hw7

May 7, 2015

1 Homework 7

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- Repro: Open up hw7.ipynb in IPython Notebook.

1.1 1. K-means Clustering

The final k-means loss does indeed vary across differ runs, depending on the random initialization

In [2]:
```
import numpy as np
import scipy.io
import math
import random
from sklearn import preprocessing
from __future__ import division
import matplotlib.pyplot as plt
%matplotlib inline

# Load the data
mat = scipy.io.loadmat('mnist_data/images.mat')
images = mat['images']
images = [images[:, :, i].astype(float) for i in range(60000)]
```

In [2]:
```
for k in [5, 10, 20]:
    # Randomly initialize centers
    # centers = [np.random.rand(28, 28) * 256 for _ in range(k)]
    centers = np.random.permutation(images)[0:k]

    prevCounts, counts = np.ones(k) * 100, np.zeros(k)
    while(True):
        # Cluster images to nearest centers
        clusters = [[] for _ in range(k)]
        for image in images:
            i = min(range(k), key=lambda i: np.linalg.norm(image - centers[i]))
            clusters[i].append(image)

        # Recompute means
        for i in range(k):
            if len(clusters[i]) > 0:
                centers[i] = sum(clusters[i]) / len(clusters[i])

        # Calculate loss
```

```
        J = sum(np.linalg.norm(image - centers[i])**2 for i in range(k) for image in clusters[i
        print(J)

        # Check for convergence
        counts = np.array([len(cluster) for cluster in clusters])
        print(counts)
        if np.linalg.norm(prevCounts - counts) < 100:
            break
        else:
            prevCounts = counts

    # Show the centers
    for i in range(k):
        plt.imshow(centers[i])
        plt.show()
```

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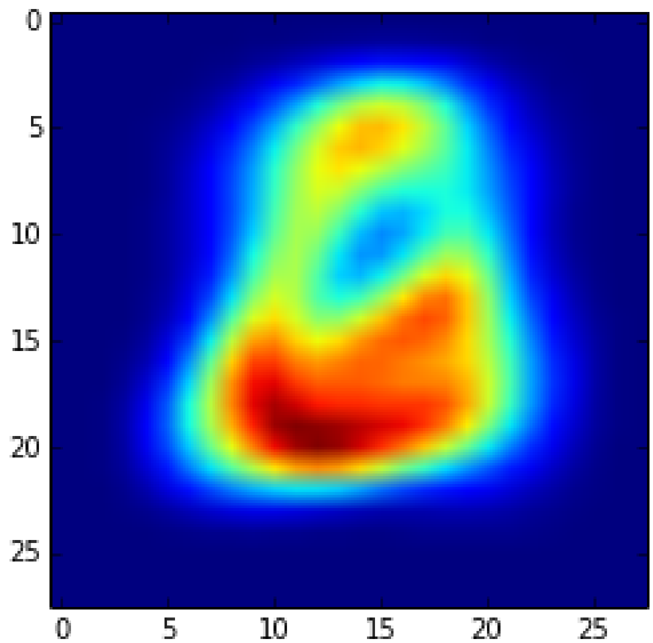
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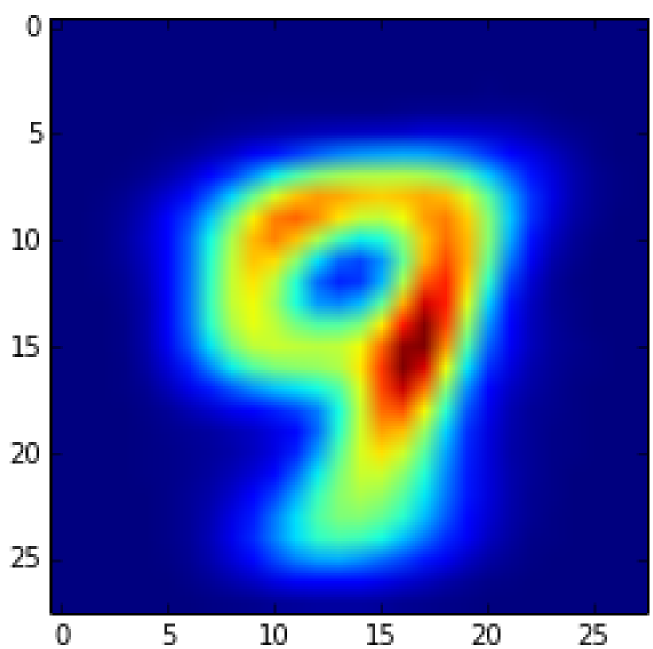
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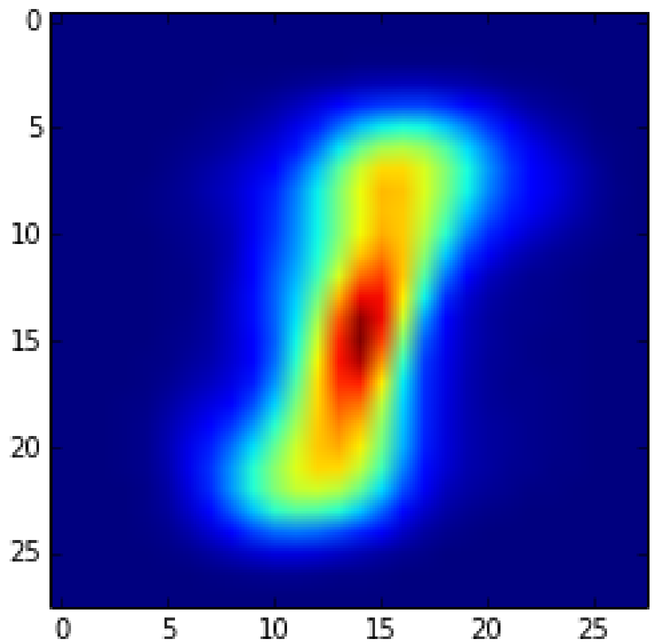
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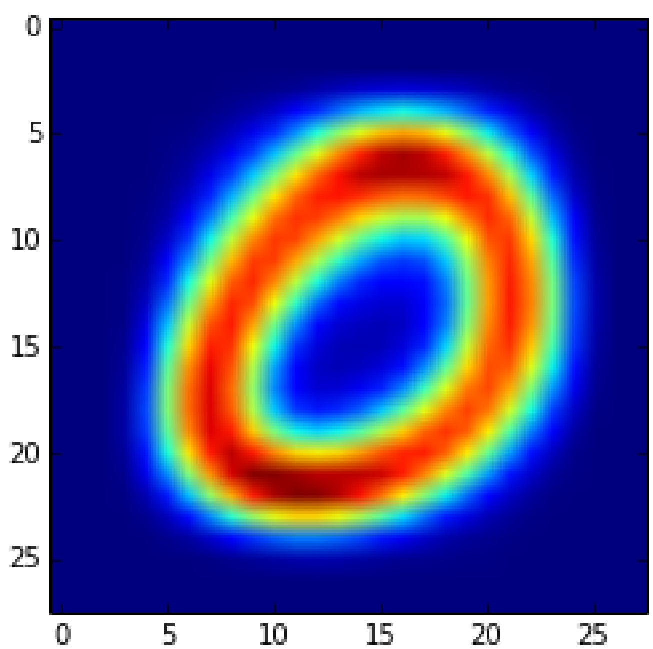
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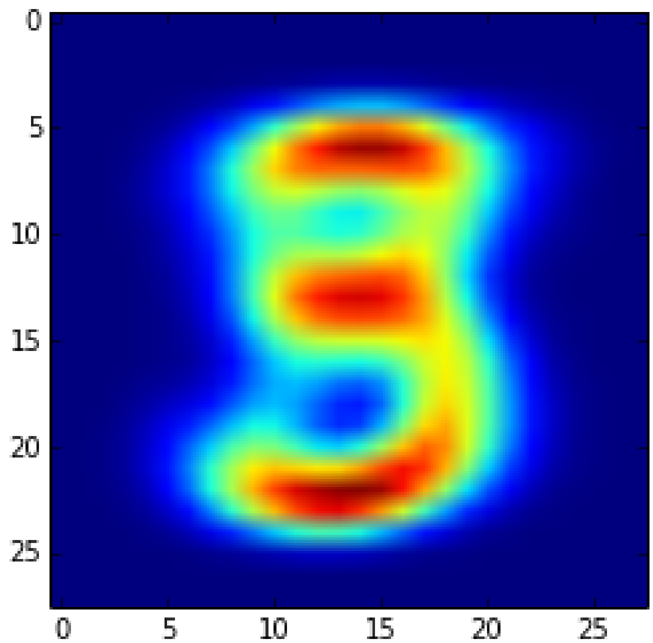


