Introduction:

You can use this ipython notebook as a template for the rest of the homework.

0. Basic Useful Setups & Read MNIST using Keras

In [1]:
```
### Basic setups
import cv2
import numpy as np
import matplotlib.pyplot as plt
import sys
sys.path.append('./models/')
# Enable automatic reload of libraries
%load_ext autoreload
# All modules are reloaded before every comment
%autoreload 2
import keras
from utils import load_mnist
(x_train, y_train), (x_test, y_test) = load_mnist()
from keras.utils.vis_utils import plot_model # can be used to plot the m
odel into a png file.
```

```
/media/qiaojun/disk/Qiaojun/virtualenv/tensorflow/lib/python3.5/site-pa
ckages/h5py/__init__.py:36: FutureWarning: Conversion of the second arg
ument of issubdtype from `float` to `np.floating` is deprecated. In fut
ure, it will be treated as `np.float64 == np.dtype(float).type`.
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
```

```
x_train shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples
```

In [2]:
```
#x_train_1 = np.reshape(x_train,(-1,28*28))
y_train_1 = np.where(y_train==1)[1]
#x_test_1 = np.reshape(x_test,(-1,28*28))
y_test_1 = np.where(y_test==1)[1]
x_train = np.squeeze(np.stack((x_train,)*3,axis = 3), axis=-1)
x_test = np.squeeze(np.stack((x_test,)*3,axis = 3), axis=-1)
```

In [3]:
```
x_train_VGG = np.zeros((60000,224,224,3),dtype = np.float32)
for index in range(60000):
    x_train_VGG[index,:,:,:] = cv2.resize(x_train[index,:,:,:],(224,224
))

x_test_VGG = np.zeros((10000,224,224,3),dtype = np.float32)
for index in range(10000):
    x_test_VGG[index,:,:,:] = cv2.resize(x_test[index,:,:,:],(224,224))
```

1. Convolutional Neural Network

1.1. LetNet Model

In [3]:
```
from LeNet import LeNet
NUM_CLASSES = 10
model = LeNet(num_classes = NUM_CLASSES)
model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])
# You can save the model by specifying a path
# modelPath = ____
# model.save(modelPath)

# You can also print out the model by typing
model.summary()

# You can plot the model into a png file and use it in your report.
pngModelPath = "images/LeNet.png"
# plot(model, to_file=pngModelPath, show_shapes=True)
plot_model(model, to_file=pngModelPath, show_shapes=True)
```

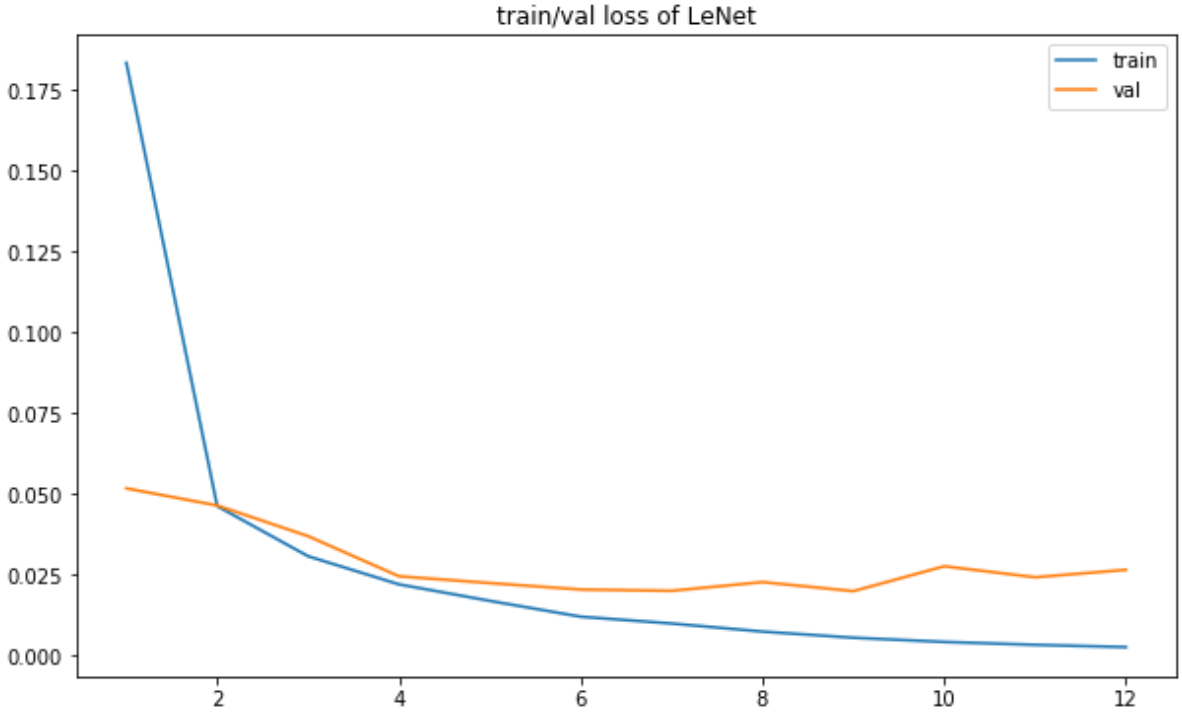
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 28, 28, 1)         0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 28, 28, 20)        520
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 14, 14, 20)        0
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 14, 14, 50)        25050
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 7, 7, 50)          0
_________________________________________________________________
flatten (Flatten)            (None, 2450)              0
_________________________________________________________________
fc1 (Dense)                  (None, 500)               1225500
_________________________________________________________________
predications (Dense)         (None, 10)                5010
=================================================================
Total params: 1,256,080
Trainable params: 1,256,080
Non-trainable params: 0
_________________________________________________________________
```

In [4]:
```
# train model
BATCH_SIZE = 128
MAX_EPOCH = 12

