10 million)
- RM average number of rooms per dwelling
- AGE proportion of owner-occupied units built prior to 1940
- DIS weighted distances to five Boston employment centres
- RAD index of accessibility to radial highways
- TAX full-value property-tax rate per \$10,000
- PTRATIO pupil-teacher ratio by town
- B $1000(B_k - 0.63)^2$ where B_k is the proportion of blacks by town
- LSTAT % lower status of the population
- MEDV Median value of owner-occupied homes in \$1000's

:Missing Attribute Values: None

:Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.

<http://archive.ics.uci.edu/ml/datasets/Housing>

This dataset was taken from the StatLib library which is maintained at Carnegie Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic prices and the demand for clean air', J. Environ. Economics & Management, vol.5, 81-102, 1978. Used in Belsley, Kuh & Welsch, 'Regression diagnostics ...', Wiley, 1980. N.B. Various transformations are used in the table on pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers that address regression analysis problems.

****References****

- Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Outliers', Wiley, 1980
- Quinlan, R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings of the AAAI Conference on Artificial Intelligence, pp. 326-337.
- many more! (see <http://archive.ics.uci.edu/ml/datasets/Housing>)

```
In [4]: %matplotlib inline
```

```
import matplotlib.pyplot as plt
```

```
#Feature order: 'CRIM ZN INDUS CHAS NOX RM AGE DIS RAD TAX PTRATIO B LSTAT MEDV'
```

```

plt.figure(figsize=(20,10))

nox_concentrations = boston.data[:, 4]
house_prices = boston.target

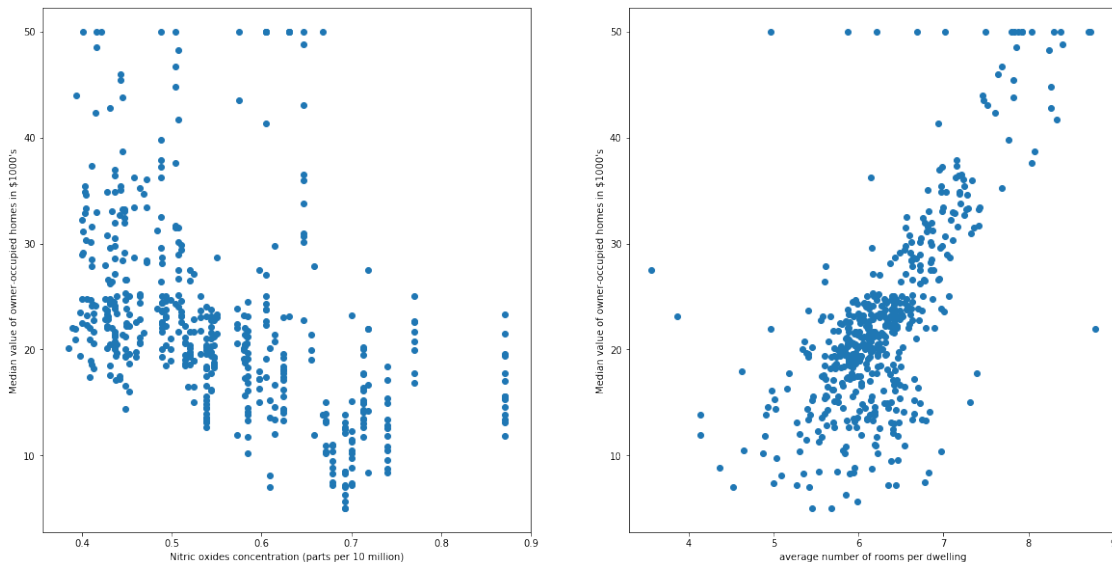
ax = plt.subplot(121)
ax.scatter(nox_concentrations, house_prices)
ax.set_xlabel("Nitric oxides concentration (parts per 10 million)")
ax.set_ylabel("Median value of owner-occupied homes in $1000's")

rooms_per_dwelling = boston.data[:, 5]
house_prices = boston.target

ax = plt.subplot(122)
ax.scatter(rooms_per_dwelling, house_prices)
ax.set_xlabel("average number of rooms per dwelling")
ax.set_ylabel("Median value of owner-occupied homes in $1000's")

