In [93]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

a) load/merge data and visualize logerror

In [164…
```python
# load data into DataFrames
train = pd.read_csv('./p1_data/train.csv')
properties = pd.read_csv('./p1_data/properties.csv')

df = train.merge(properties, on='id')
df
```

Out[164]:

	id	logerror	transactiondate	airconditioningtypeid	architecturalstyletypeid
0	14366692	-0.1684	1/1/16	NaN	NaN
1	14739064	-0.0030	1/2/16	NaN	NaN
2	10854446	0.3825	1/3/16	NaN	NaN
3	11672170	-0.0161	1/3/16	1.0	NaN
4	12524288	-0.0419	1/3/16	NaN	NaN
...	...	...	...	...	...
31720	12756771	0.0658	12/30/16	NaN	NaN
31721	11295458	-0.0294	12/30/16	1.0	NaN
31722	11308315	0.0070	12/30/16	1.0	NaN
31723	11703478	0.0431	12/30/16	NaN	NaN
31724	12566293	0.4207	12/30/16	NaN	NaN

31725 rows × 60 columns

In [165…
```python
np.percentile(df.logerror, 0)
```

Out[165]: -2.365

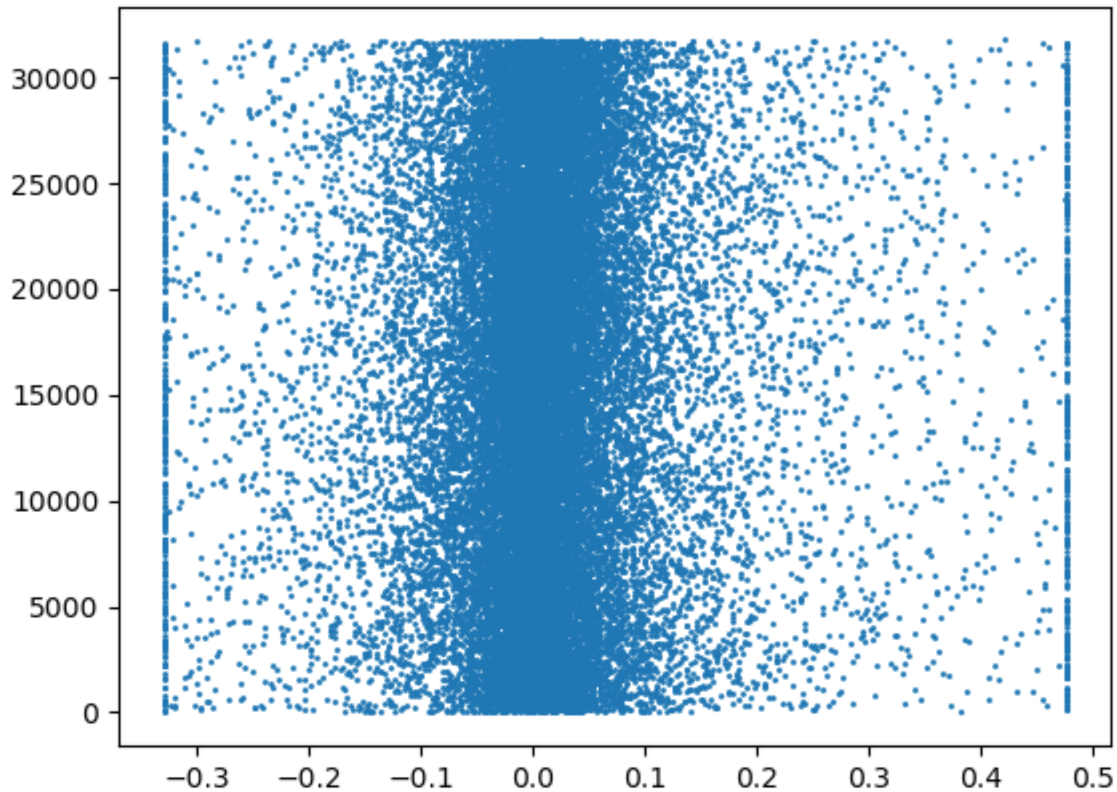
In [166…
```python
df.buildingclasstypeid.mean()
```

Out[166]: 4.0

In [167…
```python
# eliminate outliers

df.loc[df["logerror"] <= np.percentile(df.logerror, 1), "logerror"] = np.per
df.loc[df["logerror"] >= np.percentile(df.logerror, 99), "logerror"] = np.pe
```

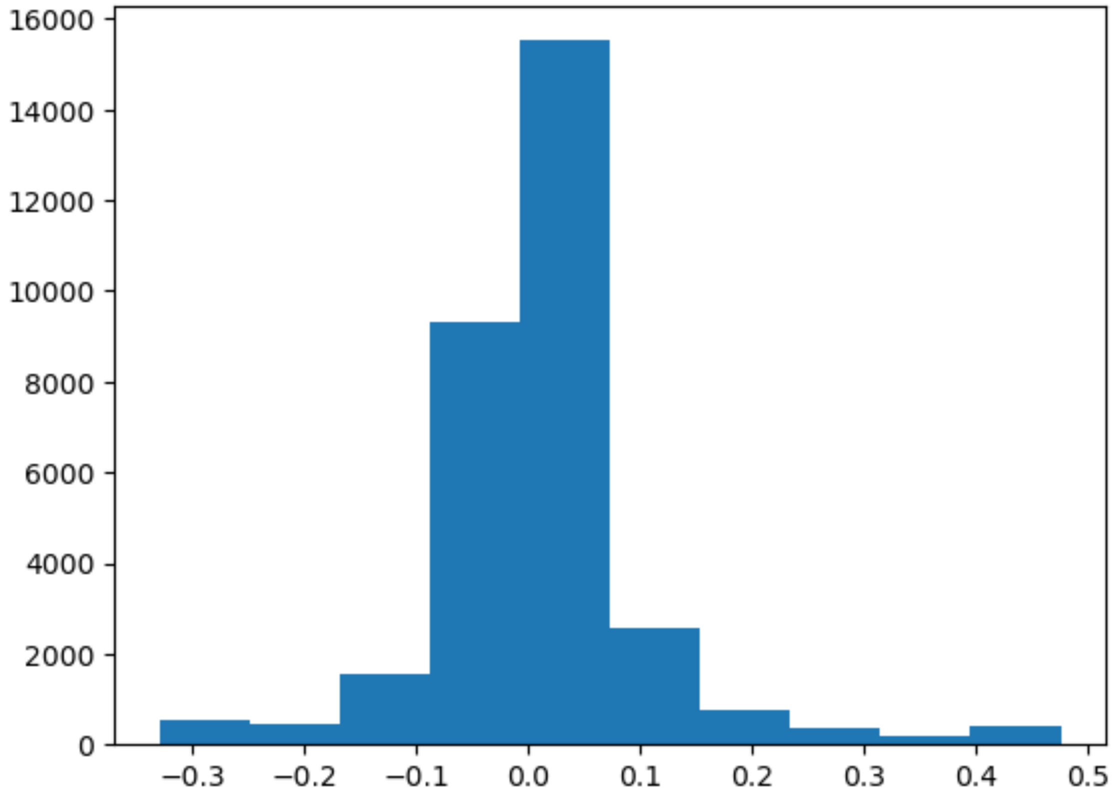
In [168…

```
# scatter of logerr

plt.scatter(df.logerror, df.index, s=1)
plt.show()
```



In [169…

```
# histogram of logerr
plt.hist(df.logerror)
plt.show()
```



b) data cleaning

In [170…
```
# build new data frame
count = [df[c].isna().sum() for c in df.columns]
missing = pd.DataFrame({'column_name':df.columns, 'missing_count': count})

missing['missing_ratio'] = [missing.missing_count[i]/len(df) for i in range(
```

In [184…
```
missing
```

Out[184]:

	column_name	missing_count	missing_ratio
0	id	0	0.000000
1	logerror	0	0.000000
2	transactiondate	0	0.000000
3	airconditioningtypeid	21563	0.679685
4	architecturalstyletypeid	31628	0.996942
5	basementsqft	31711	0.999559
6	bathroomcnt	0	0.000000
7	bedroomcnt	0	0.000000
8	buildingclasstypeid	31717	0.999748
9	buildingqualitytypeid	11488	0.362112
10	calculatedbathnbr	414	0.013050
11	decktypeid	31502	0.992971
12	finishedfloor1squarefeet	29381	0.926115
13	calculatedfinishedsquarefeet	228	0.007187
14	finishedsquarefeet12	1647	0.051915
15	finishedsquarefeet13	31711	0.999559
16	finishedsquarefeet15	30454	0.959937
17	finishedsquarefeet50	29381	0.926115
18	finishedsquarefeet6	31591	0.995776
19	fips	0	0.000000
20	fireplacecnt	28374	0.894374
21	fullbathcnt	414	0.013050
22	garagecarcnt	21280	0.670764
23	garagetotalsqft	21280	0.670764
24	hashottuborspa	30929	0.974909
25	heatingorsystemtypeid	11962	0.377053
26	latitude	0	0.000000
27	longitude	0	0.000000
28	lotsizesquarefeet	3522	0.111017
29	poolcnt	25454	0.802333
30	poolsizesum	31394	0.989567
31	pooltypeid10	31337	0.987770
32	pooltypeid2	31317	0.987139
33	pooltypeid7	25862	0.815193

	column_name	missing_count	missing_ratio
34	propertycountylandusecode	0	0.000000
35	propertylandusetypeid	0	0.000000
36	propertyzoningdesc	11135	0.350985
37	rawcensustractandblock	0	0.000000
38	regionidcity	666	0.020993
39	regionidcounty	0	0.000000
40	regionidneighborhood	19082	0.601481
41	regionidzip	12	0.000378
42	roomcnt	0	0.000000
43	storytypeid	31711	0.999559
44	threequarterbathnbr	27471	0.865910
45	typeconstructiontypeid	31613	0.996470
46	unitcnt	11127	0.350733
47	yardbuildingsqft17	30814	0.971284
48	yardbuildingsqft26	31691	0.998928
49	yearbuilt	260	0.008195
50	numberofstories	24526	0.773081
51	fireplaceflag	31631	0.997037
52	structuretaxvaluedollarcnt	128	0.004035
53	taxvaluedollarcnt	1	0.000032
54	assessmentyear	0	0.000000
55	landtaxvaluedollarcnt	1	0.000032
56	taxamount	1	0.000032
57	taxdelinquencyflag	31112	0.980678
58	taxdelinquencyyear	31112	0.980678
59	censustractandblock	208	0.006556

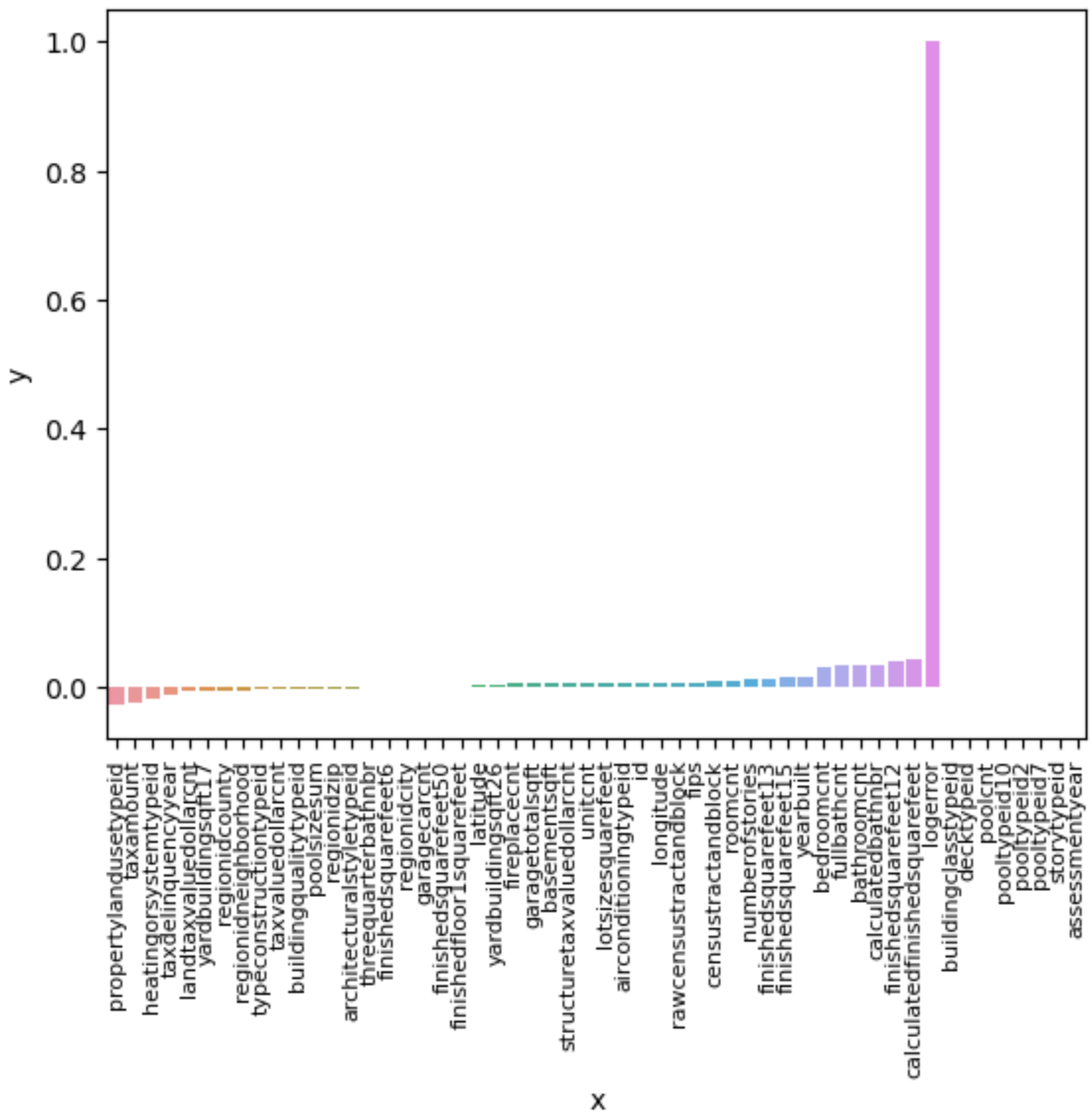
In [176…

```
# fill missing data
df = df.fillna(df.select_dtypes('number').mean())
```

c) univariate analysis

In [178…

```
# make bar chart
corr = pd.DataFrame({'x':df.select_dtypes('number').columns ,'y':[df['logerr
corr = corr.sort_values('y')

# sns.barplot(x = df.select_dtypes('number').columns, y = corr)
sns.barplot(x = corr.x, y = corr.y)
locs, labels = plt.xticks()
plt.xticks(locs, labels = labels, rotation = 'vertical', fontsize = 8)
plt.show()
```