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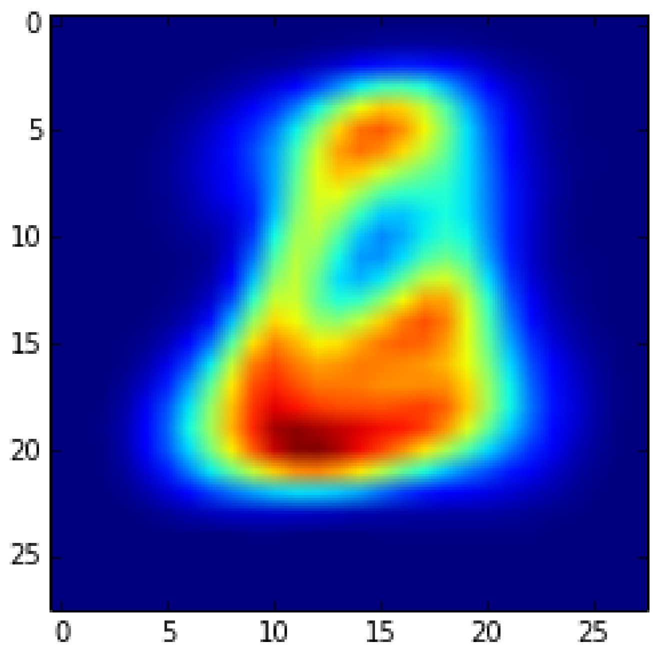