```

Out [4]: <matplotlib.text.Text at 0x7fb4bcde7668>



```

In [5]: # In the assignment, the data is already split up
from sklearn.model_selection import train_test_split
import numpy as np

X = np.array([rooms_per_dwelling, nox_concentrations]).T
y = house_prices
print("Dataset shape (X, y)      :", X.shape, y.shape)
## Split the data into a testing and training set (20% of the data for test

```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ra
print("Training set shape (X, y):", X_train.shape, y_train.shape)
```

```
Dataset shape (X, y)      : (506, 2) (506,)
Training set shape (X, y): (404, 2) (404,)
```

```
In [6]: ## Initialize the neural network
n_hidden_neurons = 20
nn = MLPRegressor(activation='logistic', solver='lbfgs', hidden_layer_sizes=
nn # Important parameters -- activation, algorithm, alpha, hidden_layer_s
```

```
Out[6]: MLPRegressor(activation='logistic', alpha=0.0001, batch_size='auto',
beta_1=0.9, beta_2=0.999, early_stopping=False, epsilon=1e-08,
hidden_layer_sizes=(20,), learning_rate='constant',
learning_rate_init=0.001, max_iter=200, momentum=0.9,
nesterovs_momentum=True, power_t=0.5, random_state=None,
shuffle=True, solver='lbfgs', tol=0.0001, validation_fraction=0.1,
verbose=False, warm_start=False)
```

```
In [7]: ## Train the network
nn.fit(X_train, y_train)
```

```
Out[7]: MLPRegressor(activation='logistic', alpha=0.0001, batch_size='auto',
beta_1=0.9, beta_2=0.999, early_stopping=False, epsilon=1e-08,
hidden_layer_sizes=(20,), learning_rate='constant',
learning_rate_init=0.001, max_iter=200, momentum=0.9,
nesterovs_momentum=True, power_t=0.5, random_state=None,
shuffle=True, solver='lbfgs', tol=0.0001, validation_fraction=0.1,
verbose=False, warm_start=False)
```

```
In [8]: ## Calculate and print the MSE
from sklearn.metrics import mean_squared_error
train_mse = mean_squared_error(y_train, nn.predict(X_train))
test_mse = mean_squared_error(y_test, nn.predict(X_test))
print("Training MSE:", train_mse)
print("Testing MSE: ", test_mse)
```

```
Training MSE: 27.7628351225
Testing MSE: 22.2361742609
```

```
In [9]: ## Predict the house prices for the entire data set
predictions = nn.predict(X)
```

```
In [10]: ## Plot network predictions and actual values
plt.figure(figsize=(20,10))

house_prices_prediction = predictions
```

```

house_prices_actual = boston.target

nox_concentrations = boston.data[:, 4]

ax = plt.subplot(121)
ax.scatter(nox_concentrations, house_prices_prediction, color='r', label='prediction')
ax.scatter(nox_concentrations, house_prices_actual, label='actual')
ax.set_xlabel("Nitric oxides concentration (parts per 10 million)")
ax.set_ylabel("Median value of owner-occupied homes in $1000's")
plt.legend()