model.fit(x_train, y_train,
          batch_size=BATCH_SIZE,
          epochs=MAX_EPOCH,
          verbose=1,
          validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 9s 149us/step - loss: 0.
1833 - acc: 0.9444 - val_loss: 0.0517 - val_acc: 0.9832
Epoch 2/12
60000/60000 [==============================] - 3s 43us/step - loss: 0.0
462 - acc: 0.9854 - val_loss: 0.0464 - val_acc: 0.9830
Epoch 3/12
60000/60000 [==============================] - 3s 44us/step - loss: 0.0
307 - acc: 0.9904 - val_loss: 0.0369 - val_acc: 0.9882
Epoch 4/12
60000/60000 [==============================] - 3s 46us/step - loss: 0.0
220 - acc: 0.9932 - val_loss: 0.0245 - val_acc: 0.9916
Epoch 5/12
60000/60000 [==============================] - 3s 42us/step - loss: 0.0
169 - acc: 0.9947 - val_loss: 0.0224 - val_acc: 0.9927
Epoch 6/12
60000/60000 [==============================] - 3s 45us/step - loss: 0.0
120 - acc: 0.9964 - val_loss: 0.0204 - val_acc: 0.9930
Epoch 7/12
60000/60000 [==============================] - 3s 43us/step - loss: 0.0
099 - acc: 0.9969 - val_loss: 0.0200 - val_acc: 0.9944
Epoch 8/12
60000/60000 [==============================] - 3s 44us/step - loss: 0.0
074 - acc: 0.9979 - val_loss: 0.0227 - val_acc: 0.9922
Epoch 9/12
60000/60000 [==============================] - 3s 44us/step - loss: 0.0
055 - acc: 0.9985 - val_loss: 0.0199 - val_acc: 0.9939
Epoch 10/12
60000/60000 [==============================] - 2s 38us/step - loss: 0.0
042 - acc: 0.9987 - val_loss: 0.0276 - val_acc: 0.9927
Epoch 11/12
60000/60000 [==============================] - 2s 40us/step - loss: 0.0
033 - acc: 0.9989 - val_loss: 0.0242 - val_acc: 0.9933
Epoch 12/12
60000/60000 [==============================] - 3s 44us/step - loss: 0.0
026 - acc: 0.9992 - val_loss: 0.0265 - val_acc: 0.9930
Test loss: 0.026506232323426637
Test accuracy: 0.993
```

In [10]:
```
train_loss_LeNet = [0.1833,0.0462,0.0307,0.0220,0.0169,0.0120,0.0099,0.0
074,0.0055,0.0042,0.0033,0.0026]
val_loss_LeNet = [0.0517,0.0464,0.0369,0.0245,0.0224,0.0204,0.0200,0.022
7,0.0199,0.0276,0.0242,0.0265]
plt.figure(figsize=(10,6))
plt.plot(range(1,len(train_loss_LeNet)+1),train_loss_LeNet)
plt.plot(range(1,len(val_loss_LeNet)+1),val_loss_LeNet)
plt.legend(['train','val'])
plt.title('train/val loss of LeNet')
plt.show()
```



1.2. VGG16

In [4]:
```
# train model
BATCH_SIZE = 128
MAX_EPOCH = 12

from keras.applications.vgg16 import VGG16
from keras.preprocessing import image
from keras.applications.vgg16 import preprocess_input
from keras.models import Model
from keras.layers import Dense, GlobalAveragePooling2D
import numpy as np