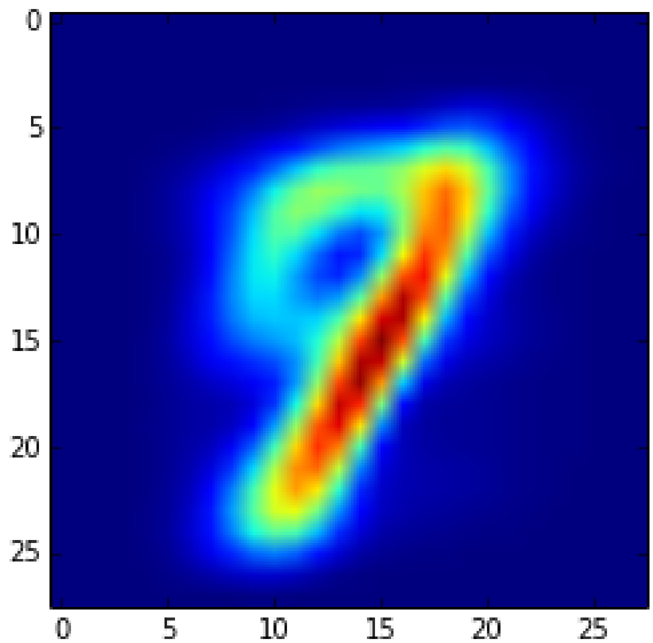
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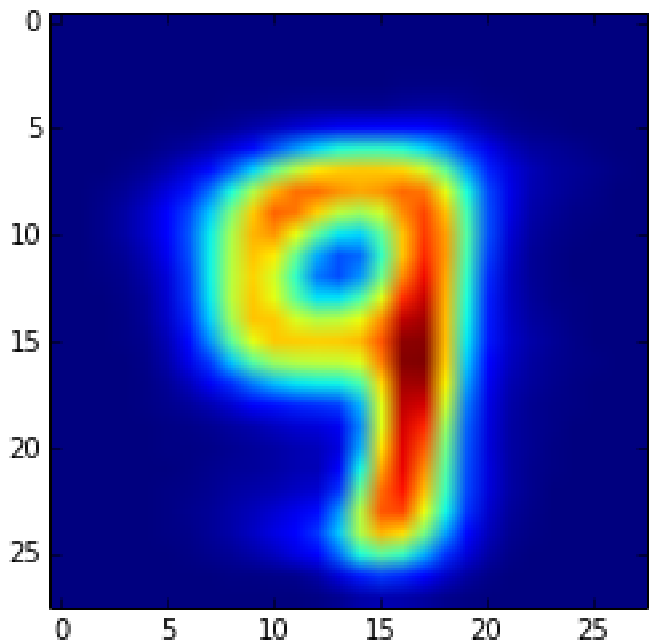
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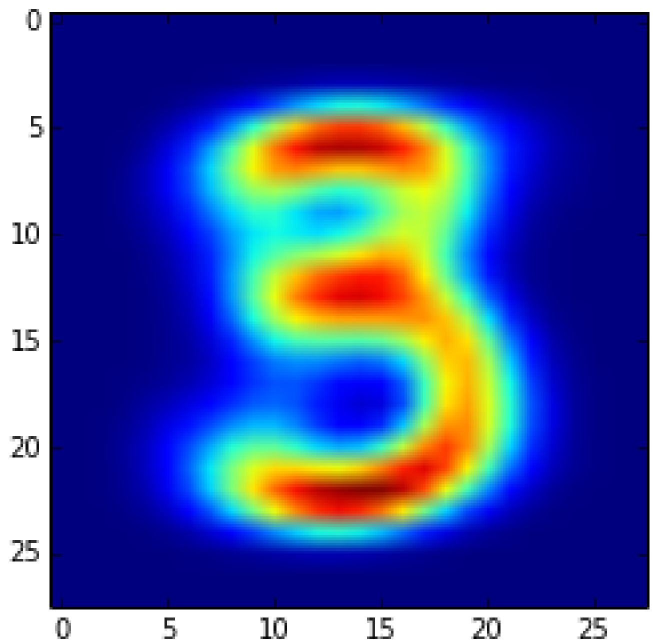
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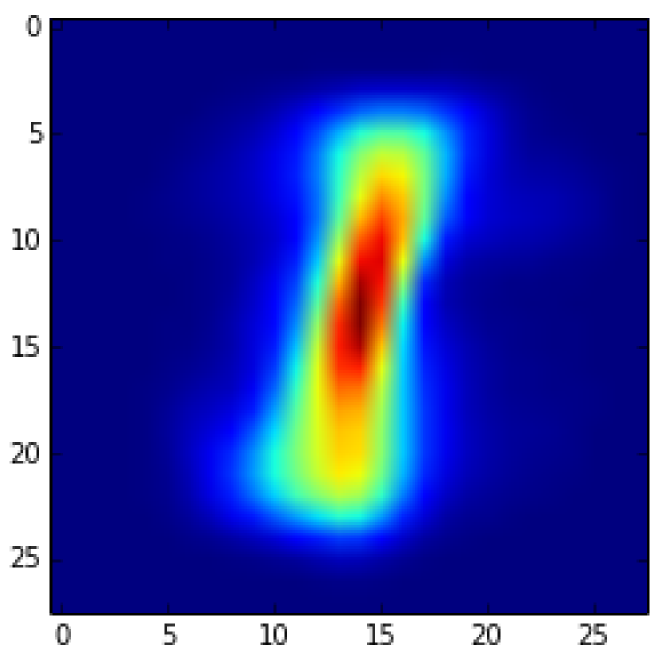
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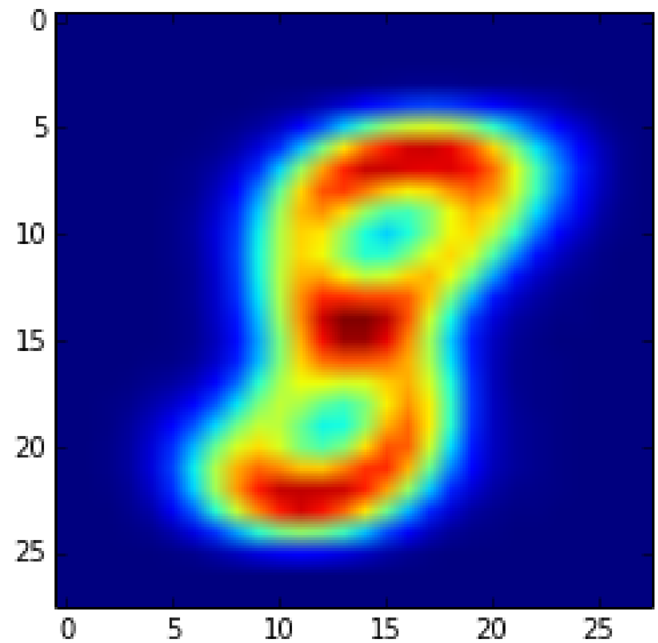
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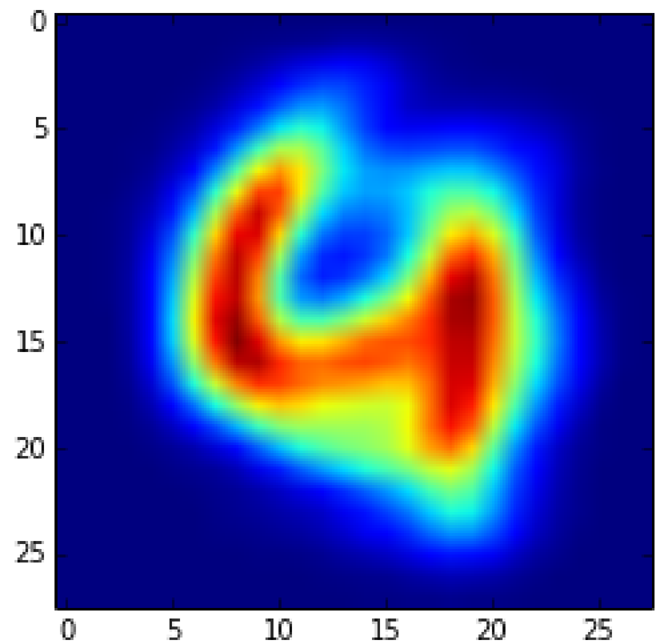
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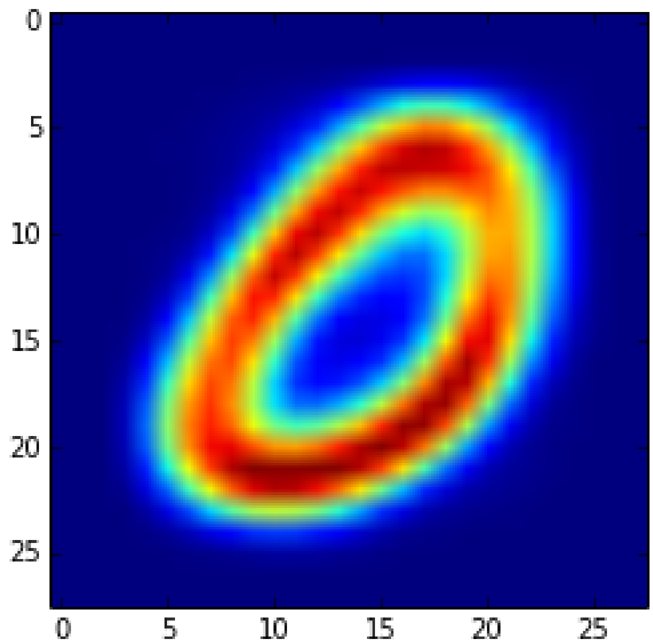
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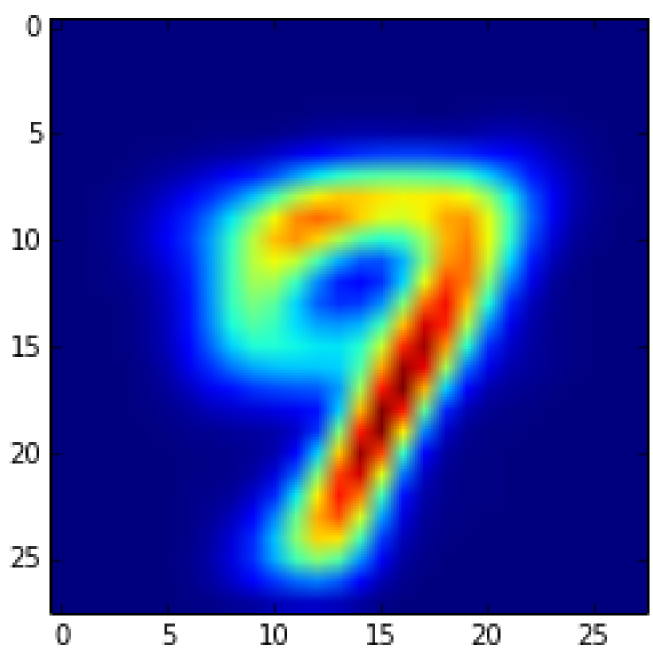
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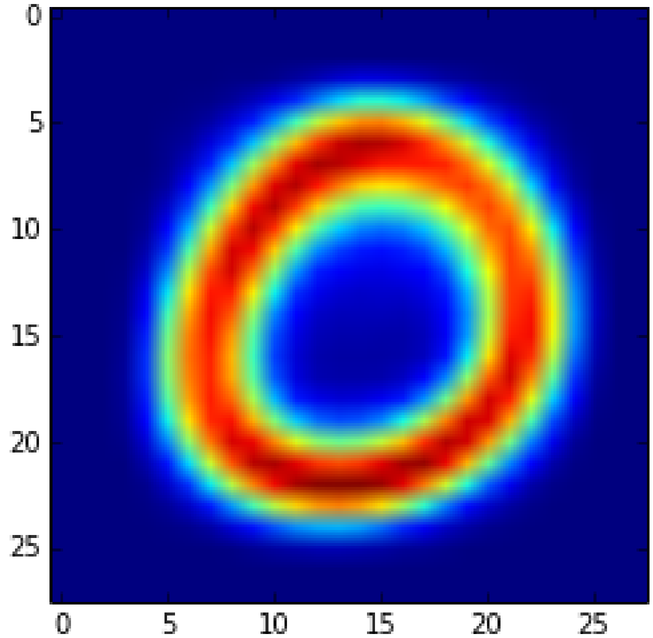