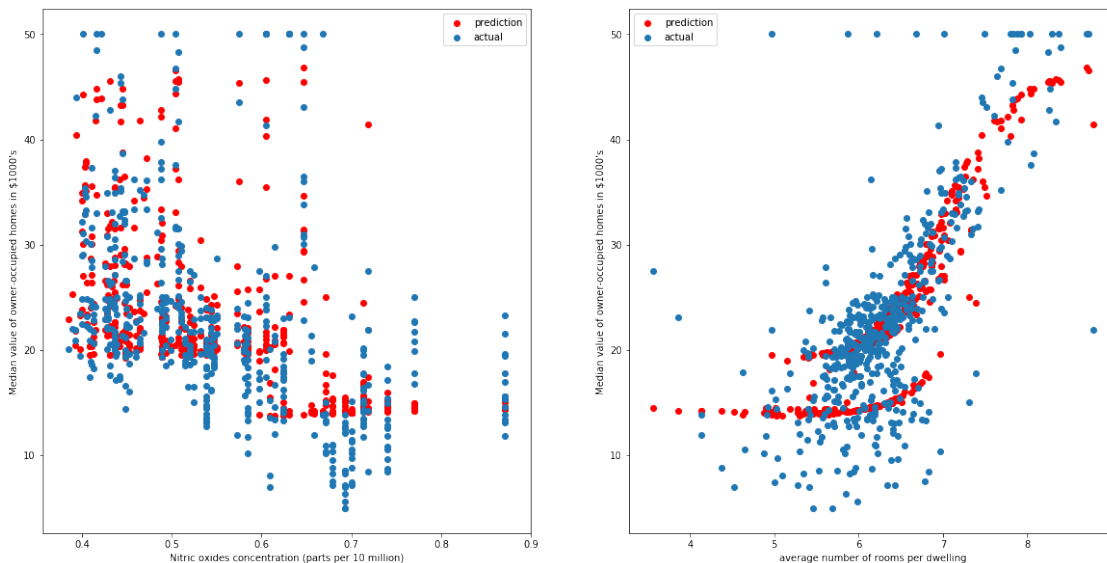
rooms_per_dwelling = boston.data[:, 5]

ax = plt.subplot(122)
ax.scatter(rooms_per_dwelling, house_prices_prediction, color='r', label='prediction')
ax.scatter(rooms_per_dwelling, house_prices_actual, label='actual')

ax.set_xlabel("average number of rooms per dwelling")
ax.set_ylabel("Median value of owner-occupied homes in $1000's")
plt.legend()

```

Out[10]: <matplotlib.legend.Legend at 0x7fb4acf683c8>



1.1.1 Experiment with parameters

```

In [11]: ## Initialize the neural network
n_hidden_neurons = 20
nn = MLPRegressor(activation='logistic', solver='lbfgs',
                  hidden_layer_sizes=(n_hidden_neurons,), random_state=1)

```

```

## Train the network
nn.fit(X_train, y_train)

## Calculate and print the MSE
from sklearn.metrics import mean_squared_error
train_mse = mean_squared_error(y_train, nn.predict(X_train))
test_mse = mean_squared_error(y_test, nn.predict(X_test))
print("Training MSE:", train_mse)
print("Testing MSE: ", test_mse)

## Predict the house prices for the entire data set
predictions = nn.predict(X)

## Plot network predictions and actual values
plt.figure(figsize=(20,10))

house_prices_prediction = predictions
house_prices_actual = boston.target

nox_concentrations = boston.data[:, 4]

ax = plt.subplot(121)
ax.scatter(nox_concentrations, house_prices_prediction, color='r', label='prediction')
ax.scatter(nox_concentrations, house_prices_actual, label='actual')
ax.set_xlabel("Nitric oxides concentration (parts per 10 million)")
ax.set_ylabel("Median value of owner-occupied homes in $1000's")
plt.legend()

rooms_per_dwelling = boston.data[:, 5]

ax = plt.subplot(122)
ax.scatter(rooms_per_dwelling, house_prices_prediction, color='r', label='prediction')
ax.scatter(rooms_per_dwelling, house_prices_actual, label='actual')