In [179…

```
df.buildingclasstypeid.std()
```

Out[179]: 0.0

explain reason

The variables at the far right of the barplot have no correlation value. This happens because of how the correlation coefficient is calculated, it includes a division by the standard deviation of the variables that it is comparing. If one of the variables has no standard deviation (all values are the same), then that would give a division by zero, so no value is obtained.

d) non-linear regression model

In [180…
```
# drop categorical features
# ("hashottuborspa", "propertycountylandusecode", "propertyzoningdesc", "fir
# drop "id" and "transactiondate"
to_drop = ["hashottuborspa", "propertycountylandusecode", "propertyzoningdes
df = df.drop(columns = to_drop)
```

In [189…
```
# split and train
from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPRegressor
from sklearn.preprocessing import normalize


x_train, x_test, y_train, y_test = train_test_split(df.iloc[:,1:], df.iloc[:

x_train = normalize(x_train)
x_test = normalize(x_test)
```

In [191…
```
regr = MLPRegressor().fit(x_train, y_train)
y_hat = regr.predict(x_test)
```

In [193…
```
# report importances and mse

from sklearn.metrics import mean_squared_error


mse = mean_squared_error(y_test, y_hat)
print("The MSE of the non-linear regressor model is: ", mse)
```

```
The MSE of the non-linear regressor model is:  0.010179118026994059
```

In [ ]:

HW3

2 a) $$L(\alpha,\beta) = \frac{1}{N}\sum_{n=1}^{N}\sum_{k=1}^{K} y^{(n)}\log(\hat{y}_k^{(n)}) = \frac{1}{N}\sum_{n=1}^{N}\sum_{k=1}^{K} y^{(n)}\log\left(\text{softmax}(b_k)\right)$$

i) $$\frac{\partial L}{\partial b_k} = \cancel{\frac{1}{N}\sum_{n=1}^{N}}\sum_{k=1}^{K} y^{(n)}\frac{\frac{\partial \hat{y}_k^{(n)}}{\partial b_k}}{\hat{y}_k^{(n)}} = \cancel{\frac{1}{N}\sum_{n=1}^{N}}\sum_{k=1}^{K} y^{(n)}(1-\hat{y}_k^{(n)})$$

$$\frac{\partial \hat{y}_k^{(n)}}{\partial b_k} = \hat{y}_k^{(n)}(1-\hat{y}_k^{(n)}) \qquad \boxed{\frac{\partial L}{\partial b_k} = \hat{y}_k - y_k}$$

For single output vector $y^{(n)}$ input vector $x^{(n)}$

$$b_k = \sum_{j=0}^{D}\beta_{kj} z_j \qquad z_j = \frac{1}{1+\exp(-a_j)}$$

ii) $$\frac{\partial L}{\partial \beta_{k,j}} = \frac{\partial L}{\partial b_k}\cdot\frac{\partial b_k}{\partial \beta_{k,j}}$$

$$\frac{\partial b_k}{\partial \beta_{k,j}} = \sum_{j=0}^{D} z_j \qquad \boxed{\frac{\partial L}{\partial \beta_{kj}} = \frac{\partial L}{\partial b_k}\cdot\sum_{j=0}^{D} z_j}$$

$$\frac{\partial L}{\partial b_k} = \cancel{\frac{1}{N}\sum_{n=1}^{N}}\sum_{k=1}^{K} y^{(n)}(1-\hat{y}_k^{(n)}) \qquad \frac{\partial L}{\partial \mathbf{b}} = \left[y^{(n)}(1-\hat{y}_1^{(n)}), y^{(n)}(1-\hat{y}_2^{(n)}), \ldots, y^{(n)}(1-\hat{y}_K^{(n)})\right]$$

$$\frac{\partial L}{\partial \beta_{k,j}} = \cancel{\frac{1}{N}\sum_{n=1}^{N}}\underbrace{\sum_{k=1}^{K} y^{(n)}(1-\hat{y}_k^{(n)})}_{\frac{\partial L}{\partial \mathbf{b}}}\cdot\underbrace{\sum_{j=0}^{D} z_j}_{\mathbf{Z}} \qquad \mathbf{Z} = [z_0, z_1, z_2, \ldots, z_D]$$

$$z_j = \frac{1}{1+\exp(-a_j)}$$

$$\frac{\partial L}{\partial \beta} = \cancel{\frac{1}{N}\sum_{n=1}^{N}}\boxed{\frac{\partial L^{(n)}}{\partial \mathbf{b}}\cdot\mathbf{Z}}$$

iii) $$\frac{\partial L}{\partial \mathbf{Z}} = \frac{\partial L}{\partial \mathbf{b}}\cdot\frac{\partial \mathbf{b}}{\mathbf{Z}} \qquad \frac{\partial \mathbf{b}}{\mathbf{Z}} = \beta'$$

$$\frac{\partial L}{\partial \mathbf{Z}} = \cancel{\frac{1}{N}\sum_{k=1}^{N}}\boxed{\frac{\partial L}{\partial \mathbf{b}}\cdot\beta'}$$

iv) $$\frac{\partial L}{\partial \alpha_{j,i}} = \frac{\partial L}{\partial b_k} \cdot \frac{\partial b_k}{\partial z_j} \cdot \frac{\partial z_j}{\partial a_j} \cdot \frac{\partial a_j}{\partial \alpha_{j,i}}$$

$$\frac{\partial L}{\partial b_k} \downarrow \quad \cancel{\frac{1}{N}\sum_{n=1}^{N}} \sum_{k=1}^{K} y^{(n)}\left(1-\hat{y}_k^{(n)}\right)$$

$$\frac{\partial b_k}{\partial z_j} \downarrow \quad \sum_{j=0}^{D} \beta_{kj}$$

$$\frac{\partial z_j}{\partial a_j} \downarrow \quad z_j(1-z_j)$$

$$\frac{\partial a_j}{\partial \alpha_{j,i}} \downarrow \quad \sum_{i=0}^{M} x_i$$

$$\frac{\partial L}{\partial z_j} = \frac{\partial L}{\partial b_k} \frac{\partial b_k}{\partial z_j} = \cancel{\frac{1}{N}\sum_{n=1}^{N}} \sum_{k=1}^{K} y^{(n)}\left(1-\hat{y}_k^{(n)}\right) \cdot \sum_{j=0}^{D} \beta_{kj}$$

$$\boxed{\frac{\partial L}{\partial \alpha_{j,i}} = \frac{\partial L}{\partial z_j} \cdot z_j(1-z_j) \cdot \sum_{i=0}^{M} x_i}$$

$$\mathbf{x} = [x_0, x_1, \ldots, x_M]$$

$$\boxed{\frac{\partial L}{\partial \boldsymbol{\alpha}} = \frac{\partial L}{\partial \mathbf{z}} \cdot \mathbf{z}(1-\mathbf{z}) \cdot \mathbf{x}}$$

Problem 2: Implementing a Multi-layer Perceptron

In [2]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

In [1]:
```
# !pip install seaborn
# Install seaborn (needed to plot confusion matrix) by uncommenting the abov
```

In [525…

```python
def sigmoid_forward(a):
    # calculates the sigmoid activation function
    # a: pre-activation values
    # returns: activated values
    return 1.0 / (1.0 + 1/np.exp(a))

def sigmoid_backward(grad_accum, a):
    # grad_accum: the gradient of the loss function w.r.t to z
    # a: the pre-activation values
    # returns: the gradient of the loss w.r.t to the preactivation values, a
    out = []
    for i in range(len(grad_accum)-1):
        out.append(grad_accum[i+1] *  np.multiply(a, (1.0 - a))[i])
    return np.array(out).T # np.dot(grad_accum[1:], np.multiply(a, (1.0 - a)

def linear_forward(x, weight, bias):
    # Computes the forward pass of the linear layer
    # x: input of layer
    # weight, bias: weights and bias of neural network layer
    # returns: output of linear layer
    x_out = []
    for i_layer, (i_w, i_b) in enumerate(zip(weight, bias)):
        x_out.append(np.dot(x, i_w) + i_b)
    return np.array(x_out)

def linear_backward(grad_accum, x, weight, bias):
    #  Derivative of the linear layer w.r.t
    # grad_accum: gradient of loss w.r.t function after linear layer
    # returns dl_dw: gradient of loss w.r.t to weights
    # returns dl_dx: gradient of loss w.r.t to input, x
    # return dl_dw, dl_dx

    dl_dw = np.dot(np.insert(x, 0, 1, axis = 0), grad_accum).T
    dl_dx = np.dot(grad_accum, np.insert(weight, 0, bias, axis = 1)).T
    return dl_dw, dl_dx

def softmax_xeloss_forward(b, labels):
    # Input parameters:
    ## b: pre-activation
    # calculates the softmax of the vector b
    # calculates the cross entropy loss between the softmax of b and the lab
    # returns: l
    y_hat = np.exp(b-100000) / np.sum(np.exp(b-100000))
    l = np.multiply(labels, np.log(y_hat).T)
    return l

def softmax_xeloss_backward(yhat, labels):
    # Input parameters:
    # yhat: predictions of the neural network
    # labels: target of the network
    # returns: dl_db gradient of loss w.r.t to b
    return yhat - labels

def data_load():
    # load in the data provided in "data/"
    # Unzip fashion mnist.zip
```

```
    # Unzipped manually because I wasn unsure if I could import zipfile for
    x_train = pd.read_csv('./data/train.csv', header=None)
    x_test = pd.read_csv('./data/test.csv', header=None)

    y_train = x_train.iloc[:,-1]
    x_train = x_train.drop(x_train.columns[[-1]], axis = 1)
    y_test = x_test.iloc[:,-1]
    x_test = x_test.drop(x_test.columns[[-1]], axis = 1)

    return x_train, y_train, x_test, y_test

def load_params():
    alpha_weights = np.loadtxt('params/alpha1.txt', delimiter=',')
    beta_weights = np.loadtxt('params/alpha2.txt', delimiter=',')
    alpha_bias= np.loadtxt('params/beta1.txt', delimiter=',')
    beta_bias = np.loadtxt('params/beta2.txt', delimiter=',')
    return alpha_weights, beta_weights, alpha_bias, beta_bias

def one_hot_encode(y):
    # convert categorical target features to one hot encoded data
    labels = np.sort(y.unique())
    y_encoded = pd.DataFrame(np.zeros((len(y), len(labels))), columns = labe
    for i in labels:
        y_encoded.loc[y == i, str(i)] = 1
    return y_encoded




def train(batchsize=1 , eta = 0.01, num_epochs=100, h = 256, init='default')
    X_train, y_train, X_test, y_test = data_load()

    y_train = one_hot_encode(y_train)
    y_test = one_hot_encode(y_test)

    if init == 'default':
        alpha_weights, beta_weights, alpha_bias, beta_bias = load_params()
    elif init=='zeros':
        # initialize weights and biases to 0
        alpha_weights = np.zeros(h * len(X_train.columns))
        beta_weights = np.zeros(h * len(y_train.columns))
        alpha_bias = np.zeros(h)
        beta_bias = np.zeros(len(y_train.columns))
    elif init=='ones':
        # initialize weights and biases to 1
        alpha_weights = np.ones(h * len(X_train.columns))
        beta_weights = np.ones(h * len(y_train.columns))
        alpha_bias = np.ones(h)
        beta_bias = np.ones(len(y_train.columns))
    elif init=='random':
        # initialize weights and biases to random values between -1 and 1
        alpha_weights = np.random.uniform(-1, 1, h * len(X_train.columns))
        beta_weights = np.random.uniform(-1, 1, h * len(y_train.columns))
        alpha_bias = np.random.uniform(-1, 1, h)
        beta_bias = np.random.uniform(-1, 1, len(y_train.columns))
```

```
train_loss_list = []
test_loss_list = []
acc_list = []


for epoch in (range(num_epochs)):
    #continue
    error = []
    y_pred_train = np.zeros_like(y_train)
    # Iterate over batches of data
    for i in range(batchsize):

        # do not shuffle data

        # select batch
        X_sample = X_train[i: i + 1]
        y_sample = y_train[i: i + 1]


        ######## FORWARD
        # Linear -> Sigmoid -> Linear -> Softmax
        forward1 = linear_forward(X_sample, alpha_weights, alpha_bias)
        activation1 = sigmoid_forward(forward1)
        forward2 = linear_forward(activation1.T, beta_weights, beta_bias
        y_pred_train[i:i+1] = (np.exp(forward2) / np.sum(np.exp(forward2
        error.append(softmax_xeloss_forward(forward2, y_sample))

        ######## BACKWARD
        grad_softmax = softmax_xeloss_backward(y_pred_train[i], y_sample
        grad_beta, grad_z = linear_backward(grad_softmax, activation1, b
        grad_sigmoid = sigmoid_backward(grad_z, forward1)
        grad_alpha, grad_x = linear_backward(grad_sigmoid, X_sample.to_n

        ######## UPDATE
        alpha_weights = alpha_weights - eta * grad_alpha[:,1:]
        alpha_bias = alpha_bias - eta * grad_alpha[:,0]
        beta_weights = beta_weights - eta * grad_beta[:,1:]
        beta_bias = beta_bias - eta * grad_beta[:,0]



    # store average training loss for the epoch
    error.append(softmax_xeloss_forward(forward2, y_sample))
    train_loss_list.append(np.mean(error))

    # calculate test predictions and loss
    error = []
    y_pred_test = np.zeros_like(y_test)
    # Iterate over batches of data
    for i in range(batchsize):

        # do not shuffle data

        # select batch
        x_sample = X_test[i: i + 1]
        y_sample = y_test[i: i + 1]
```

```
#             alpha_weights = alpha_weights[i:((i + 1) * 784)]
#             beta_weights = beta_weights[i:((i + 1) * 256)]

            ######## FORWARD
            forward1 = linear_forward(X_sample, alpha_weights, alpha_bias)
            activation1 = sigmoid_forward(forward1)
            forward2 = linear_forward(activation1.T, beta_weights, beta_bias
            y_pred_test[i:i+1] = (np.exp(forward2) / np.sum(np.exp(forward2)
            error.append(softmax_xeloss_forward(forward2, y_sample))
        error.append(softmax_xeloss_forward(forward2, y_sample))
        test_loss_list.append(np.mean(error))

        # calculate test accuracy
        total = len(y_test)
        correct = (y_pred_test == y_test).sum()
        acc_list.append(correct/float(total))
    # return train_loss_list, test_loss_list, as well as test and train pred
    #pass
    return train_loss_list, test_loss_list, y_pred_train, y_pred_test
```