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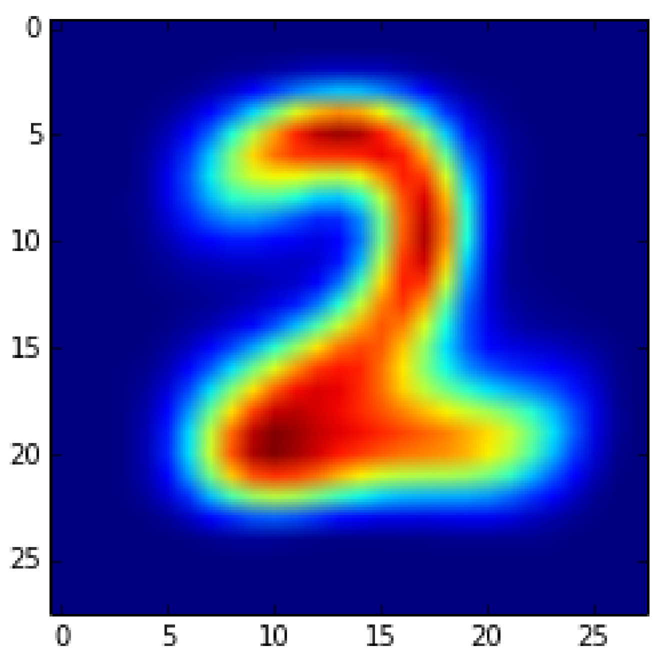