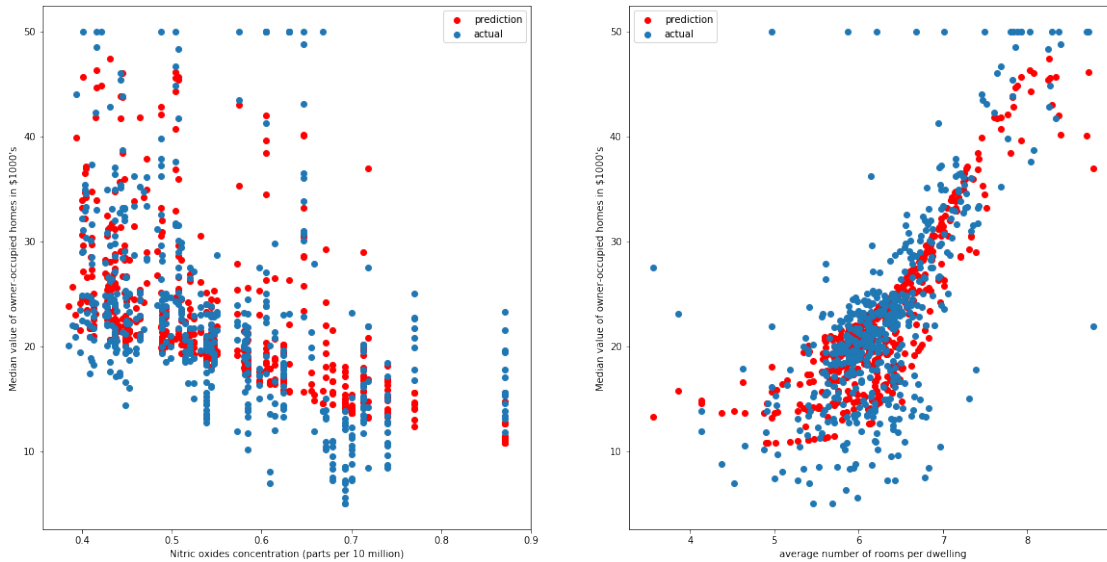
ax.set_xlabel("average number of rooms per dwelling")
ax.set_ylabel("Median value of owner-occupied homes in $1000's")
plt.legend()

```

Training MSE: 29.8548485819

Testing MSE: 26.4834499233

Out[11]: <matplotlib.legend.Legend at 0x7fb4acf41b38>



1.2 Warm start

```
In [12]: from IPython import display
         from sklearn.metrics import mean_squared_error, log_loss, accuracy_score

         ## Initialize the neural network
         n_hidden_neurons = 20
         max_iterations = 2000
         nn = MLPRegressor(activation='logistic', solver='lbfgs',
                           hidden_layer_sizes=(n_hidden_neurons,), random_state=0)

         fig = plt.figure(figsize=(20,10))
         for i in range(max_iterations):
             ## Train the network
             nn.fit(X_train, y_train)

             if i % 50 == 0 or i < 10:

                 ## Calculate and print the MSE

                 train_mse = mean_squared_error(y_train, nn.predict(X_train))
                 test_mse = mean_squared_error(y_test, nn.predict(X_test))
                 print("Iteration:", i)
                 print("Training MSE:", train_mse)
                 print("Testing MSE: ", test_mse)

                 ## Predict the house prices for the entire data set
```

```

predictions = nn.predict(X)

## Plot network predictions and actual values
display.clear_output(wait=True)

house_prices_prediction = predictions
house_prices_actual = boston.target

nox_concentrations = boston.data[:, 4]

ax = plt.subplot(121)
plt.gca().cla()
ax.scatter(nox_concentrations, house_prices_prediction, color='r',
ax.scatter(nox_concentrations, house_prices_actual, label='actual')
ax.set_xlabel("Nitric oxides concentration (parts per 10 million)")
ax.set_ylabel("Median value of owner-occupied homes in $1000's")