Plot Loss

In [240…

```
# Plot training loss, testing loss as a function of epochs
```

In [526…

```
train_loss, test_loss, train_pred, test_pred = train()
```

```
/var/folders/9_/zlyt_0jn1cj4plrbb7kf80d80000gn/T/ipykernel_45340/615367044.
py:43: RuntimeWarning: invalid value encountered in true_divide
  y_hat = np.exp(b-100000) / np.sum(np.exp(b-100000))
/var/folders/9_/zlyt_0jn1cj4plrbb7kf80d80000gn/T/ipykernel_45340/615367044.
py:5: RuntimeWarning: overflow encountered in exp
  return 1.0 / (1.0 + 1/np.exp(a))
/var/folders/9_/zlyt_0jn1cj4plrbb7kf80d80000gn/T/ipykernel_45340/615367044.
py:5: RuntimeWarning: divide by zero encountered in true_divide
  return 1.0 / (1.0 + 1/np.exp(a))
/var/folders/9_/zlyt_0jn1cj4plrbb7kf80d80000gn/T/ipykernel_45340/615367044.
py:5: RuntimeWarning: overflow encountered in true_divide
  return 1.0 / (1.0 + 1/np.exp(a))
/var/folders/9_/zlyt_0jn1cj4plrbb7kf80d80000gn/T/ipykernel_45340/615367044.
py:13: RuntimeWarning: overflow encountered in multiply
  out.append(grad_accum[i+1] *  np.multiply(a, (1.0 - a))[i])
```

Confusion Matrix

In [484…
```python
def plot_confusion(yhat, y, title = '[Training or Test] Set'):

    pred_train = np.argmax(yhat, axis=1)
    true_train = np.argmax(y, axis=1)
    print(true_train.shape)
    conf_train = np.zeros((10,10))
    for i in range(len(y)):
        conf_train[ true_train[i], pred_train[i] ] += int(1)

    sns.heatmap(conf_train, annot=True, fmt='.3g')
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.title('Title')
    plt.show()
# plot_confusion(yhat_train, y_train, title = "Training Set")
# plot_confusion(yhat_test, y_test, title = "Test Set")
#yhat: predictions
#y: one-hot-encoded labels
```

Correct and Incorrect Classification Samples

In [485…
```python
def plot_image(vector, out_f_name, label=None):
    """
    Takes a vector as input of size (784) and saves as an image
    """
    image = np.asarray(vector).reshape(28, 28)
    plt.imshow(image, cmap='gray')
    if label:
        plt.title(label)
    plt.axis('off')
    plt.savefig(f'{out_f_name}.png', bbox_inches='tight')
    plt.show()
```

In [ ]:
```python
# Use plot_image function to display samples that are correctly and incorrec
```

Effect Of Learning Rate

Effect of Initialization

Question 3: CIFAR-10 Classification using CNN

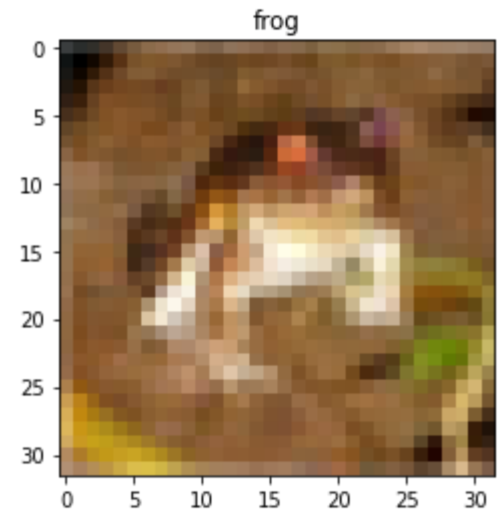
- Please **do not** change the default variable names in this problem, as we will use them in different parts.
- The default variables are initially set to "None".

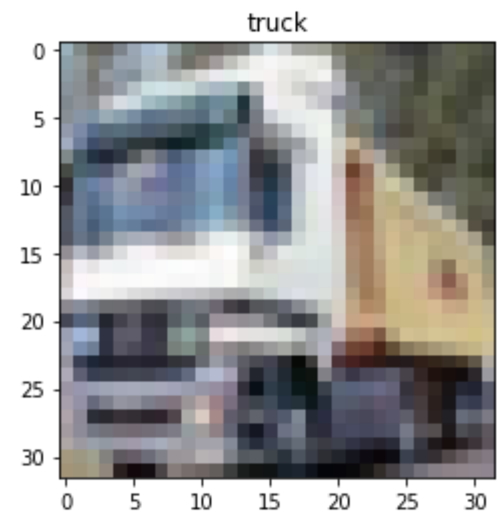
In [1]:
```
import numpy as np # linear algebra
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torchvision
from torchvision import datasets, transforms, models
from torch.utils.data import *
import random
from tqdm import tqdm
import warnings
```

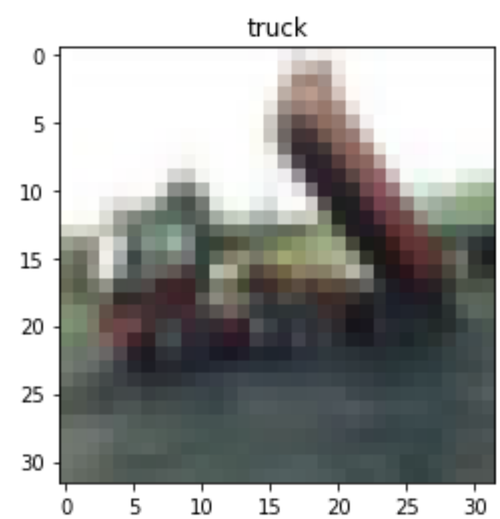
In [2]:
```
def imshow(img):
  img = img / 2 + 0.5    # unnormalize
  npimg = img.numpy()    # convert from tensor
  plt.imshow(np.transpose(npimg, (1, 2, 0)))
  plt.show()
```

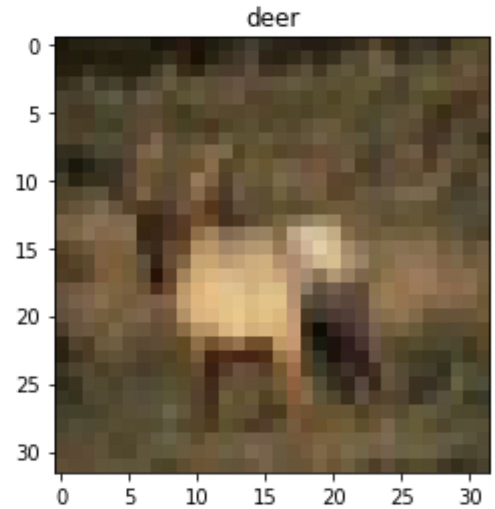
In [3]:
```
# The below two lines are optional and are just there to avoid any SSL
# related errors while downloading the CIFAR-10 dataset
import ssl
ssl._create_default_https_context = ssl._create_unverified_context

#Initializing normalizing transform for the dataset
normalize_transform = torchvision.transforms.Compose([
    torchvision.transforms.ToTensor(),
    torchvision.transforms.Normalize(mean = (0.5, 0.5, 0.5),
                                     std = (0.5, 0.5, 0.5))])

#Downloading the CIFAR10 dataset into train and test sets
train_dataset = torchvision.datasets.CIFAR10(
    root="./CIFAR10/train", train=True,
    transform=normalize_transform,
    download=True)

test_dataset = torchvision.datasets.CIFAR10(
    root="./CIFAR10/test", train=False,
    transform=normalize_transform,
    download=True)


#Generating data loaders from the corresponding datasets
batch_size = 128
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_size)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_size)




classes = ('plane', 'car', 'bird', 'cat', 'deer', 'dog',
'frog', 'horse', 'ship', 'truck')

# get first 100 training images
dataiter = iter(train_loader)
imgs, lbls = dataiter.next()

for i in range(20):
    plt.title(classes[lbls[i]])
    imshow(imgs[i])
```

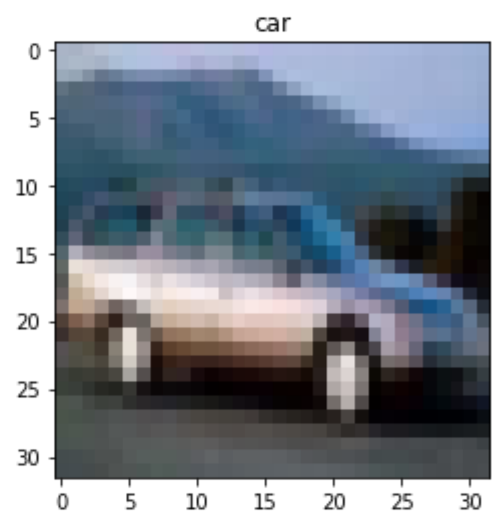
```
Files already downloaded and verified
Files already downloaded and verified
```