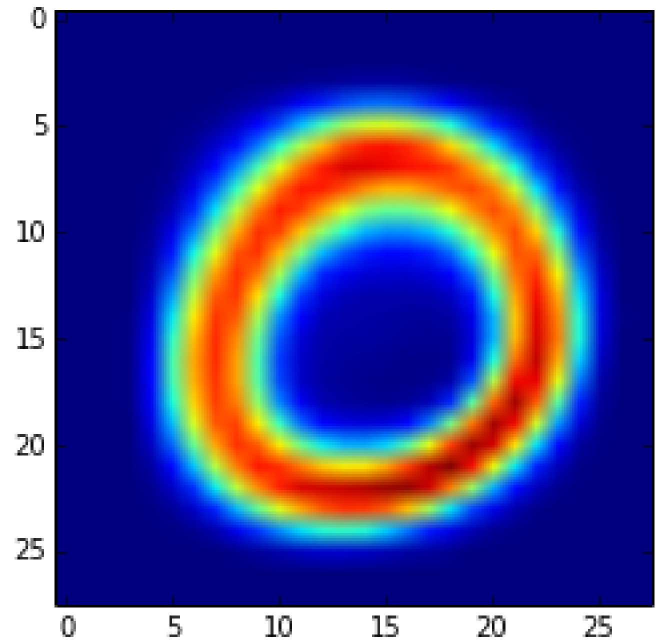
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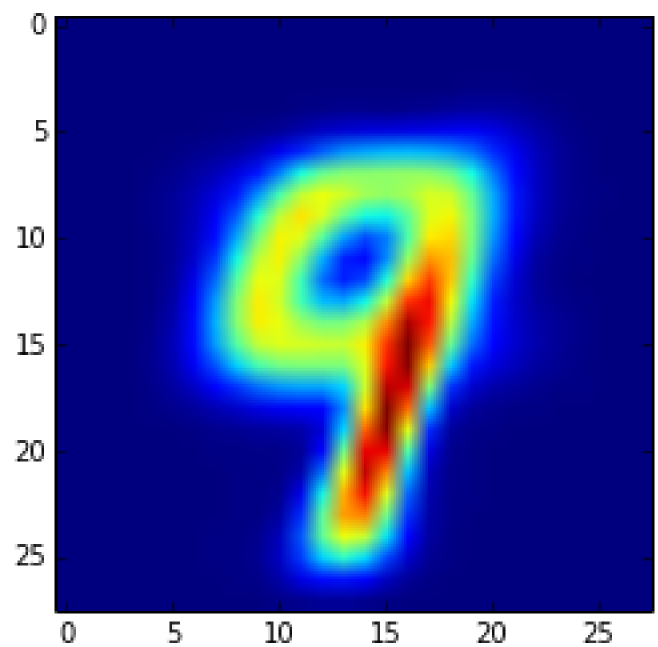
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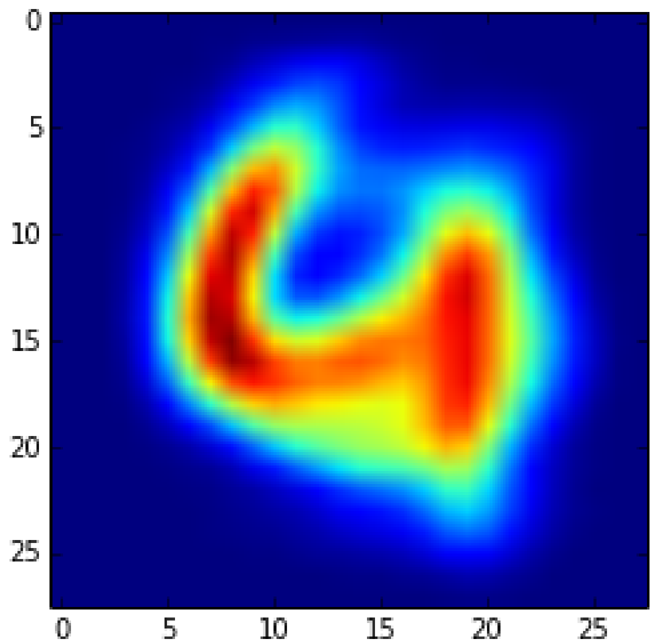
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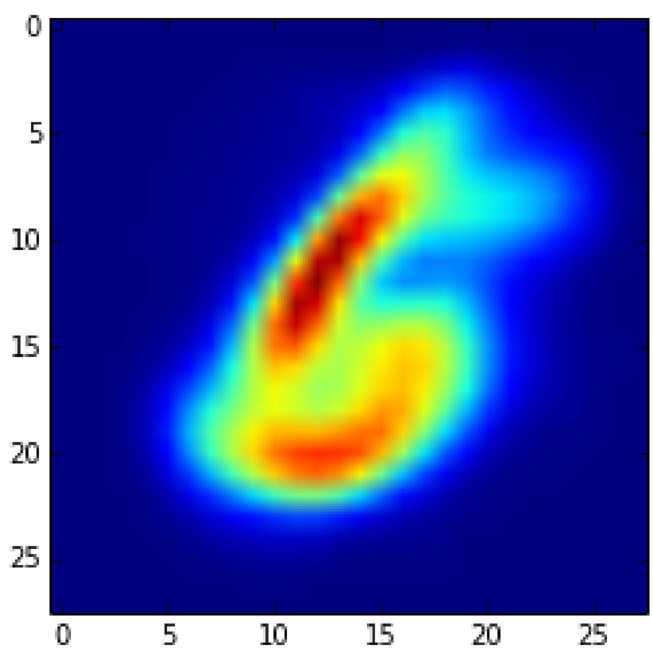
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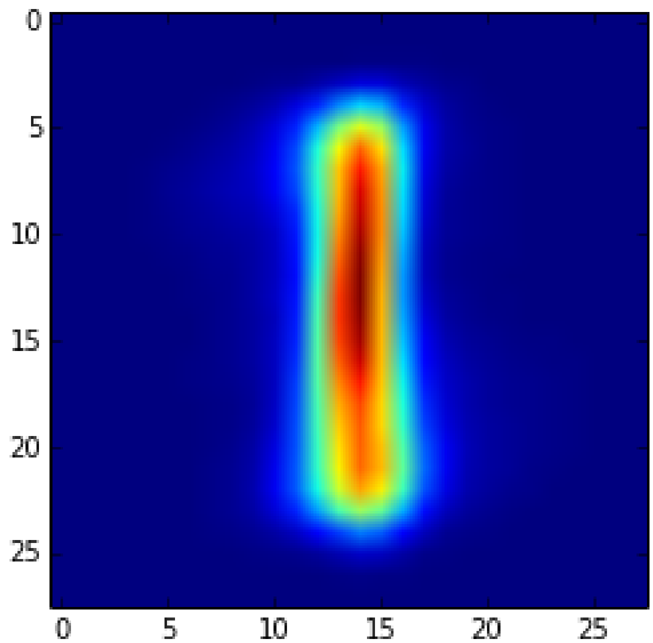
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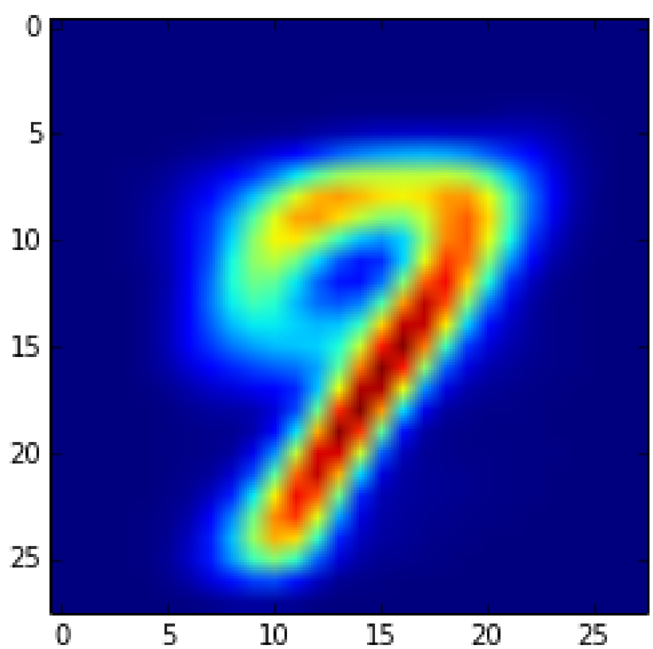
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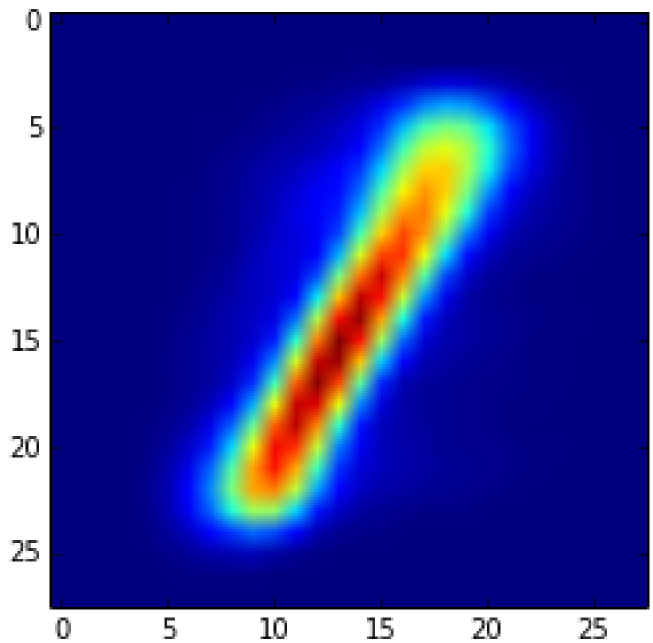