# create the base pre-trained model
base_model = VGG16(weights='imagenet', include_top=False)

# add a global spatial average pooling layer
x = base_model.output
x = GlobalAveragePooling2D()(x)
# let's add a fully-connected layer
x = Dense(128, activation='relu')(x)
# and a logistic layer -- let's say we have 10 classes
predictions = Dense(10, activation='softmax')(x)

# this is the model we will train
model = Model(inputs=base_model.input, outputs=predictions)

# first: train only the top layers (which were randomly initialized)
# i.e. freeze all convolutional InceptionV3 layers
for layer in base_model.layers:
    layer.trainable = False

# compile the model (should be done *after* setting layers to non-traina
ble)
# model.compile(optimizer='rmsprop', loss='categorical_crossentropy', me
trics=['accuracy'])
model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])
# You can also print out the model by typing
model.summary()

# You can plot the model into a png file and use it in your report.
#pngModelPath = "images/VGG16.png"
# plot(model, to_file=pngModelPath, show_shapes=True)
#plot_model(model, to_file=pngModelPath, show_shapes=True)
```

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, None, None, 3)	0
block1_conv1 (Conv2D)	(None, None, None, 64)	1792
block1_conv2 (Conv2D)	(None, None, None, 64)	36928
block1_pool (MaxPooling2D)	(None, None, None, 64)	0
block2_conv1 (Conv2D)	(None, None, None, 128)	73856
block2_conv2 (Conv2D)	(None, None, None, 128)	147584
block2_pool (MaxPooling2D)	(None, None, None, 128)	0
block3_conv1 (Conv2D)	(None, None, None, 256)	295168
block3_conv2 (Conv2D)	(None, None, None, 256)	590080
block3_conv3 (Conv2D)	(None, None, None, 256)	590080
block3_pool (MaxPooling2D)	(None, None, None, 256)	0
block4_conv1 (Conv2D)	(None, None, None, 512)	1180160
block4_conv2 (Conv2D)	(None, None, None, 512)	2359808
block4_conv3 (Conv2D)	(None, None, None, 512)	2359808
block4_pool (MaxPooling2D)	(None, None, None, 512)	0
block5_conv1 (Conv2D)	(None, None, None, 512)	2359808
block5_conv2 (Conv2D)	(None, None, None, 512)	2359808
block5_conv3 (Conv2D)	(None, None, None, 512)	2359808
block5_pool (MaxPooling2D)	(None, None, None, 512)	0
global_average_pooling2d_1 (	(None, 512)	0
dense_1 (Dense)	(None, 64)	32832
dense_2 (Dense)	(None, 10)	650

Total params: 14,748,170
Trainable params: 33,482
Non-trainable params: 14,714,688

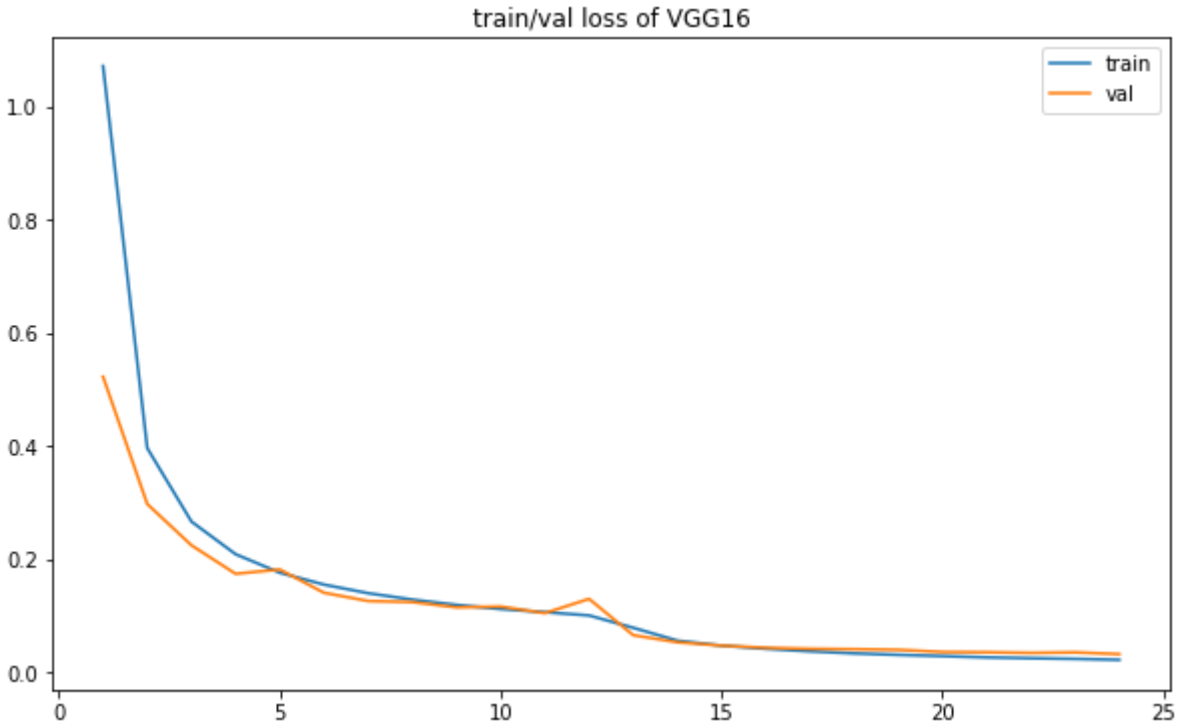
In [5]:
```
model.fit(x_train_VGG, y_train,
          batch_size=BATCH_SIZE,