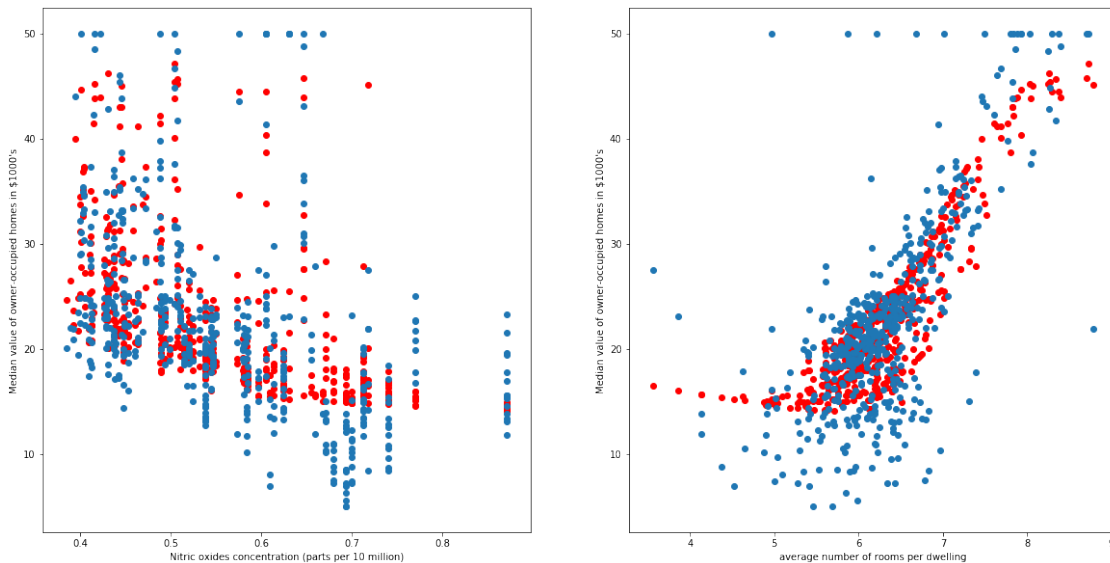
rooms_per_dwelling = boston.data[:, 5]

ax = plt.subplot(122)
plt.gca().cla()
ax.scatter(rooms_per_dwelling, house_prices_prediction, color='r',
ax.scatter(rooms_per_dwelling, house_prices_actual, label='actual')

ax.set_xlabel("average number of rooms per dwelling")
ax.set_ylabel("Median value of owner-occupied homes in $1000's")

display.display(plt.gcf())
display.clear_output(wait=True)

```



1.3 Classification with Neural Networks

```
In [13]: from sklearn.datasets import load_digits
         digits = load_digits()

         # from sklearn.datasets import fetch_mldata
         # digits = fetch_mldata('MNIST original')

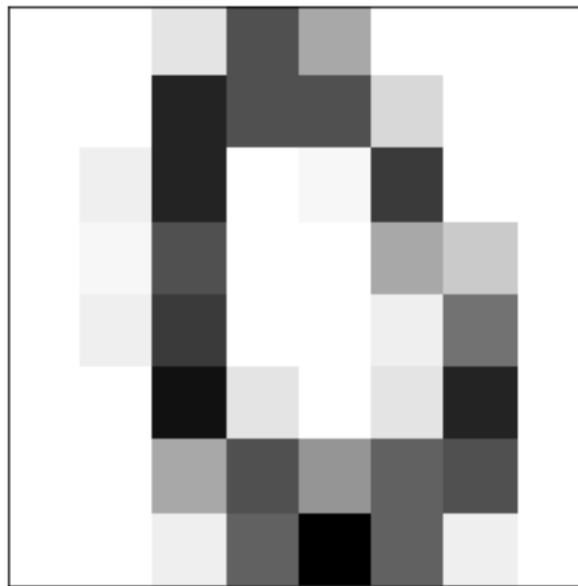
         print(digits.data.shape)
         digits.data[5].shape
```

(1797, 64)

Out[13]: (64,)

```
In [14]: ## Show a random digit
         IMAGE_DIM = (8, 8)
         plt.figure()
         plt.imshow(digits.data[np.random.randint(1797)].reshape(*IMAGE_DIM),
                    interpolation='nearest')
         plt.xticks([])
         plt.yticks([])
```

Out[14]: ([], <a list of 0 Text yticklabel objects>)