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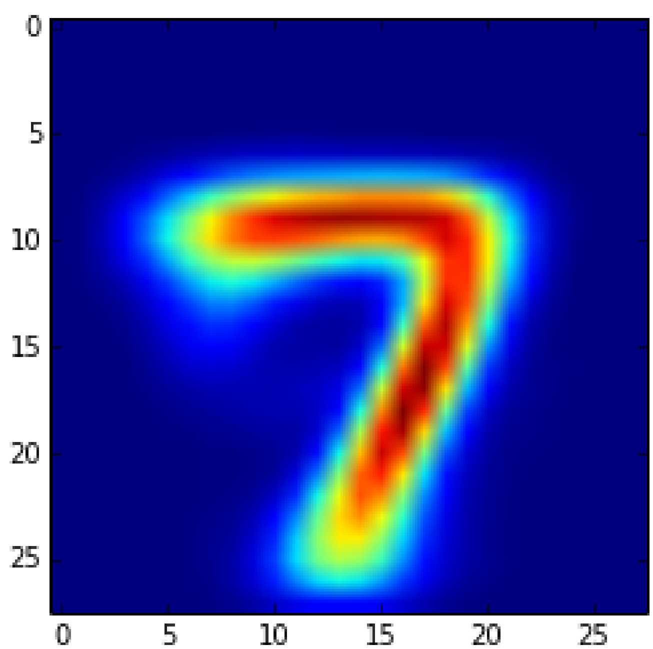
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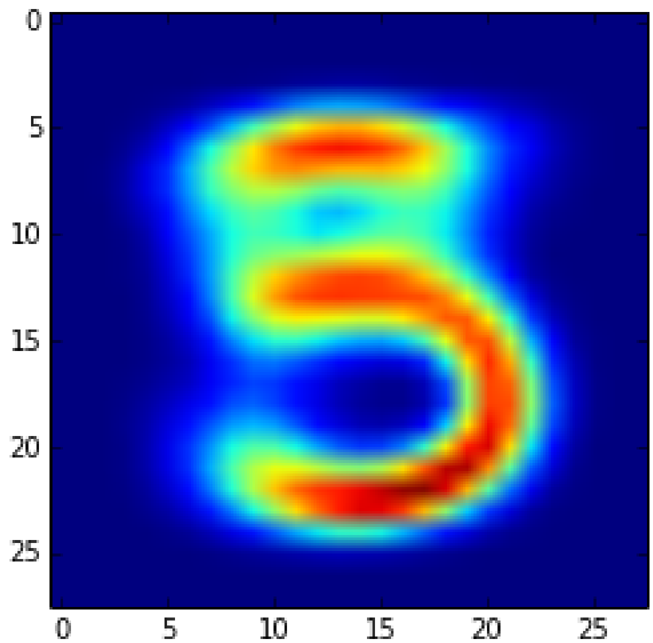
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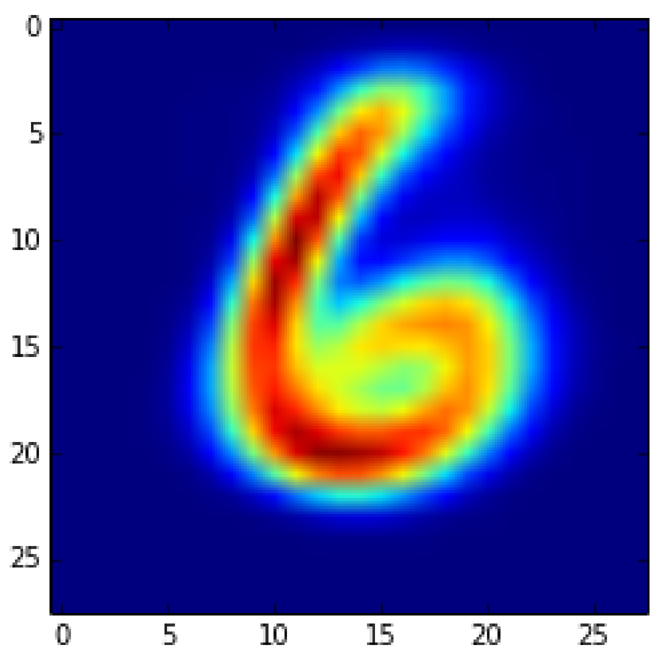
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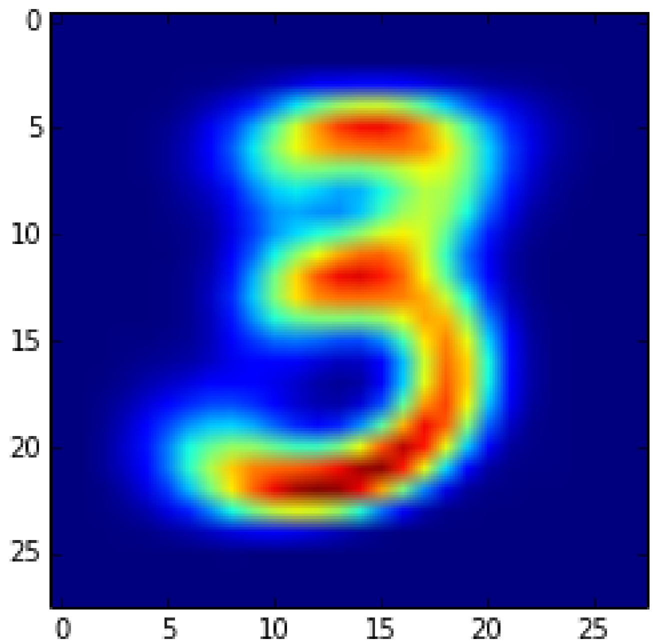
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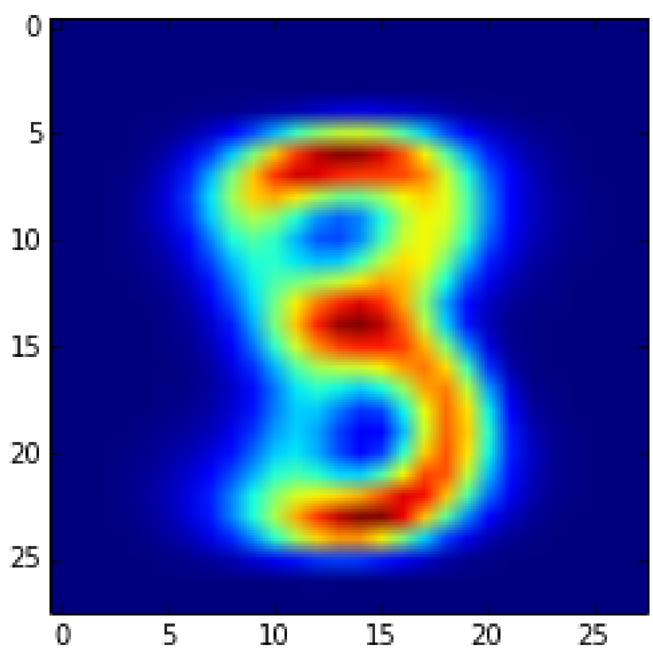
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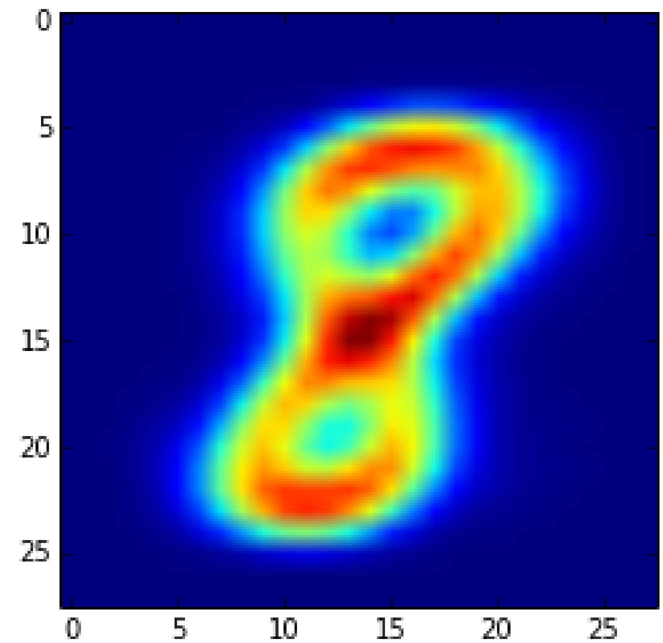