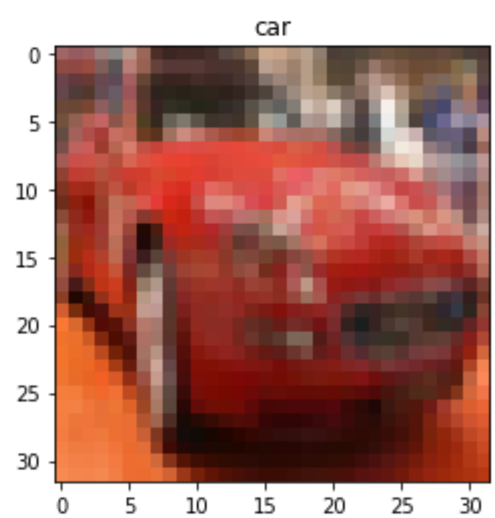

frog
0
5
10
15
20
25
30
0 5 10 15 20 25 30


truck
0
5
10
15
20
25
30
0 5 10 15 20 25 30

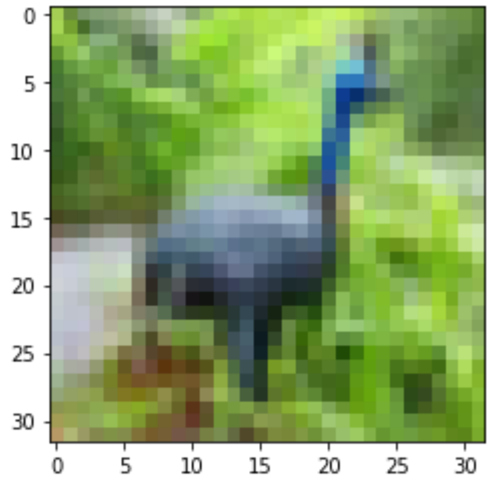

truck
0
5
10
15
20
25
30
0 5 10 15 20 25 30


deer

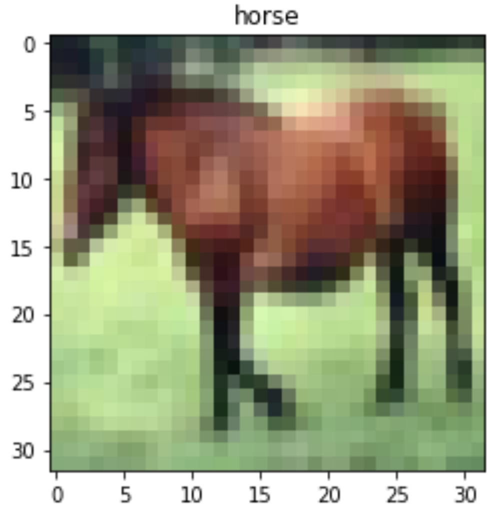

car


car

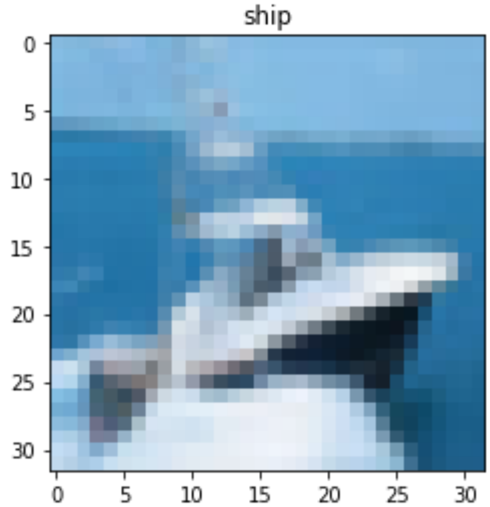
bird



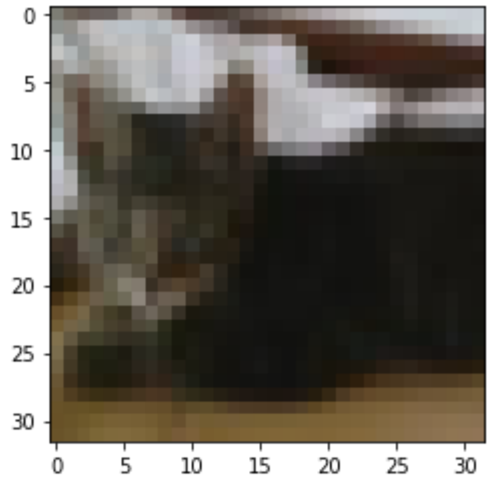
horse



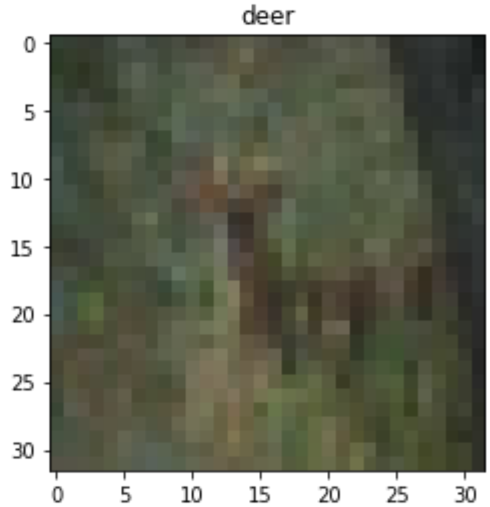
ship



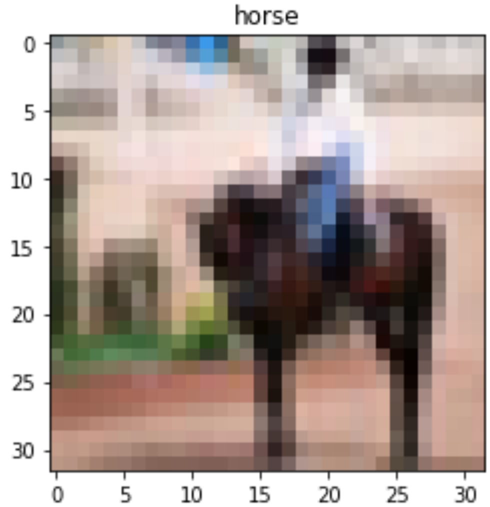
cat



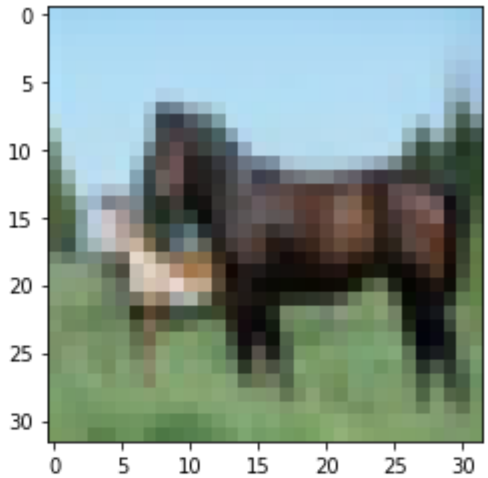
deer



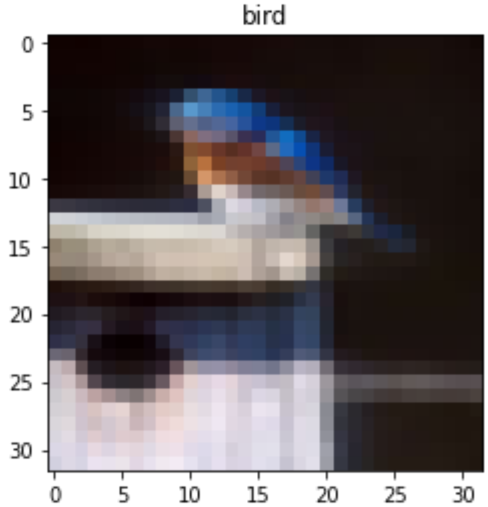
horse



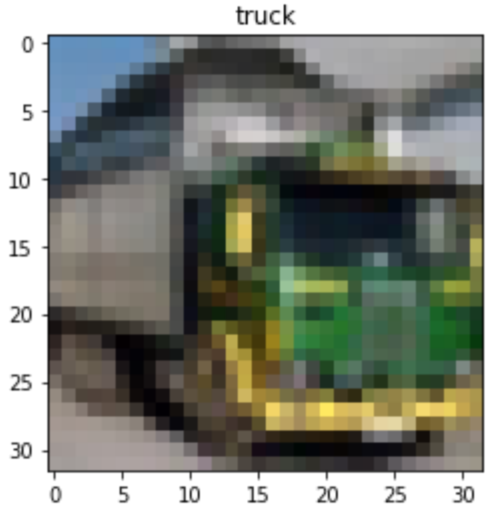
horse



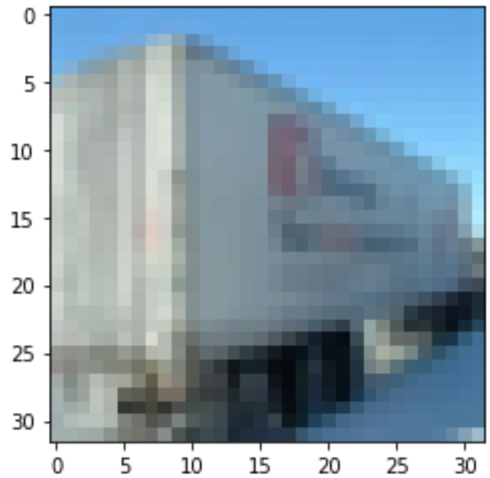
bird



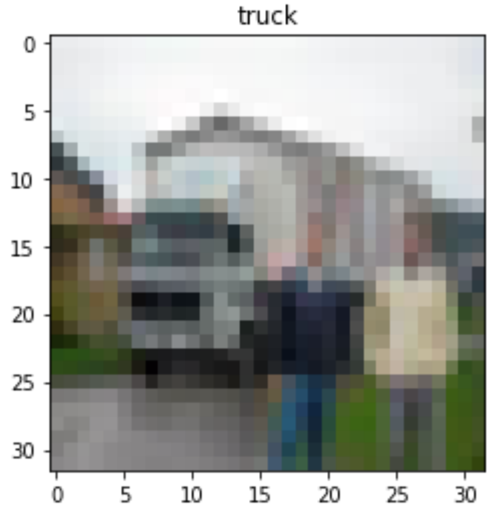
truck



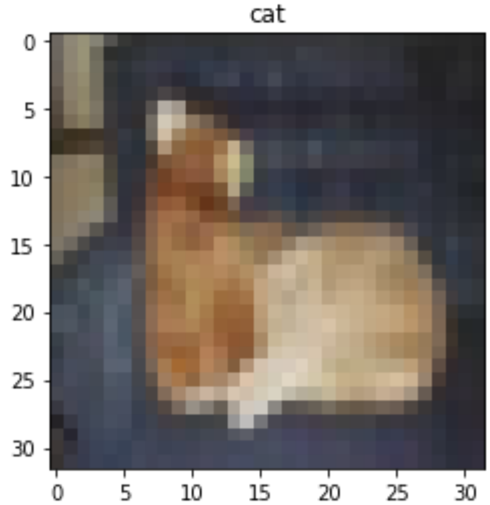
truck

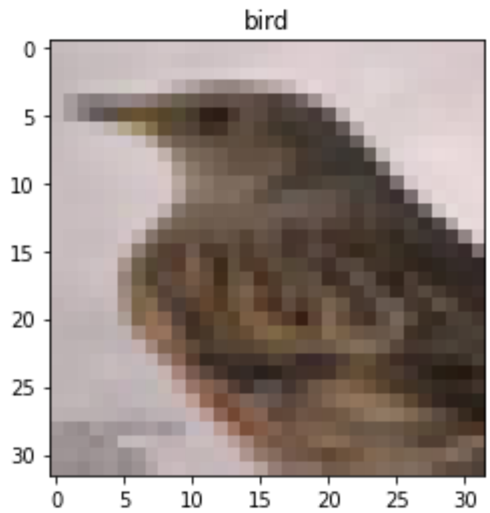


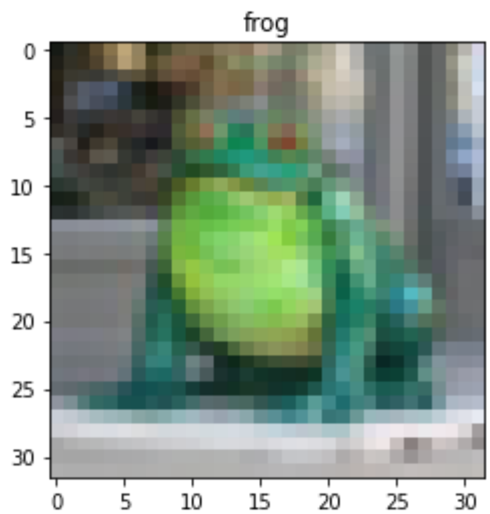
truck



cat







In [4]:
```
# check pytorch cuda and use cuda if possible
device = torch.cuda.is_available()
print('*' * 50)
if torch.cuda.is_available():
  print('CUDA is found! Tranining on %s.......'%torch.cuda.get_device_name(0))
else:
  warnings.warn('CUDA not found! Training may be slow......')
```

```
**************************************************
CUDA is found! Tranining on NVIDIA GeForce RTX 2070 SUPER.......
```

P1. Build you own CNN model

TODO

- Design your model class in **CNNModel(nn.Module)** and write forward pass in **forward(self, x)**
- Create loss function in **error**, optimizer in **optimizer**
- Define hyparparameters: **learning_rate**, **num_epochs**
- Plot your **loss vs num_epochs** and **accuracy vs num_epochs**

Hints

- Start with low number of epochs for debugging. (eg. num_epochs=1)
- Be careful with the input dimension of fully connected layer.
- The dimension calculation of the output tensor from the input tensor is \ $D_{out} = \frac{D_{in} - K + 2P}{S} + 1$ \ D_{out} : Dimension of output tensor \ D_{in} : Dimension of input tensor \ K : width/height of the kernel \ S : stride \ P : padding