```
In [15]: from sklearn.model_selection import train_test_split
         import numpy as np
```

```

X = digits.data
y = digits.target
print("Dataset shape (X, y)      :", X.shape, y.shape)
## Split the data into a testing and training set (20% of the data for test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, r
print("Training set shape (X, y):", X_train.shape, y_train.shape)

```

```

Dataset shape (X, y)      : (1797, 64) (1797,)
Training set shape (X, y): (1437, 64) (1437,)

```

```

In [16]: ## Initialize the neural network
nn = MLPClassifier(activation='logistic', solver='adam', hidden_layer_sizes=

## Train the network
nn.fit(X_train, y_train)

## Calculate and print the MSE
from sklearn.metrics import mean_squared_error, accuracy_score
train_mse = mean_squared_error(y_train, nn.predict(X_train))
test_mse = mean_squared_error(y_test, nn.predict(X_test))
print("Training MSE:", train_mse)
print("Testing MSE: ", test_mse)

test_accuracy = accuracy_score(y_test, nn.predict(X_test))
print("Test accuracy: ", test_accuracy)

```

```

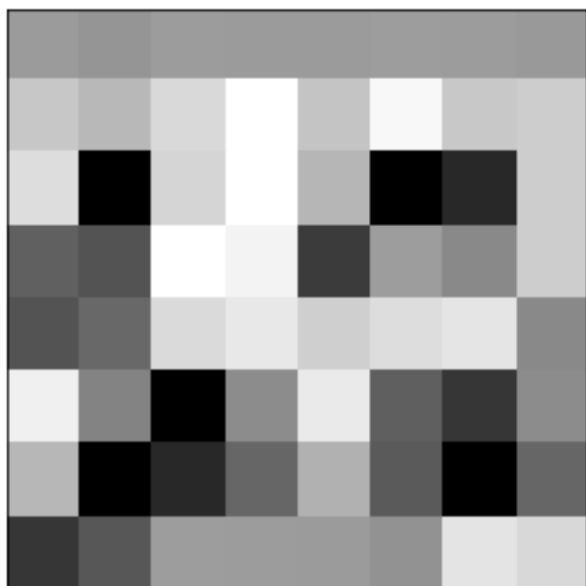
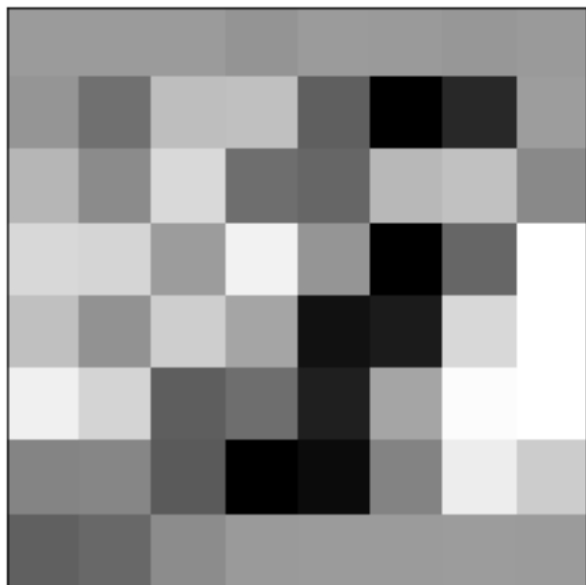
Training MSE: 0.310368823939
Testing MSE:  0.177777777778
Test accuracy: 0.980555555556