          epochs=MAX_EPOCH,
          verbose=1,
          validation_data=(x_test_VGG, y_test))
score = model.evaluate(x_test_VGG, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 667s 11ms/step - loss:
1.0711 - acc: 0.7268 - val_loss: 0.5223 - val_acc: 0.8770
Epoch 2/12
60000/60000 [==============================] - 693s 12ms/step - loss:
0.3962 - acc: 0.9013 - val_loss: 0.2974 - val_acc: 0.9251
Epoch 3/12
60000/60000 [==============================] - 865s 14ms/step - loss:
0.2664 - acc: 0.9315 - val_loss: 0.2245 - val_acc: 0.9406
Epoch 4/12
60000/60000 [==============================] - 823s 14ms/step - loss:
0.2087 - acc: 0.9439 - val_loss: 0.1741 - val_acc: 0.9551
Epoch 5/12
60000/60000 [==============================] - 931s 16ms/step - loss:
0.1760 - acc: 0.9512 - val_loss: 0.1817 - val_acc: 0.9447
Epoch 6/12
60000/60000 [==============================] - 843s 14ms/step - loss:
0.1550 - acc: 0.9566 - val_loss: 0.1406 - val_acc: 0.9596
Epoch 7/12
60000/60000 [==============================] - 940s 16ms/step - loss:
0.1398 - acc: 0.9609 - val_loss: 0.1260 - val_acc: 0.9648
Epoch 8/12
60000/60000 [==============================] - 845s 14ms/step - loss:
0.1285 - acc: 0.9643 - val_loss: 0.1241 - val_acc: 0.9643
Epoch 9/12
60000/60000 [==============================] - 946s 16ms/step - loss:
0.1191 - acc: 0.9657 - val_loss: 0.1148 - val_acc: 0.9666
Epoch 10/12
60000/60000 [==============================] - 854s 14ms/step - loss:
0.1118 - acc: 0.9681 - val_loss: 0.1162 - val_acc: 0.9644
Epoch 11/12
60000/60000 [==============================] - 821s 14ms/step - loss:
0.1063 - acc: 0.9695 - val_loss: 0.1046 - val_acc: 0.9675
Epoch 12/12
60000/60000 [==============================] - 709s 12ms/step - loss:
0.1005 - acc: 0.9704 - val_loss: 0.1298 - val_acc: 0.9571
Test loss: 0.12977995154857636
Test accuracy: 0.9571
```

In [6]:
```
for layer in model.layers[-6:]:
    layer.trainable = True
from keras.optimizers import SGD
model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=SGD(lr=0.0001, momentum=0.9),
              metrics=['accuracy'])
model.fit(x_train_VGG, y_train,
          batch_size=BATCH_SIZE,
          epochs=MAX_EPOCH,
          verbose=1,
          validation_data=(x_test_VGG, y_test))
score = model.evaluate(x_test_VGG, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 757s 13ms/step - loss:
0.0787 - acc: 0.9759 - val_loss: 0.0656 - val_acc: 0.9785
Epoch 2/12
60000/60000 [==============================] - 723s 12ms/step - loss:
0.0560 - acc: 0.9824 - val_loss: 0.0531 - val_acc: 0.9831
Epoch 3/12
60000/60000 [==============================] - 785s 13ms/step - loss:
0.0472 - acc: 0.9851 - val_loss: 0.0472 - val_acc: 0.9851
Epoch 4/12
60000/60000 [==============================] - 741s 12ms/step - loss:
0.0416 - acc: 0.9875 - val_loss: 0.0434 - val_acc: 0.9860
Epoch 5/12
60000/60000 [==============================] - 801s 13ms/step - loss:
0.0371 - acc: 0.9883 - val_loss: 0.0416 - val_acc: 0.9871
Epoch 6/12
60000/60000 [==============================] - 740s 12ms/step - loss:
0.0335 - acc: 0.9901 - val_loss: 0.0409 - val_acc: 0.9878
Epoch 7/12
60000/60000 [==============================] - 801s 13ms/step - loss:
0.0309 - acc: 0.9909 - val_loss: 0.0398 - val_acc: 0.9876
Epoch 8/12
60000/60000 [==============================] - 744s 12ms/step - loss:
0.0287 - acc: 0.9916 - val_loss: 0.0359 - val_acc: 0.9885
Epoch 9/12
60000/60000 [==============================] - 788s 13ms/step - loss:
0.0264 - acc: 0.9925 - val_loss: 0.0355 - val_acc: 0.9887
Epoch 10/12
60000/60000 [==============================] - 736s 12ms/step - loss:
0.0249 - acc: 0.9927 - val_loss: 0.0343 - val_acc: 0.9900
Epoch 11/12
60000/60000 [==============================] - 803s 13ms/step - loss:
0.0238 - acc: 0.9931 - val_loss: 0.0353 - val_acc: 0.9892
Epoch 12/12
60000/60000 [==============================] - 744s 12ms/step - loss:
0.0221 - acc: 0.9937 - val_loss: 0.0322 - val_acc: 0.9902
Test loss: 0.03215658742006635
Test accuracy: 0.9902
```

In [11]:
```
train_loss_VGG = [1.0711,0.3962,0.2664,0.2087,0.1760,0.1550,0.1398,0.128
5,0.1191,0.1118,0.1063,0.1005,0.0787,0.0560,0.0472,0.0416,0.0371,0.0335,
0.0309,0.0287,0.0264,0.0249,0.0238,0.0221]
val_loss_VGG = [0.5223,0.2974,0.2245,0.1741,0.1817,0.1406,0.1260,0.1241,
0.1148,0.1162,0.1046,0.1298,0.0656,0.0531,0.0472,0.0434,0.0416,0.0409,0.
0398,0.0359,0.0355,0.0343,0.0353,0.0322]
plt.figure(figsize=(10,6))
plt.plot(range(1,len(train_loss_VGG)+1),train_loss_VGG)
plt.plot(range(1,len(val_loss_VGG)+1),val_loss_VGG)
plt.legend(['train','val'])
plt.title('train/val loss of VGG16')
plt.show()
```



2. 1-Nearest Neighbor

Using the raw pixel values (28 × 28) as feature vector, use 1-Nearest Neighbor to train a model and report its performance on the test set and the confusion matrix. Also report other details of the experiments like the distance functions used, prototype selection (if you have used), etc.

Use euclidean_distance (l2)

In [63]:
```
from sklearn import neighbors