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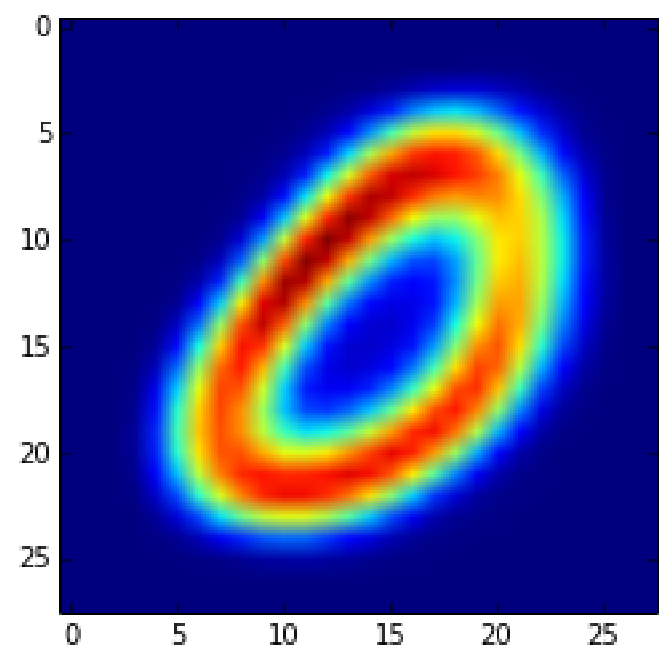
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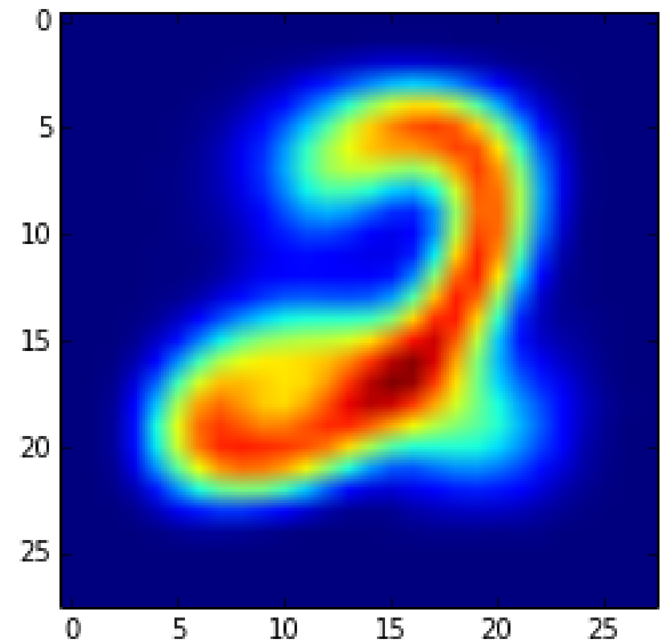
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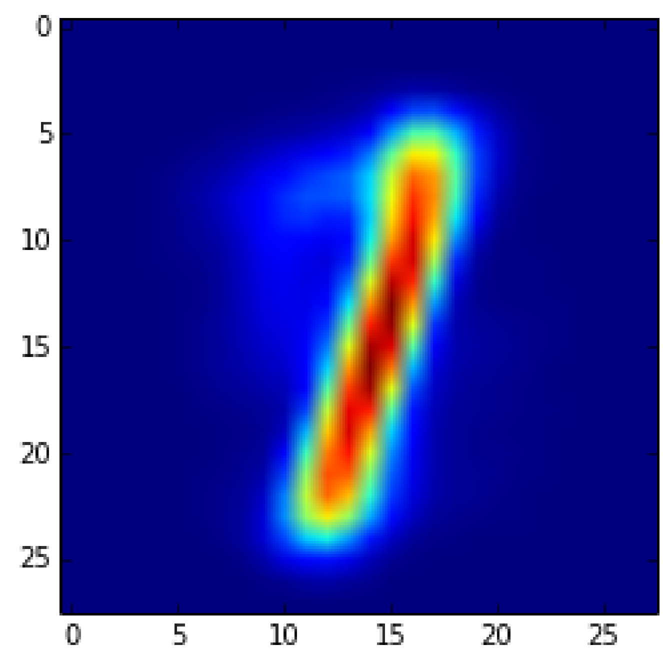
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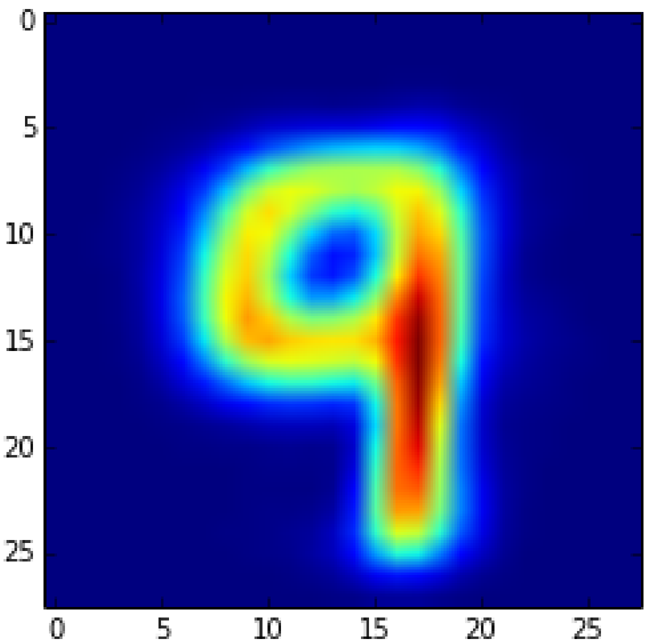
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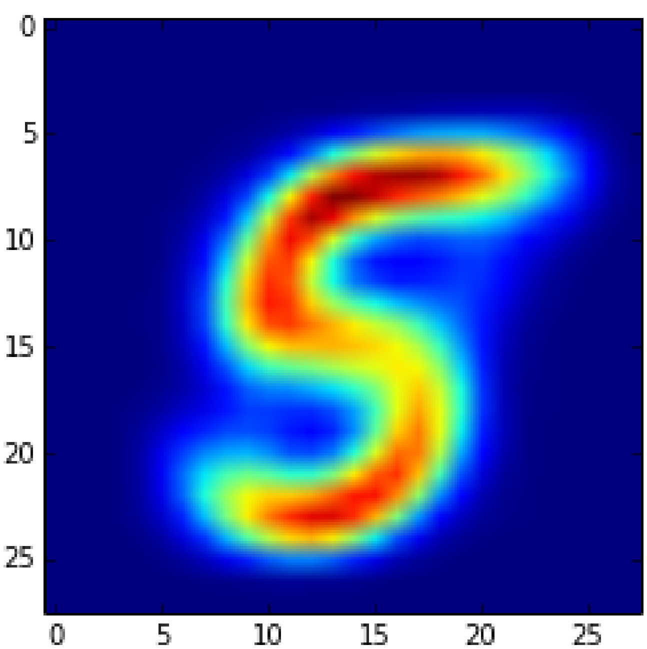
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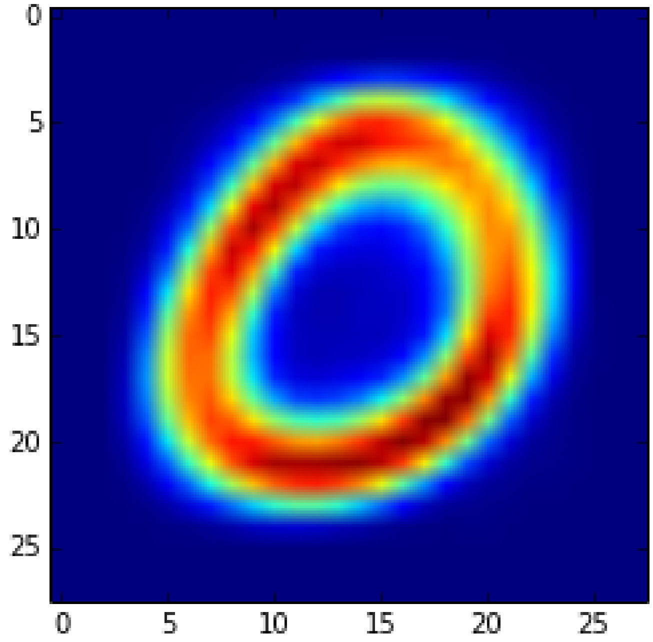