Convolutional and Pooling Layers

A convolutional layer using pyTorch:

```
torch.nn.Conv2d(num_in_channels, num_out_channels, kernel_size,
stride=1, padding=0, dilation=1, groups=1, bias=True,
padding_mode='zeros', device=None, dtype=None)
```

For example:

```
torch.nn.Conv2d(3, 32, 3)
```

It applies a 2D convolution over an input signal composed of several input planes. If we have input size with (N, C_{in}, H, W) and output size with $(N, C_{out}, H_{out}, W_{out})$, the 2D convolution can described as

$$out(N_i, C_{out_j}) = bias(C_{out_j}) + \sum_{k=0}^{C_{in}-1} weight(C_{out_j}, k) \star input(N_i, k)$$

num_in_channels: is the number of channels of the input tensor. If the previous layer is the input layer, num_in_channels is the number of channels of the image (3 channels for RGB images), otherwise num_in_channels is equal to the number of feature maps of the previous layer.

num_out_channels: is the number of filters (feature extractor) that this layer will apply over the image or feature maps generated by the previous layer.

the image or feature maps generated by the previous layer.

kernel_size: is the size of the convolving kernel

stride: is the stride of the convolution. Default: 1

padding: is the padding added to all four sides of the input. Default: 0

dilation: is the spacing between kernel elements. Default: 1

group: is the number of blocked connections from input channels to output channels. Default: 1

bias: If True, adds a learnable bias to the output. Default: True

A Simple Convolutional Neural Network

In our convnet we'll initally use this structure shown below:

input -> convolution -> fully connected -> output \

At the end of the last convolutional layer, we get a tensor of dimension (num_channels, height, width). Since now we are going to feed it to a fully connected layer, we need to convert it into a 1-D vector, and for that we use the reshape method:

```
x = x.view(x.size(0), -1)
```

The way of calculating size of the output size from previous convolution layer can be formulized as below:

$$H_{output} = \frac{H_{in} + 2 \times padding - kernel\_Size}{stride} + 1$$

For more details, you can refer to this link: \ https://pytorch.org/docs/stable/generated/torch.nn.Conv2d.html

In [26]:
```
class CNNModel(nn.Module):
  def __init__(self):
    super(CNNModel, self).__init__()
    # TODO: Create CNNModel using 2D convolution. You should vary the number of con
    # In this function, you should define each of the individual components of the
    # Example:
    # self.cnn1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=5, stride=1
    # self.relu1 = nn.ReLU()
    # self.maxpool1 = nn.MaxPool2d(kernel_size=2)

    # convolution layer 1. using kernel_size = 5 to obtain the output of 28x28
    self.cnn1 = nn.Conv2d(in_channels=3, out_channels=6, kernel_size=5, stride=1, p
    self.relu1 = nn.ReLU()

    # convolution layer 2. using kernel_size = 3 to obtain the output of 26x26
    self.cnn2 = nn.Conv2d(in_channels=6, out_channels=16, kernel_size=3, stride=1,
```

```
        self.relu2 = nn.ReLU()

        # convolution layer 3. using kernel_size = 3 to obtain the output of 24x24
        self.cnn3 = nn.Conv2d(in_channels=16, out_channels=24, kernel_size=3, stride=1,
        self.relu3 = nn.ReLU()

        # TODO: Create Fully connected layers. You should calculate the dimension of th
        # Example:
        # self.fc1 = nn.Linear(16 *110 * 110, 5)

        # Fully connected 1
        self.fc1 = nn.Linear(24 * 24 * 24, 120)
        self.relu4 = nn.ReLU()

        # Fully connected 2
        self.fc2 = nn.Linear(120, 84)
        self.relu5 = nn.ReLU()

        # Fully connected 3
        self.fc3 = nn.Linear(84, 10)

        self.i = 0

    def forward(self,x):

        # TODO: Perform forward pass in below section
        # In this function, you will apply the components defined earlier to the input,
        # Example:
        # out = self.cnn1(x)
        # out = self.relu1(out)
        # out = self.maxpool1(out)
        # to visualize feature map in part a, part b.i), use the following three lines:
        # plt.imshow(out[0][0].cpu().detach().numpy())
        # plt.show()
```

In [27]:

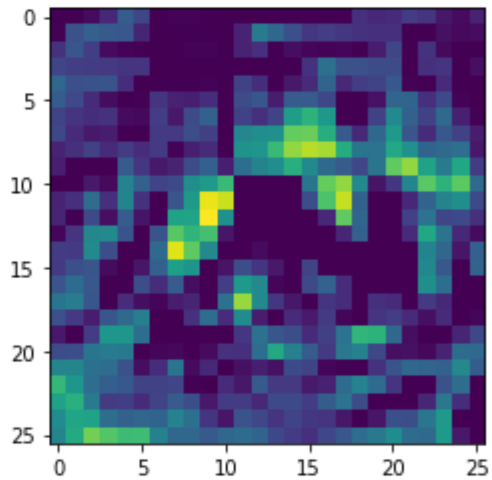
```
# Create CNN
device = "cuda" if torch.cuda.is_available() else "cpu"
model = CNNModel()
model.to(device)

# TODO: define Cross Entropy Loss
error = nn.CrossEntropyLoss()

# TODO: create Adam Optimizer and define your hyperparameters
learning_rate = 0.001
optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
num_epochs = 20
```

```
            plt.close('all')
            self.i += 1

        out = self.cnn3(out)
        out = self.relu3(out)

        out = out.view(out.size(0), -1)
        out = self.fc1(out)
        out = self.fc2(out)
        out = self.fc3(out)

        return out
```

In [28]:

```
count = 0
loss_list = []
iteration_list = []
accuracy_list = []
for epoch in tqdm(range(num_epochs)):
    model.train()
    for i, (images, labels) in enumerate(train_loader):
        images, labels = images.to(device), labels.to(device)

        # Clear gradients
        optimizer.zero_grad()

        # TODO: Forward propagation
        outputs = model(images)

        # TODO: Calculate softmax and cross entropy loss
        loss = error(outputs, labels)

        # Backprop agate your Loss
        loss.backward()

        # Update CNN model
        optimizer.step()

        count += 1

        if count % 50 == 0:
            model.eval()
            # Calculate Accuracy
            correct = 0
            total = 0
            # Iterate through test dataset
            for images, labels in test_loader:
                images, labels = images.to(device), labels.to(device)

                # Forward propagation
                outputs = model(images)

                # Get predictions from the maximum value
                predicted = torch.argmax(outputs,1)

                # Total number of labels
                total += len(labels)

                correct += (predicted == labels).sum()

            accuracy = 100 * correct / float(total)

            # store loss and iteration
            loss_list.append(loss.item())
            iteration_list.append(count)
            accuracy_list.append(accuracy.item())
        if count % 500 == 0:
            # Print Loss
            print('Iteration: {}  Loss: {}  Accuracy: {} %'.format(count, loss.data
```

```
  0%|          | 0/20 [00:00<?, ?it/s]
```



```
  5%|▌         | 1/20 [00:19<06:01, 19.03s/it]
Iteration: 500  Loss: 1.33452570438385  Accuracy: 52.84000015258789 %
 10%|█         | 2/20 [00:39<05:57, 19.84s/it]
Iteration: 1000  Loss: 1.1488442420959473  Accuracy: 58.63999938964844 %
 15%|█▌        | 3/20 [00:59<05:41, 20.06s/it]
Iteration: 1500  Loss: 0.913888156414032  Accuracy: 61.1099967956543 %
 25%|██▌       | 5/20 [01:40<05:03, 20.25s/it]
Iteration: 2000  Loss: 0.8821907043457031  Accuracy: 60.56999969482422 %
 30%|███       | 6/20 [01:59<04:36, 19.77s/it]
Iteration: 2500  Loss: 0.7237609028816223  Accuracy: 59.119998931884766 %
 35%|███▌      | 7/20 [02:19<04:19, 19.97s/it]
Iteration: 3000  Loss: 0.8468115925788879  Accuracy: 55.03999710083008 %
 40%|████      | 8/20 [02:40<04:00, 20.08s/it]
Iteration: 3500  Loss: 0.5502995252609253  Accuracy: 55.209999084472656 %
 50%|█████     | 10/20 [03:20<03:22, 20.22s/it]
Iteration: 4000  Loss: 0.5978149175643921  Accuracy: 51.44999694824219 %
 55%|█████▌    | 11/20 [03:41<03:02, 20.26s/it]
Iteration: 4500  Loss: 0.4748920500278473  Accuracy: 53.459999084472656 %
 60%|██████    | 12/20 [03:59<02:38, 19.81s/it]
Iteration: 5000  Loss: 0.41435378789901733  Accuracy: 51.709999084472656 %
 70%|███████   | 14/20 [04:40<02:00, 20.05s/it]
Iteration: 5500  Loss: 0.5298575162887573  Accuracy: 53.89999771118164 %
 75%|███████▌  | 15/20 [05:00<01:40, 20.13s/it]
Iteration: 6000  Loss: 0.6019865870475769  Accuracy: 50.04999923706055 %
 80%|████████  | 16/20 [05:21<01:20, 20.18s/it]
Iteration: 6500  Loss: 0.5004005432128906  Accuracy: 50.369998931884766 %
 85%|████████▌ | 17/20 [05:39<00:59, 19.76s/it]
Iteration: 7000  Loss: 0.3183412253856659  Accuracy: 52.16999816894531 %
 95%|█████████▌| 19/20 [06:20<00:20, 20.02s/it]
Iteration: 7500  Loss: 0.20209279656410217  Accuracy: 51.59000015258789 %
100%|██████████| 20/20 [06:40<00:00, 20.03s/it]
```

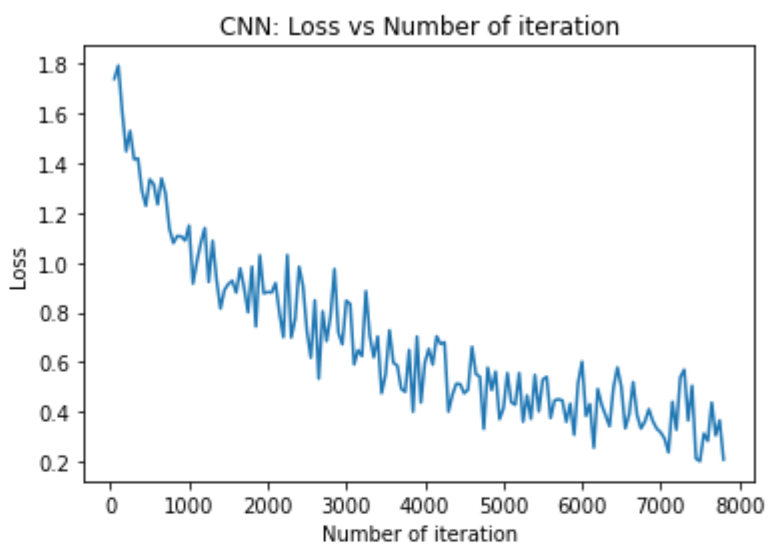
In [29]:

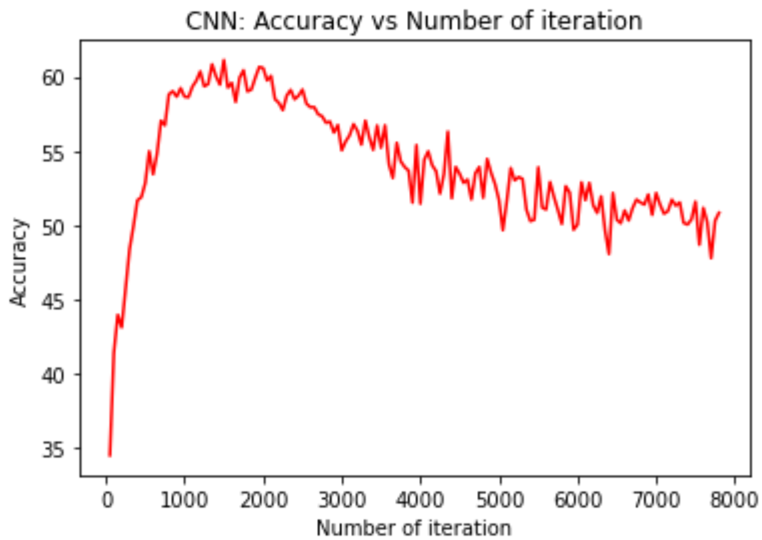
```
# !pip install torchsummary
# uncomment above line if you don't have torchsummary installed yet
# Print torchsummary of model
from torchsummary import summary
print(summary(model, input_size=(3, 32, 32)))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1            [-1, 6, 28, 28]             456
              ReLU-2            [-1, 6, 28, 28]               0
            Conv2d-3           [-1, 16, 26, 26]             880
              ReLU-4           [-1, 16, 26, 26]               0
            Conv2d-5           [-1, 24, 24, 24]           3,480
              ReLU-6           [-1, 24, 24, 24]               0
            Linear-7                  [-1, 120]       1,659,000
            Linear-8                   [-1, 84]          10,164
            Linear-9                   [-1, 10]             850
================================================================
Total params: 1,674,830
Trainable params: 1,674,830
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 0.45
Params size (MB): 6.39
Estimated Total Size (MB): 6.85
----------------------------------------------------------------
None
```