# the number of neighbors
n_neighbors = 1

# n_neighbors=5, weights='uniform', algorithm='auto', p=2, metric='minko
wski', n_jobs=1
# weights: 'uniform', 'distance'
# p: distance norm
clf = neighbors.KNeighborsClassifier(n_neighbors, weights='uniform', n_j
obs=-1)
clf.fit(x_train_1, y_train_1)

y_predict_1nn_1 = clf.predict(x_test_1)
acc_1nn_1 = sum(y_predict_1nn_1 == y_test_1)/len(y_test_1)
print("Test accuracy of 1-Nearest Neighbor: %.3f"%acc_1nn_1)
confusion_matrix(y_test_1, y_predict_1nn_1, labels=range(10))
```

```
Test accuracy of 1-Nearest Neighbor: 0.969
```

Out[63]:
```
array([[ 973,    1,    1,    0,    0,    1,    3,    1,    0,    0],
       [   0, 1129,    3,    0,    1,    1,    1,    0,    0,    0],
       [   7,    6,  992,    5,    1,    0,    2,   16,    3,    0],
       [   0,    1,    2,  970,    1,   19,    0,    7,    7,    3],
       [   0,    7,    0,    0,  944,    0,    3,    5,    1,   22],
       [   1,    1,    0,   12,    2,  860,    5,    1,    6,    4],
       [   4,    2,    0,    0,    3,    5,  944,    0,    0,    0],
       [   0,   14,    6,    2,    4,    0,    0,  992,    0,   10],
       [   6,    1,    3,   14,    5,   13,    3,    4,  920,    5],
       [   2,    5,    1,    6,   10,    5,    1,   11,    1,  967]])
```

Use manhattan_distance (l1)

In [65]:
```
from sklearn import neighbors
n_neighbors = 1
clf = neighbors.KNeighborsClassifier(n_neighbors, p=1, n_jobs=-1)
clf.fit(x_train_1, y_train_1)
y_predict_1nn_2 = clf.predict(x_test_1)
acc_1nn_2 = sum(y_predict_1nn_2 == y_test_1)/len(y_test_1)
print("Test accuracy of 1-Nearest Neighbor: %.3f"%acc_1nn_2)
confusion_matrix(y_test_1, y_predict_1nn_2, labels=range(10))
```

```
Test accuracy of 1-Nearest Neighbor: 0.963
```

Out[65]:
```
array([[ 973,    2,    1,    0,    0,    1,    2,    1,    0,    0],
       [   0, 1129,    3,    0,    1,    1,    1,    0,    0,    0],
       [   9,    8,  987,    6,    1,    0,    2,   17,    2,    0],
       [   0,    2,    4,  965,    1,   21,    0,    9,    4,    4],
       [   1,    9,    0,    0,  937,    0,    3,    4,    1,   27],
       [   2,    1,    0,   17,    2,  848,    9,    1,    5,    7],
       [   5,    2,    1,    0,    2,    5,  943,    0,    0,    0],
       [   0,   20,    4,    2,    4,    0,    0,  989,    0,    9],
       [   9,    5,    6,   21,    4,   18,    3,    4,  894,   10],
       [   1,    5,    1,    7,   13,    5,    1,    9,    1,  966]])
```

3. Support Vector Machines

Using the same feature vector, use SVM to train a model and report its performance on the test set and the confusion matrix. Report other relevant details of the experiments.

In [ ]:
```
# C : float, optional (default=1.0)
#   Penalty parameter C of the error term.
# kernel : string, optional (default='rbf')
#   Specifies the kernel type to be used in the algorithm.
#   It must be one of 'linear', 'poly', 'rbf', 'sigmoid', 'precomputed'
 or a callable.
#   If none is given, 'rbf' will be used.
# degree : int, optional (default=3)
#   Degree of the polynomial kernel function ('poly'). Ignored by all ot
her kernels.
# gamma : float, optional (default='auto')
#   Kernel coefficient for 'rbf', 'poly' and 'sigmoid'. If gamma is 'aut
o' then 1/n_features will be used instead.

#SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
#    decision_function_shape='ovr', degree=3, gamma='auto', kernel='rb
f',
#    max_iter=-1, probability=False, random_state=None, shrinking=True,
#    tol=0.001, verbose=False)
```

Use Radial basis function(RBF) kernel

In [67]:
```
from sklearn.svm import SVC
clf = SVC()
clf.fit(x_train_1, y_train_1)
y_predict_SVM_1 = clf.predict(x_test_1)
acc_SVM_1 = sum(y_predict_SVM_1 == y_test_1)/len(y_test_1)
print("Test accuracy of Support Vector Machines: %.3f"%acc_SVM_1)
confusion_matrix(y_test_1, y_predict_SVM_1, labels=range(10))
```