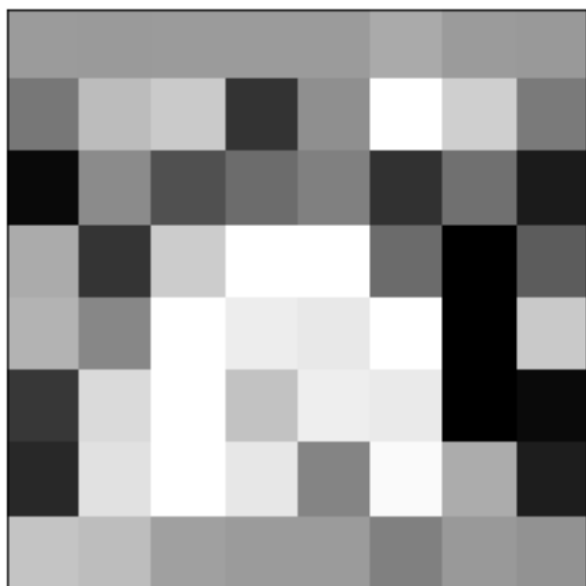
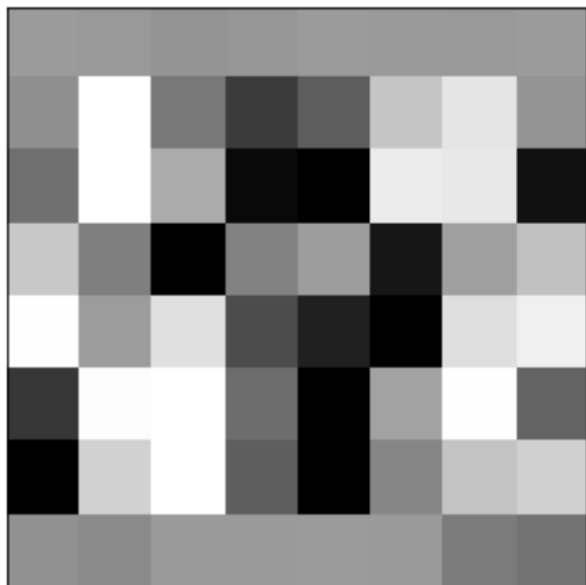
```

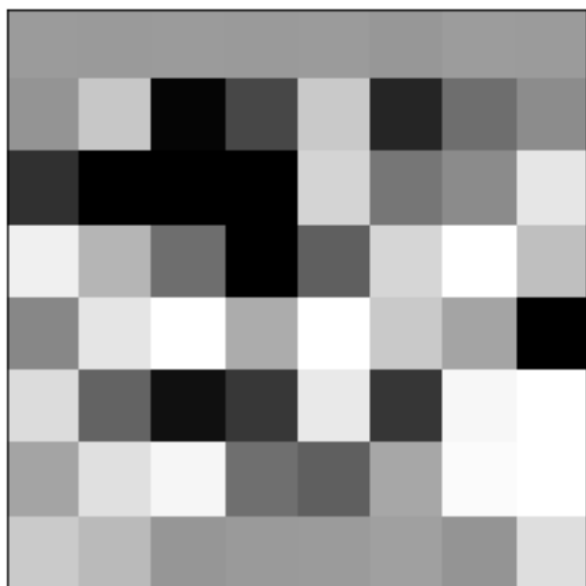
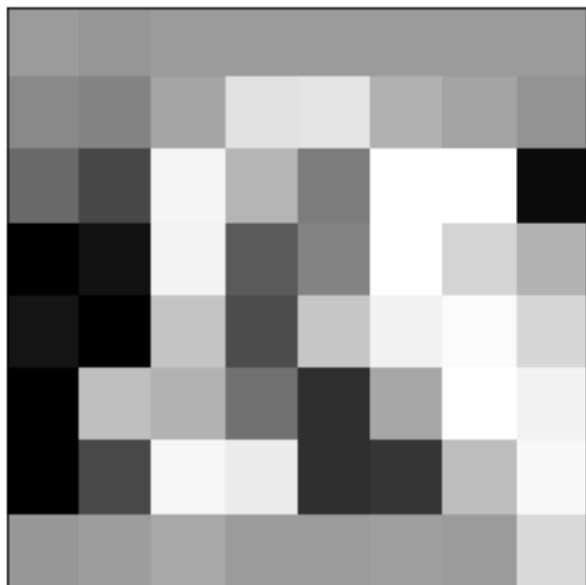
```