In [30]:

```
# visualization loss
plt.plot(iteration_list,loss_list)
plt.xlabel("Number of iteration")
plt.ylabel("Loss")
plt.title("CNN: Loss vs Number of iteration")
plt.show()

# visualization accuracy
plt.plot(iteration_list,accuracy_list,color = "red")
plt.xlabel("Number of iteration")
plt.ylabel("Accuracy")
plt.title("CNN: Accuracy vs Number of iteration")
plt.show()
```

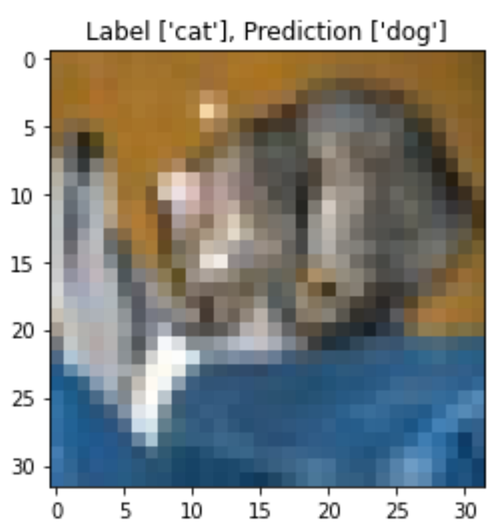




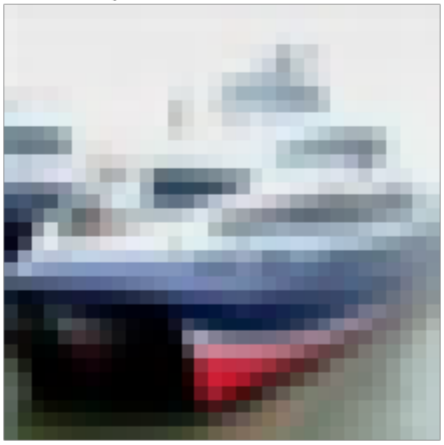
Evaluating the Model

In [33]:

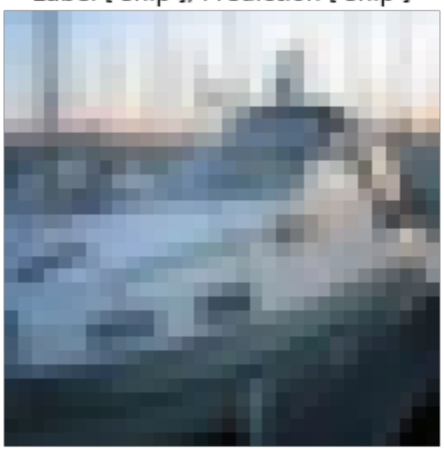
```
#To-do: evaluate on test set, instead of training set
random_image = random.randint(0,len(test_dataset))
image = test_dataset.__getitem__(random_image)
model.eval()
images, labels = next(iter(test_loader))
images, labels = images.to(device), labels.to(device)
predictions = torch.argmax(model(images),1)
num_cols=1
num_rows = 5# len(labels)
label_map = [['airplane'],['automobile'],['bird'],['cat'], ['deer'], ['dog'], ['fro

for idx in range(num_rows):
  img = images.cpu()[idx]

  plt.title(f"Label {label_map[labels[idx]]}, Prediction {label_map[predictions[idx
  imshow(img)

  plt.axis('off')
plt.show()
```



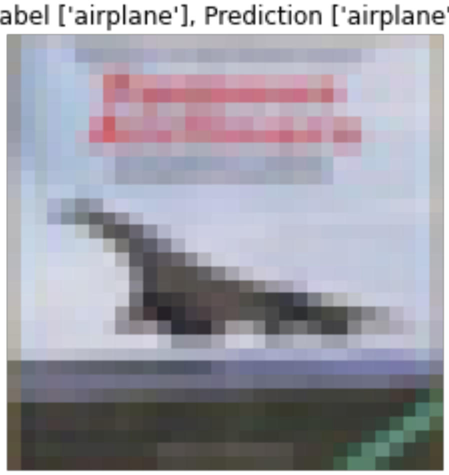
Label ['ship'], Prediction ['automobile']



Label ['ship'], Prediction ['ship']



Label ['airplane'], Prediction ['airplane']



Label ['frog'], Prediction ['frog']

In [36]:
```
class CNNModel2(nn.Module):
  def __init__(self):
    super(CNNModel2, self).__init__()
    # TODO: Create CNNModel using 2D convolution. You should vary the number of con
    # In this function, you should define each of the individual components of the
    # Example:
    # self.cnn1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=5, stride=1
    # self.relu1 = nn.ReLU()
    # self.maxpool1 = nn.MaxPool2d(kernel_size=2)

    # convolution layer 1. using kernel_size = 5 to obtain the output of 28x28
    self.cnn1 = nn.Conv2d(in_channels=3, out_channels=6, kernel_size=5, stride=1, p
    self.relu1 = nn.ReLU()

    # convolution layer 2. using kernel_size = 3 to obtain the output of 26x26
    self.cnn2 = nn.Conv2d(in_channels=6, out_channels=16, kernel_size=3, stride=1,
    self.relu2 = nn.ReLU()
    # maxpool layer 1 added to obtain output of 13x13
    self.maxpool1 = nn.MaxPool2d(kernel_size=2)

    # convolution layer 3. using kernel_size = 3 to obtain the output of 11x11
    self.cnn3 = nn.Conv2d(in_channels=16, out_channels=24, kernel_size=3, stride=1,
    self.relu3 = nn.ReLU()

    # TODO: Create Fully connected layers. You should calculate the dimension of th
    # Example:
    # self.fc1 = nn.Linear(16 *110 * 110, 5)

    # Fully connected 1
    self.fc1 = nn.Linear(24 * 11 * 11, 120)
    self.relu4 = nn.ReLU()

    # Fully connected 2
    self.fc2 = nn.Linear(120, 84)
    self.relu5 = nn.ReLU()

    # Fully connected 3
    self.fc3 = nn.Linear(84, 10)

    self.i = 0

  def forward(self,x):

    # TODO: Perform forward pass in below section
    # In this function, you will apply the components defined earlier to the input,
    # Example:
    # out = self.cnn1(x)
    # out = self.relu1(out)
    # out = self.maxpool1(out)
    # to visualize feature map in part a, part b.i), use the following three lines:
    # plt.imshow(out[0][0].cpu().detach().numpy())
    # plt.show()
    # plt.close('all')
    # out = out.view(out.size(0), -1)
    # out = self.fc1(out)

    out = self.cnn1(x)
    out = self.relu1(out)
```

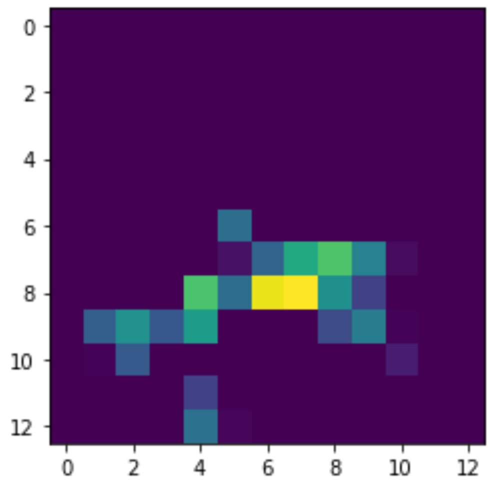
```
        out = self.cnn2(out)
        out = self.relu2(out)
        out = self.maxpool1(out)

        if self.i == 0:
            plt.imshow(out[0][0].cpu().detach().numpy())
            plt.show()
            plt.close('all')
            self.i += 1

        out = self.cnn3(out)
        out = self.relu3(out)

        out = out.view(out.size(0), -1)
        out = self.fc1(out)
        out = self.fc2(out)
        out = self.fc3(out)

        return out
```

In [37]:
```
# Create CNN
device = "cuda" if torch.cuda.is_available() else "cpu"
model2 = CNNModel2()
model2.to(device)

# TODO: define Cross Entropy Loss
error = nn.CrossEntropyLoss()

# TODO: create Adam Optimizer and define your hyperparameters

optimizer2 = torch.optim.Adam(model2.parameters(), lr=learning_rate)
```

In [38]:

```python
count = 0
loss_list2 = []
iteration_list2 = []
accuracy_list2 = []
for epoch in tqdm(range(num_epochs)):
    model2.train()
    for i, (images, labels) in enumerate(train_loader):
        images, labels = images.to(device), labels.to(device)

        # Clear gradients
        optimizer2.zero_grad()

        # TODO: Forward propagation
        outputs = model2(images)

        # TODO: Calculate softmax and cross entropy loss
        loss = error(outputs, labels)

        # Backprop agate your Loss
        loss.backward()

        # Update CNN model
        optimizer2.step()

        count += 1

        if count % 50 == 0:
            model2.eval()
            # Calculate Accuracy
            correct = 0
            total = 0
            # Iterate through test dataset
            for images, labels in test_loader:
                images, labels = images.to(device), labels.to(device)

                # Forward propagation
                outputs = model2(images)

                # Get predictions from the maximum value
                predicted = torch.argmax(outputs,1)

                # Total number of labels
                total += len(labels)

                correct += (predicted == labels).sum()

            accuracy = 100 * correct / float(total)

            # store loss and iteration
            loss_list2.append(loss.item())
            iteration_list2.append(count)
            accuracy_list2.append(accuracy.item())
        if count % 500 == 0:
            # Print Loss
            print('Iteration: {}  Loss: {}  Accuracy: {} %'.format(count, loss.data
```

```
  0%|          | 0/20 [00:00<?, ?it/s]
```




```
  5%|▌         | 1/20 [00:19<06:03, 19.11s/it]
Iteration: 500  Loss: 1.340271234512329  Accuracy: 51.28999710083008 %
 10%|█         | 2/20 [00:39<05:58, 19.92s/it]
Iteration: 1000  Loss: 1.136545181274414  Accuracy: 59.029998779296875 %
 15%|█▌        | 3/20 [00:59<05:42, 20.12s/it]
Iteration: 1500  Loss: 0.966973066329956  Accuracy: 61.46999740600586 %
 25%|██▌       | 5/20 [01:40<05:04, 20.29s/it]
Iteration: 2000  Loss: 0.9164866209030151  Accuracy: 63.22999954223633 %
 30%|███       | 6/20 [01:59<04:38, 19.88s/it]
Iteration: 2500  Loss: 1.0408035516738892  Accuracy: 64.33000183105469 %
 35%|███▌      | 7/20 [02:20<04:20, 20.05s/it]
Iteration: 3000  Loss: 1.1702224016189575  Accuracy: 64.4000015258789 %
 40%|████      | 8/20 [02:40<04:02, 20.19s/it]
Iteration: 3500  Loss: 0.7907053232192993  Accuracy: 65.05999755859375 %
 50%|█████     | 10/20 [03:21<03:23, 20.34s/it]
Iteration: 4000  Loss: 0.7402896881103516  Accuracy: 62.369998931884766 %
 55%|█████▌    | 11/20 [03:42<03:03, 20.37s/it]
Iteration: 4500  Loss: 0.6377255320549011  Accuracy: 64.15999603271484 %
 60%|██████    | 12/20 [04:01<02:39, 19.95s/it]
Iteration: 5000  Loss: 0.7986494898796082  Accuracy: 64.18000030517578 %
 70%|███████   | 14/20 [04:42<02:01, 20.28s/it]
Iteration: 5500  Loss: 0.7745624780654907  Accuracy: 63.34000015258789 %
 75%|███████▌  | 15/20 [05:02<01:41, 20.32s/it]
Iteration: 6000  Loss: 0.5210683941841125  Accuracy: 63.23999786376953 %
 80%|████████  | 16/20 [05:23<01:21, 20.33s/it]
Iteration: 6500  Loss: 0.7801148295402527  Accuracy: 63.21999740600586 %
 85%|████████▌ | 17/20 [05:42<00:59, 19.89s/it]
Iteration: 7000  Loss: 0.7312436103820801  Accuracy: 64.0999984741211 %
 95%|█████████▌| 19/20 [06:22<00:20, 20.12s/it]
Iteration: 7500  Loss: 0.8021711111068726  Accuracy: 62.18000030517578 %
100%|██████████| 20/20 [06:43<00:00, 20.15s/it]
```

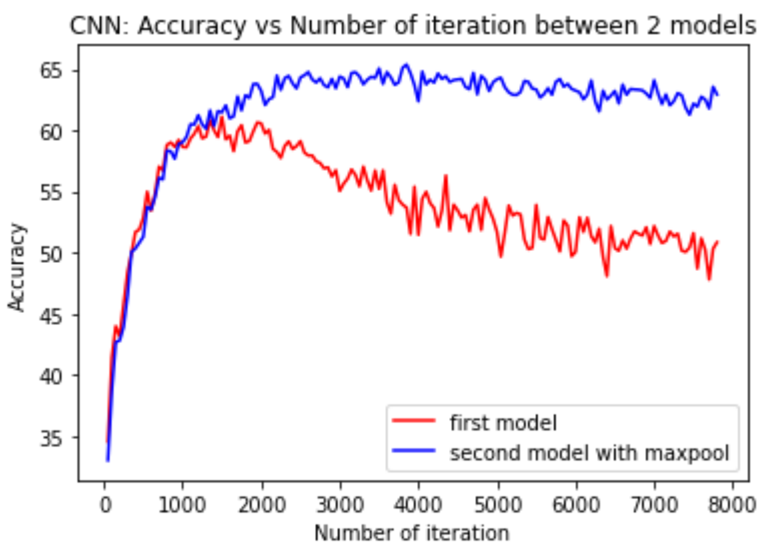
In [39]:

```python
from torchsummary import summary
print(summary(model2, input_size=(3, 32, 32)))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1            [-1, 6, 28, 28]             456
              ReLU-2            [-1, 6, 28, 28]               0
            Conv2d-3           [-1, 16, 26, 26]             880
              ReLU-4           [-1, 16, 26, 26]               0
         MaxPool2d-5           [-1, 16, 13, 13]               0
            Conv2d-6           [-1, 24, 11, 11]           3,480
              ReLU-7           [-1, 24, 11, 11]               0
            Linear-8                  [-1, 120]         348,600
            Linear-9                   [-1, 84]          10,164
           Linear-10                   [-1, 10]             850
================================================================
Total params: 364,430
Trainable params: 364,430
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 0.30
Params size (MB): 1.39
Estimated Total Size (MB): 1.71
----------------------------------------------------------------
None
```

Adding the maxpool layer reduces the memory of the model by 6 MB, basically using 1/6 the amount of memory.