```
Test accuracy of Support Vector Machines: 0.945
```

Out[67]:
```
array([[ 967,    0,    2,    0,    0,    5,    4,    1,    1,    0],
       [   0, 1121,    2,    2,    0,    1,    4,    1,    4,    0],
       [   9,    1,  961,    9,   10,    1,   13,    9,   17,    2],
       [   1,    1,   15,  951,    1,   15,    1,   10,   11,    4],
       [   1,    1,    7,    0,  938,    0,    7,    2,    2,   24],
       [   7,    4,    5,   30,    7,  810,   12,    2,   10,    5],
       [   9,    3,    4,    1,    5,    9,  926,    0,    1,    0],
       [   2,   13,   22,    5,    8,    1,    0,  956,    3,   18],
       [   4,    7,    7,   14,    8,   23,   10,    6,  892,    3],
       [   8,    7,    0,   12,   31,    6,    1,   13,    7,  924]])
```

Use linear kernel

In [70]:
```
from sklearn.linear_model import SGDClassifier
clf = SGDClassifier(tol = 1e-3)
clf.fit(x_train_1, y_train_1)
y_predict_SVM_2 = clf.predict(x_test_1)
acc_SVM_2 = sum(y_predict_SVM_2 == y_test_1)/len(y_test_1)
print("Test accuracy of Support Vector Machines: %.3f"%acc_SVM_2)
confusion_matrix(y_test_1, y_predict_SVM_2, labels=range(10))
```

```
Test accuracy of Support Vector Machines: 0.918
```

Out[70]:
```
array([[ 951,    0,    1,    2,    2,   11,    5,    6,    1,    1],
       [   0, 1108,    4,    0,    0,    2,    4,    2,   15,    0],
       [   4,    5,  939,   10,   12,    5,    9,   12,   33,    3],
       [   5,    0,   30,  893,    3,   29,    3,   13,   25,    9],
       [   1,    5,    5,    0,  931,    0,    6,    2,    8,   24],
       [   8,    4,    3,   28,   20,  770,   17,    4,   30,    8],
       [   5,    3,    7,    3,   10,   13,  907,    3,    7,    0],
       [   1,    7,   28,    3,   10,    2,    1,  947,    2,   27],
       [   6,    9,    8,   13,   14,   32,   10,   11,  859,   12],
       [   5,   11,    3,    8,   50,   12,    0,   34,   12,  874]])
```

4. Spatial Pyramid Matching

In [111]:
```
%cd Image-recognition/
%run example.py
%cd ../
```

```
/media/qiaojun/disk/Qiaojun/Courses/COGS260/assignment/assignment2/hw2/
Image-recognition
Training data load from None
Test data load from None
x_train shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples
Codebook Size: 100
Pyramid level: 1
Dense SIFT feature extraction
Building the codebook, it will take some time
Spatial Pyramid Matching encoding
Tuning hyper-parameters

Best parameters set found on development set:

SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=100.0, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)

Grid scores on development set:

0.112 (+/-0.000) for {'C': 0.001, 'gamma': 0.001}
0.112 (+/-0.000) for {'C': 0.001, 'gamma': 0.01}
0.112 (+/-0.000) for {'C': 0.001, 'gamma': 0.1}
0.112 (+/-0.000) for {'C': 0.001, 'gamma': 1.0}
0.433 (+/-0.004) for {'C': 0.001, 'gamma': 10.0}
0.612 (+/-0.013) for {'C': 0.001, 'gamma': 100.0}
0.112 (+/-0.000) for {'C': 0.01, 'gamma': 0.001}
0.112 (+/-0.000) for {'C': 0.01, 'gamma': 0.01}
0.112 (+/-0.000) for {'C': 0.01, 'gamma': 0.1}
0.525 (+/-0.009) for {'C': 0.01, 'gamma': 1.0}
0.726 (+/-0.015) for {'C': 0.01, 'gamma': 10.0}
0.775 (+/-0.015) for {'C': 0.01, 'gamma': 100.0}
0.112 (+/-0.000) for {'C': 0.1, 'gamma': 0.001}
0.112 (+/-0.000) for {'C': 0.1, 'gamma': 0.01}
0.529 (+/-0.010) for {'C': 0.1, 'gamma': 0.1}
0.730 (+/-0.015) for {'C': 0.1, 'gamma': 1.0}
0.794 (+/-0.012) for {'C': 0.1, 'gamma': 10.0}
0.835 (+/-0.013) for {'C': 0.1, 'gamma': 100.0}
0.112 (+/-0.000) for {'C': 1.0, 'gamma': 0.001}
0.530 (+/-0.010) for {'C': 1.0, 'gamma': 0.01}
0.730 (+/-0.015) for {'C': 1.0, 'gamma': 0.1}
0.790 (+/-0.014) for {'C': 1.0, 'gamma': 1.0}
0.829 (+/-0.010) for {'C': 1.0, 'gamma': 10.0}
0.862 (+/-0.010) for {'C': 1.0, 'gamma': 100.0}
0.530 (+/-0.010) for {'C': 10.0, 'gamma': 0.001}
0.730 (+/-0.016) for {'C': 10.0, 'gamma': 0.01}
0.789 (+/-0.015) for {'C': 10.0, 'gamma': 0.1}
0.816 (+/-0.010) for {'C': 10.0, 'gamma': 1.0}
0.852 (+/-0.011) for {'C': 10.0, 'gamma': 10.0}
0.858 (+/-0.010) for {'C': 10.0, 'gamma': 100.0}
0.731 (+/-0.015) for {'C': 100.0, 'gamma': 0.001}
0.789 (+/-0.015) for {'C': 100.0, 'gamma': 0.01}
0.812 (+/-0.010) for {'C': 100.0, 'gamma': 0.1}
0.835 (+/-0.010) for {'C': 100.0, 'gamma': 1.0}
```

```
0.860 (+/-0.010) for {'C': 100.0, 'gamma': 10.0}
0.844 (+/-0.010) for {'C': 100.0, 'gamma': 100.0}

Detailed classification report:

The model is trained on the full development set.
The scores are computed on the full evaluation set.

             precision    recall  f1-score   support

          0       0.89      0.94      0.92       980
          1       0.98      0.99      0.98      1135
          2       0.87      0.86      0.87      1032
          3       0.79      0.80      0.80      1010
          4       0.92      0.88      0.90       982
          5       0.82      0.78      0.80       892
          6       0.93      0.93      0.93       958
          7       0.85      0.88      0.86      1028
          8       0.80      0.75      0.77       974
          9       0.81      0.84      0.83      1009

avg / total       0.87      0.87      0.87     10000

Test accuracy of SPM: 0.868
[[ 922    3    3    1    5    5   19    5   12    5]
 [   1 1119    2    3    0    1    4    1    4    0]
 [   5    2  888   79    6    5    2   33   10    2]
 [   0    0   74  813    2   30    0   61   25    5]
 [  10    0    4    0  866    9   18    2   13   60]
 [  11    3    6   52    7  699    8   10   58   38]
 [  36    4    3    0    9    6  887    0   13    0]
 [   2    1   27   38    5    5    0  907    9   34]
 [  29    4   12   41   13   56    8   30  730   51]
 [  16    4    0    8   25   37    4   23   40  852]]
/media/qiaojun/disk/Qiaojun/Courses/COGS260/assignment/assignment2/hw2
```

In [113]:
```
acc_SPM = 0.868
```

5. Deep Belief Nets

In [115]:
```
#Test accuracy of Deep Belief Nets: 0.985
# [[ 975    1    0    0    0    1    2    1    0    0]
# [   0 1129    2    1    0    1    1    0    1    0]
# [   6    0 1017    1    1    0    1    4    2    0]
# [   1    0    3  991    0    4    0    5    4    2]
# [   2    0    2    0  957    0    5    1    0   15]
# [   2    0    0    1    1  878    4    0    4    2]
# [   2    2    0    1    2    2  945    0    4    0]
# [   2    3    6    0    1    0    0 1009    1    6]
# [   2    1    1    2    0    1    0    1  962    4]
# [   2    3    1    2    3    2    0    3    3  990]]
```

Evaluation

In [7]:
```
name_list = ['LeNet','VGG16','1-NN','SVM','SPM','DBN']
acc_list = [0.993, 0.990, 0.969, 0.945, 0.868, 0.985]

plt.figure(figsize=(10,6))
plt.bar(range(len(name_list)), acc_list, color='rgbymc',tick_label=name_
list)
plt.title('Evaluation of classification accuracy on MNIST')
plt.show()
```