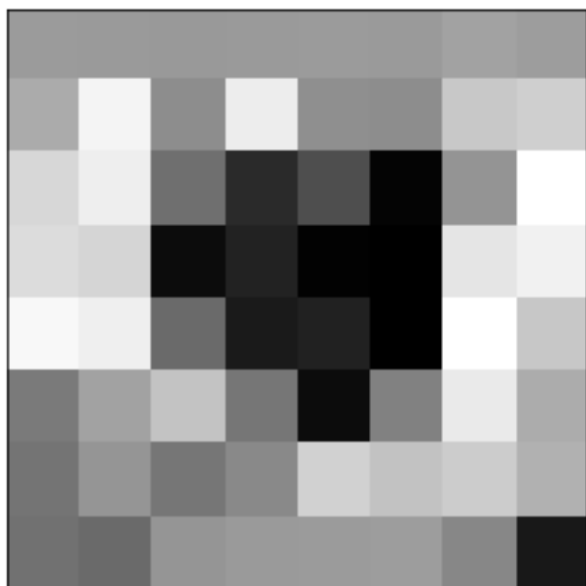
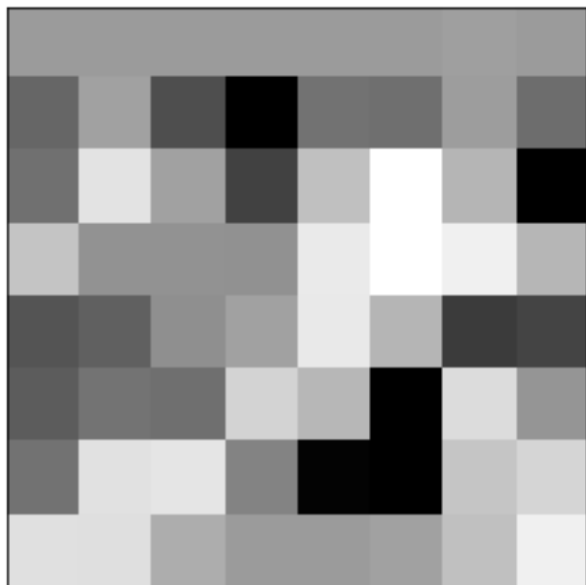
In [17]: hidden_layer_weights = nn.coefs_[0]
for hidden_neuron_num in range(hidden_layer_weights.shape[1])[:10]:
    plt.figure()
    vmin, vmax = hidden_layer_weights.min(), hidden_layer_weights.max()
    plt.imshow(hidden_layer_weights[:, hidden_neuron_num].reshape(*IM
                    vmin=.5 * vmin, vmax=.5 * vmax, interpolation='none')
    plt.xticks(())
    plt.yticks(())
plt.close()

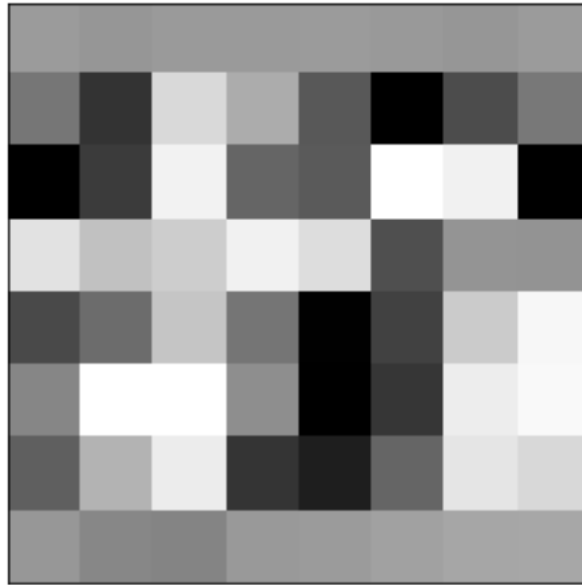
```











Experiment with values of α and $n_{\text{hidden_neurons}}$