In [41]:
```
# visualization accuracy
plt.plot(iteration_list,accuracy_list,color = "red")
plt.plot(iteration_list2,accuracy_list2,color = "blue")
plt.xlabel("Number of iteration")
plt.ylabel("Accuracy")
plt.title("CNN: Accuracy vs Number of iteration between 2 models")
plt.legend(['first model', 'second model with maxpool'])
plt.show()
```



Adding the maxpool layer noticeably improved the accuracy of the model. The original model seems to start overfitting after around 2000 iterations, with the accuracy after that dropping. Adding the maxpool layer in the second model helps reduce the overfitting and gives a stable accuracy.

In [42]:
```
class CNNModel3(nn.Module):
  def __init__(self):
    super(CNNModel3, self).__init__()
    # TODO: Create CNNModel using 2D convolution. You should vary the number of con
    # In this function, you should define each of the individual components of the
    # Example:
    # self.cnn1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=5, stride=1
    # self.relu1 = nn.ReLU()
    # self.maxpool1 = nn.MaxPool2d(kernel_size=2)

    # convolution layer 1. using kernel_size = 5 to obtain the output of 28x28
    self.cnn1 = nn.Conv2d(in_channels=3, out_channels=6, kernel_size=5, stride=1, p
    self.relu1 = nn.ReLU()

    # convolution layer 2. using kernel_size = 3 to obtain the output of 26x26
    self.cnn2 = nn.Conv2d(in_channels=6, out_channels=16, kernel_size=3, stride=1,
    self.relu2 = nn.ReLU()
    # maxpool layer 1 added to obtain output of 13x13
    self.maxpool1 = nn.MaxPool2d(kernel_size=2)

    # convolution layer 3. using kernel_size = 3 to obtain the output of 11x11
    self.cnn3 = nn.Conv2d(in_channels=16, out_channels=24, kernel_size=3, stride=1,
    self.relu3 = nn.ReLU()

    # convolution layer 4. using kernel_size = 3 to obtain the output of 9x9
    self.cnn4 = nn.Conv2d(in_channels=24, out_channels=24, kernel_size=3, stride=1,
    self.relu4 = nn.ReLU()

    # convolution layer 5. using kernel_size = 3 to obtain the output of 7x7
    self.cnn5 = nn.Conv2d(in_channels=24, out_channels=24, kernel_size=3, stride=1,
    self.relu5 = nn.ReLU()

    # TODO: Create Fully connected layers. You should calculate the dimension of th
    # Example:
    # self.fc1 = nn.Linear(16 *110 * 110, 5)

    # Fully connected 1
    self.fc1 = nn.Linear(24 * 7 * 7, 120)
    self.relu4 = nn.ReLU()

    # Fully connected 2
    self.fc2 = nn.Linear(120, 84)
    self.relu5 = nn.ReLU()

    # Fully connected 3
    self.fc3 = nn.Linear(84, 10)

    self.i = 0

  def forward(self,x):

    # TODO: Perform forward pass in below section
    # In this function, you will apply the components defined earlier to the input,
    # Example:
    # out = self.cnn1(x)
    # out = self.relu1(out)
    # out = self.maxpool1(out)
    # to visualize feature map in part a, part b.i), use the following three lines:
```

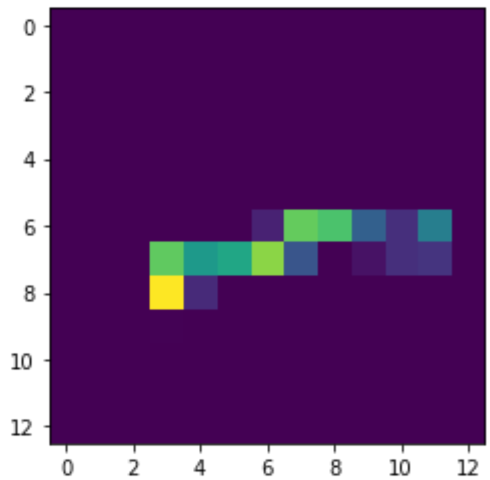
```python
        # plt.imshow(out[0][0].cpu().detach().numpy())
        # plt.show()
        # plt.close('all')
        # out = out.view(out.size(0), -1)
        # out = self.fc1(out)

        out = self.cnn1(x)
        out = self.relu1(out)
        out = self.cnn2(out)
        out = self.relu2(out)
        out = self.maxpool1(out)

        if self.i == 0:
            plt.imshow(out[0][0].cpu().detach().numpy())
            plt.show()
            plt.close('all')
            self.i += 1

        out = self.cnn3(out)
        out = self.relu3(out)
        out = self.cnn4(out)
        out = self.relu4(out)
        out = self.cnn5(out)
        out = self.relu5(out)

        out = out.view(out.size(0), -1)
        out = self.fc1(out)
        out = self.fc2(out)
        out = self.fc3(out)

        return out
```

In [43]:

```python
# Create CNN
device = "cuda" if torch.cuda.is_available() else "cpu"
model3 = CNNModel3()
model3.to(device)

# TODO: define Cross Entropy Loss
error = nn.CrossEntropyLoss()

# TODO: create Adam Optimizer and define your hyperparameters

optimizer3 = torch.optim.Adam(model3.parameters(), lr=learning_rate)
```

In [44]:
```python
count = 0
loss_list3 = []
iteration_list3 = []
accuracy_list3 = []
for epoch in tqdm(range(num_epochs)):
    model3.train()
    for i, (images, labels) in enumerate(train_loader):
        images, labels = images.to(device), labels.to(device)

        # Clear gradients
        optimizer3.zero_grad()

        # TODO: Forward propagation
        outputs = model3(images)

        # TODO: Calculate softmax and cross entropy loss
        loss = error(outputs, labels)

        # Backprop agate your Loss
        loss.backward()

        # Update CNN model
        optimizer3.step()

        count += 1

        if count % 50 == 0:
            model3.eval()
            # Calculate Accuracy
            correct = 0
            total = 0
            # Iterate through test dataset
            for images, labels in test_loader:
                images, labels = images.to(device), labels.to(device)

                # Forward propagation
                outputs = model3(images)

                # Get predictions from the maximum value
                predicted = torch.argmax(outputs,1)

                # Total number of labels
                total += len(labels)

                correct += (predicted == labels).sum()

            accuracy = 100 * correct / float(total)

            # store loss and iteration
            loss_list3.append(loss.item())
            iteration_list3.append(count)
            accuracy_list3.append(accuracy.item())
        if count % 500 == 0:
            # Print Loss
            print('Iteration: {}  Loss: {}  Accuracy: {} %'.format(count, loss.data
```

```
  0%|          | 0/20 [00:00<?, ?it/s]
```




```
  5%|▌         | 1/20 [00:19<06:12, 19.62s/it]
Iteration: 500  Loss: 1.4272009134292603  Accuracy: 47.19999694824219 %
 10%|█         | 2/20 [00:40<06:05, 20.30s/it]
Iteration: 1000  Loss: 1.269968867301941  Accuracy: 51.40999984741211 %
 15%|█▌        | 3/20 [01:01<05:48, 20.52s/it]
Iteration: 1500  Loss: 1.0139206647872925  Accuracy: 57.34000015258789 %
 25%|██▌       | 5/20 [01:42<05:09, 20.66s/it]
Iteration: 2000  Loss: 1.1258167028427124  Accuracy: 58.099998474121094 %
 30%|███       | 6/20 [02:02<04:42, 20.21s/it]
Iteration: 2500  Loss: 1.1712369918823242  Accuracy: 60.54999923706055 %
 35%|███▌      | 7/20 [02:22<04:25, 20.39s/it]
Iteration: 3000  Loss: 1.2697153091430664  Accuracy: 61.209999084472656 %
 40%|████      | 8/20 [02:43<04:06, 20.51s/it]
Iteration: 3500  Loss: 0.9665572047233582  Accuracy: 62.39999771118164 %
 50%|█████     | 10/20 [03:25<03:26, 20.64s/it]
Iteration: 4000  Loss: 0.9614195227622986  Accuracy: 61.96999740600586 %
 55%|█████▌    | 11/20 [03:45<03:06, 20.67s/it]
Iteration: 4500  Loss: 0.9483880996704102  Accuracy: 62.18000030517578 %
 60%|██████    | 12/20 [04:05<02:42, 20.26s/it]
Iteration: 5000  Loss: 0.9546028971672058  Accuracy: 63.75 %
 70%|███████   | 14/20 [04:46<02:03, 20.53s/it]
Iteration: 5500  Loss: 0.9173708558082581  Accuracy: 64.18999481201172 %
 75%|███████▌  | 15/20 [05:07<01:43, 20.60s/it]
Iteration: 6000  Loss: 0.7497398853302002  Accuracy: 64.26000213623047 %
 80%|████████  | 16/20 [05:28<01:22, 20.68s/it]
Iteration: 6500  Loss: 0.9469053745269775  Accuracy: 64.33000183105469 %
 85%|████████▌ | 17/20 [05:47<01:00, 20.28s/it]
Iteration: 7000  Loss: 0.820540726184845  Accuracy: 63.88999938964844 %
 95%|█████████▌| 19/20 [06:29<00:20, 20.53s/it]
Iteration: 7500  Loss: 0.9097587466239929  Accuracy: 65.38999938964844 %
100%|██████████| 20/20 [06:50<00:00, 20.50s/it]
```

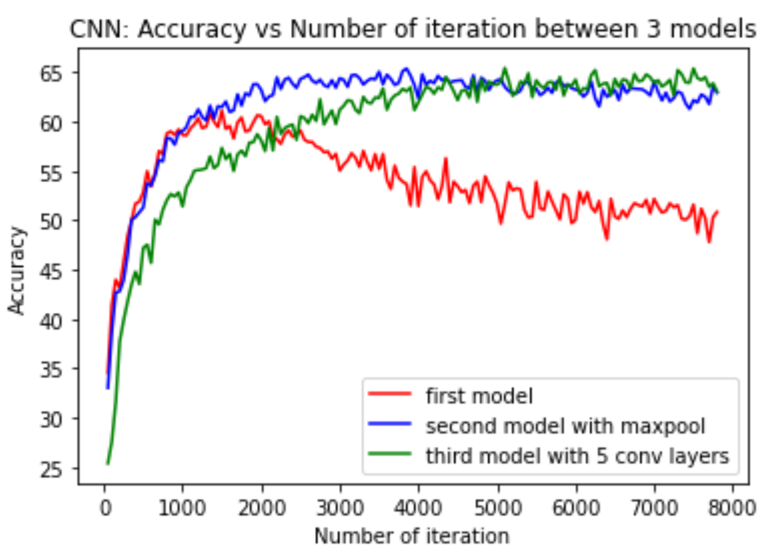
In [45]:

```
from torchsummary import summary
print(summary(model3, input_size=(3, 32, 32)))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1            [-1, 6, 28, 28]             456
              ReLU-2            [-1, 6, 28, 28]               0
            Conv2d-3           [-1, 16, 26, 26]             880
              ReLU-4           [-1, 16, 26, 26]               0
         MaxPool2d-5           [-1, 16, 13, 13]               0
            Conv2d-6           [-1, 24, 11, 11]           3,480
              ReLU-7           [-1, 24, 11, 11]               0
            Conv2d-8             [-1, 24, 9, 9]           5,208
              ReLU-9             [-1, 24, 9, 9]               0
           Conv2d-10             [-1, 24, 7, 7]           5,208
             ReLU-11             [-1, 24, 7, 7]               0
           Linear-12                  [-1, 120]         141,240
           Linear-13                   [-1, 84]          10,164
           Linear-14                   [-1, 10]             850
================================================================
Total params: 167,486
Trainable params: 167,486
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 0.35
Params size (MB): 0.64
Estimated Total Size (MB): 1.00
----------------------------------------------------------------
None
```

In [46]:

```
# visualization accuracy
plt.plot(iteration_list,accuracy_list,color = "red")
plt.plot(iteration_list2,accuracy_list2,color = "blue")
plt.plot(iteration_list3,accuracy_list3,color = "green")

plt.xlabel("Number of iteration")
plt.ylabel("Accuracy")
plt.title("CNN: Accuracy vs Number of iteration between 3 models")
plt.legend(['first model', 'second model with maxpool', 'third model with 5 conv la
plt.show()
```



Slightly lower memory usage, similar accuracy to the previous model but it converges slower. This happens because there are more layers, with more convolution parameters to train, while reducing the fully connected parameters.