1.2 2.2 Warm-up

Average rating returns an accuracy of 62.03%. With kNN of k = [10, 100, 1000], we get accuracies of [64.90%, 68.94%, 69.40%].

In [4]:
```
# Load the data
mat = scipy.io.loadmat('joke_data/joke_train.mat')
R = mat['train']
validation = np.loadtxt(open("joke_data/validation.txt","rb"),delimiter=",")

# Zero-index the validation data
validation[:,0] -= np.ones(len(validation))
validation[:,1] -= np.ones(len(validation))
```

In [5]:
```
averages = np.nanmean(R, axis=0)
ratings = [averages[j] for u, j, s in validation]

def score(ratings, validation):
    return sum(v[2] == (1 if r > 0 else 0) for r, v in zip(ratings, validation)) / len(validati

score(ratings, validation)
```

Out[5]: 0.62032520325203255

In [6]:
```
R = np.nan_to_num(R)

def knn(u, R, k):
    distances = np.linalg.norm(R - R[u], axis=1)
    return np.argsort(distances)[1:k+1]
```

```
    for k in [10, 100, 1000]:
        # Memoize k nearest neighbors for each user in the validation set
        neighbors = {u: knn(u, R, k) for u in {v[0] for v in validation}}
        ratings = [np.mean(R[neighbors[u]], axis=0)[j] for u, j, s in validation]

        print(k, score(ratings, validation))
```

```
10 0.649051490515
100 0.689430894309
1000 0.694037940379
```

1.3 2.3 Latent Factor Model

The minimum squared error decreases as d increases, but prediction accuracies stabilize at around d=8, to be about 73%.

```
In [41]: R = np.nan_to_num(R)
         X = R
         # X = R - np.mean(R, axis=0)

         def PCA(X, d):
             U, S, V = np.linalg.svd(X, full_matrices=False)
             users = V.dot(X.T)[:d]
             jokes = U.T.dot(X)[:d]
             return users.T, jokes.T

         for d in [0, 5, 8, 10, 20]:
             users, jokes = PCA(X, d)
             ratings = [users[u].dot(jokes[j]) for u, j, s in validation]
             mse = sum(cell**2 for cell in (users.dot(jokes.T) - mat['train']).flat if not np.isnan(cel
             print("d =", d)
             print("MSE:", mse)
             print("Prediction accuracy:", score(ratings, validation))
             print("-------------")
```

```
d = 0
MSE: 25507785.5073
Prediction accuracy: 0.420054200542
-------------
d = 5
MSE: 7.02857508057e+12
Prediction accuracy: 0.715718157182
-------------
d = 8
MSE: 7.52370927693e+12
Prediction accuracy: 0.726287262873
-------------
d = 10
MSE: 7.81864088295e+12
Prediction accuracy: 0.728184281843
-------------
d = 20
MSE: 9.16652944487e+12
Prediction accuracy: 0.731436314363
-------------
```

In []:
```
l = 10
step = 0.01
# step = 1
Ud, Vd = PCA(X, 5)
Ud = np.random.normal(0, 5, Ud.shape)
Vd = np.random.normal(0, 5, Vd.shape)

R = mat['train']
n, m = R.shape

def loss(Ud, Vd, R, l):
    return sum(cell**2 for cell in (Ud.dot(Vd.T) - R).flat if not np.isnan(cell)) + \
            l * (sum(np.linalg.norm(Ud, axis=1)**2) + sum(np.linalg.norm(Ud, axis=1)))

print("HI")
ratings = [Ud[u].dot(Vd[j]) for u, j, s in validation]
print(score(ratings, validation))
print("HI")

for _ in range(1000):
    i = random.randrange(0, n)
    # print("Ud[i]", Ud[i])
    # print("R[i]", R[i])
    dLdui = sum(2 * (Ud[i].dot(Vd[j]) - R[i][j]) * Vd[j] for j in range(m) if not np.isnan(R[i][
#     print(step * dLdui)

    j = random.randrange(0, m)
    dLdvj = sum(2 * (Ud[i].dot(Vd[j]) - R[i][j]) * Ud[j] for i in range(n) if not np.isnan(R[i][

    Vd[j] -= step * dLdvj
    Ud[i] -= step * dLdui

#     if _ % 20 == 0:
#         print(step * dLdvj)
#         ratings = [Ud[u].dot(Vd[j]) for u, j, s in validation]
#         print(score(ratings, validation))

print("HI")
ratings = [Ud[u].dot(Vd[j]) for u, j, s in validation]
print(score(ratings, validation))
print("HI")
```

In [39]:
```
# Load and zero-index the query data
query = np.loadtxt(open("joke_data/query.txt","rb"),delimiter=",")
query[:,1] -= np.ones(len(query))
query[:,2] -= np.ones(len(query))

# Use Latent Factor Analysis to predict ratings
Ud, Vd = PCA(X, 8)
ratings = [Ud[i].dot(Vd[j]) for id, i, j in query]
result = [1 if rating > 0 else 0 for rating in ratings]

# Write the results to a csv
f = open('kaggle_submission.txt', 'w')
```

```
f.write('Id,Category\n')
for i in range(len(result)):
    f.write("{0},{1}\n".format(i + 1, result[i]))
f.close()
```