In [60]:

```python
class CNNModel4(nn.Module):
  def __init__(self):
    super(CNNModel4, self).__init__()
    # TODO: Create CNNModel using 2D convolution. You should vary the number of con
    # In this function, you should define each of the individual components of the
    # Example:
    # self.cnn1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=5, stride=1
    # self.relu1 = nn.ReLU()
    # self.maxpool1 = nn.MaxPool2d(kernel_size=2)

    # convolution layer 1. using kernel_size = 5 to obtain the output of 28x28
    self.cnn1 = nn.Conv2d(in_channels=3, out_channels=24, kernel_size=5, stride=1,
    self.relu1 = nn.ReLU()

    # convolution layer 2. using kernel_size = 3 to obtain the output of 26x26
    self.cnn2 = nn.Conv2d(in_channels=24, out_channels=64, kernel_size=3, stride=1,
    self.relu2 = nn.ReLU()
    # maxpool layer 1 added to obtain output of 13x13
    self.maxpool1 = nn.MaxPool2d(kernel_size=2)

    # convolution layer 3. using kernel_size = 3 to obtain the output of 11x11
    self.cnn3 = nn.Conv2d(in_channels=64, out_channels=96, kernel_size=3, stride=1,
    self.relu3 = nn.ReLU()

    # convolution layer 4. using kernel_size = 3 to obtain the output of 9x9
    self.cnn4 = nn.Conv2d(in_channels=96, out_channels=96, kernel_size=3, stride=1,
    self.relu4 = nn.ReLU()

    # convolution layer 5. using kernel_size = 3 to obtain the output of 7x7
    self.cnn5 = nn.Conv2d(in_channels=96, out_channels=96, kernel_size=3, stride=1,
    self.relu5 = nn.ReLU()

    # TODO: Create Fully connected layers. You should calculate the dimension of th
    # Example:
    # self.fc1 = nn.Linear(16 *110 * 110, 5)

    # Fully connected 1
    self.fc1 = nn.Linear(96 * 7 * 7, 120)
    self.relu4 = nn.ReLU()

    # Fully connected 2
    self.fc2 = nn.Linear(120, 84)
    self.relu5 = nn.ReLU()

    # Fully connected 3
    self.fc3 = nn.Linear(84, 10)

    self.i = 0

  def forward(self,x):

    # TODO: Perform forward pass in below section
    # In this function, you will apply the components defined earlier to the input,
    # Example:
    # out = self.cnn1(x)
    # out = self.relu1(out)
    # out = self.maxpool1(out)
    # to visualize feature map in part a, part b.i), use the following three lines:
    # plt.imshow(out[0][0].cpu().detach().numpy())
```

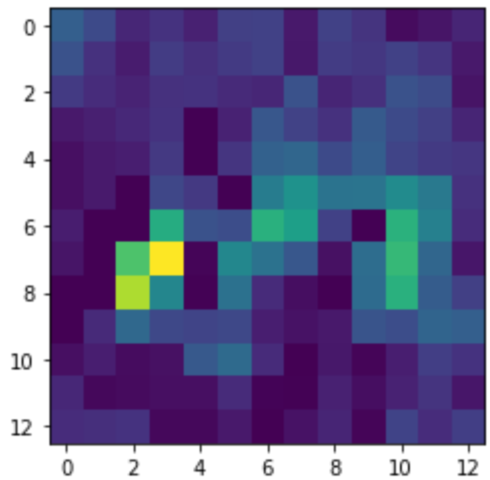
```
        # plt.imshow(out[0][0].cpu().detach().numpy())
        # plt.show()
        # plt.close('all')
        # out = out.view(out.size(0), -1)
        # out = self.fc1(out)

        out = self.cnn1(x)
        out = self.relu1(out)
        out = self.cnn2(out)
        out = self.relu2(out)
        out = self.maxpool1(out)

        if self.i == 0:
            plt.imshow(out[0][0].cpu().detach().numpy())
            plt.show()
            plt.close('all')
            self.i += 1

        out = self.cnn3(out)
        out = self.relu3(out)
        out = self.cnn4(out)
        out = self.relu4(out)
        out = self.cnn5(out)
        out = self.relu5(out)

        out = out.view(out.size(0), -1)
        out = self.fc1(out)
        out = self.fc2(out)
        out = self.fc3(out)

        return out
```

In [61]:

```
# Create CNN
device = "cuda" if torch.cuda.is_available() else "cpu"
model4 = CNNModel4()
model4.to(device)

# TODO: define Cross Entropy Loss
error = nn.CrossEntropyLoss()

# TODO: create Adam Optimizer and define your hyperparameters

optimizer4 = torch.optim.Adam(model4.parameters(), lr=learning_rate)
```

In [62]:
```
count = 0
loss_list4 = []
iteration_list4 = []
accuracy_list4 = []
for epoch in tqdm(range(num_epochs)):
    model4.train()
    for i, (images, labels) in enumerate(train_loader):
        images, labels = images.to(device), labels.to(device)

        # Clear gradients
        optimizer4.zero_grad()

        # TODO: Forward propagation
        outputs = model4(images)

        # TODO: Calculate softmax and cross entropy loss
        loss = error(outputs, labels)

        # Backprop agate your Loss
        loss.backward()

        # Update CNN model
        optimizer4.step()

        count += 1

        if count % 50 == 0:
            model4.eval()
            # Calculate Accuracy
            correct = 0
            total = 0
            # Iterate through test dataset
            for images, labels in test_loader:
                images, labels = images.to(device), labels.to(device)

                # Forward propagation
                outputs = model4(images)

                # Get predictions from the maximum value
                predicted = torch.argmax(outputs,1)

                # Total number of labels
                total += len(labels)

                correct += (predicted == labels).sum()

            accuracy = 100 * correct / float(total)

            # store loss and iteration
            loss_list4.append(loss.item())
            iteration_list4.append(count)
            accuracy_list4.append(accuracy.item())
        if count % 500 == 0:
            # Print Loss
            print('Iteration: {}  Loss: {}  Accuracy: {} %'.format(count, loss.data
```

```
  0%|          | 0/20 [00:00<?, ?it/s]
```




```
  5%|▌         | 1/20 [00:21<06:45, 21.33s/it]
Iteration: 500  Loss: 1.2672182321548462  Accuracy: 54.0099983215332 %
 10%|█         | 2/20 [00:43<06:35, 21.97s/it]
Iteration: 1000  Loss: 1.0334415435791016  Accuracy: 61.7599983215332 %
 15%|█▌        | 3/20 [01:06<06:17, 22.18s/it]
Iteration: 1500  Loss: 0.7224817276000977  Accuracy: 69.08999633789062 %
 25%|██▌       | 5/20 [01:51<05:34, 22.32s/it]
Iteration: 2000  Loss: 0.8392762541770935  Accuracy: 70.0199966430664 %
 30%|███       | 6/20 [02:11<05:06, 21.86s/it]
Iteration: 2500  Loss: 0.670225977897644  Accuracy: 69.91999816894531 %
 35%|███▌      | 7/20 [02:34<04:46, 22.03s/it]
Iteration: 3000  Loss: 0.5854135155677795  Accuracy: 71.33999633789062 %
 40%|████      | 8/20 [02:56<04:25, 22.15s/it]
Iteration: 3500  Loss: 0.3949741721153259  Accuracy: 70.48999786376953 %
 50%|█████     | 10/20 [03:41<03:42, 22.27s/it]
Iteration: 4000  Loss: 0.44109004735946655  Accuracy: 68.68000030517578 %
 55%|█████▌    | 11/20 [04:03<03:20, 22.31s/it]
Iteration: 4500  Loss: 0.3924218714237213  Accuracy: 68.29999542236328 %
 60%|██████    | 12/20 [04:24<02:55, 21.89s/it]
Iteration: 5000  Loss: 0.36824512481689453  Accuracy: 69.88999938964844 %
 70%|███████   | 14/20 [05:09<02:12, 22.13s/it]
Iteration: 5500  Loss: 0.5079470872879028  Accuracy: 68.0199966430664 %
 75%|███████▌  | 15/20 [05:31<01:51, 22.21s/it]
Iteration: 6000  Loss: 0.29775315523147583  Accuracy: 68.61000061035156 %
 80%|████████  | 16/20 [05:54<01:29, 22.26s/it]
Iteration: 6500  Loss: 0.21079687774181366  Accuracy: 68.8499984741211 %
 85%|████████▌ | 17/20 [06:15<01:05, 21.85s/it]
Iteration: 7000  Loss: 0.23195303976535797  Accuracy: 69.33999633789062 %
 95%|█████████▌| 19/20 [06:59<00:22, 22.12s/it]
Iteration: 7500  Loss: 0.2877177596092224  Accuracy: 69.0199966430664 %
100%|██████████| 20/20 [07:22<00:00, 22.12s/it]
```

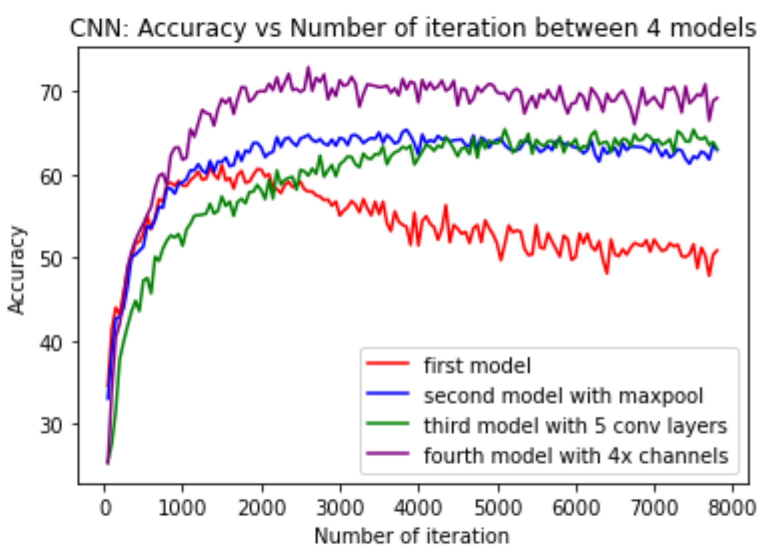
In [63]:

```
from torchsummary import summary
print(summary(model4, input_size=(3, 32, 32)))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 24, 28, 28]           1,824
              ReLU-2           [-1, 24, 28, 28]               0
            Conv2d-3           [-1, 64, 26, 26]          13,888
              ReLU-4           [-1, 64, 26, 26]               0
         MaxPool2d-5           [-1, 64, 13, 13]               0
            Conv2d-6           [-1, 96, 11, 11]          55,392
              ReLU-7           [-1, 96, 11, 11]               0
            Conv2d-8             [-1, 96, 9, 9]          83,040
              ReLU-9             [-1, 96, 9, 9]               0
           Conv2d-10             [-1, 96, 7, 7]          83,040
             ReLU-11             [-1, 96, 7, 7]               0
           Linear-12                  [-1, 120]         564,600
           Linear-13                   [-1, 84]          10,164
           Linear-14                   [-1, 10]             850
================================================================
Total params: 812,798
Trainable params: 812,798
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 1.40
Params size (MB): 3.10
Estimated Total Size (MB): 4.51
----------------------------------------------------------------
None
```

In [64]:

```
# visualization accuracy
plt.plot(iteration_list,accuracy_list,color = "red")
plt.plot(iteration_list2,accuracy_list2,color = "blue")
plt.plot(iteration_list3,accuracy_list3,color = "green")
plt.plot(iteration_list4,accuracy_list4,color = "purple")

plt.xlabel("Number of iteration")
plt.ylabel("Accuracy")
plt.title("CNN: Accuracy vs Number of iteration between 4 models")
plt.legend(['first model', 'second model with maxpool', 'third model with 5 conv la
plt.show()
```



This model manages a higher accuracy than the others, by a good margin. This is because there are more features to train on and detect from the images at each layer. The drawback to this model is the memory usage is higher than the previous 2, and it has longer training time.