In [1]:

```
# if you keras is not using tensorflow as backend set "KERAS_BACKEND=tensorflow" use this command

from keras.utils import np_utils
from keras.datasets import mnist
import seaborn as sns
from keras.initializers import RandomNormal
import warnings
warnings.filterwarnings('ignore')
```

```
Using TensorFlow backend.
```

In [0]:

```
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import time
```

In [4]:

```
# Loading MNIST dataset
mn = mnist.load_data()

print("MNIST dataset/n")
mn
```

```
MNIST dataset/n
```

Out[4]:

```
((array([[[0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          ...,
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0]],

         [[0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          ...,
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0]],

         [[0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          ...,
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0]],

         ...,

         [[0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          ...,
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0]],

         [[0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          ...,
          [0, 0, 0, ..., 0, 0, 0],
```

```
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0]],

         [[0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          ...,
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0]]], dtype=uint8),
  array([5, 0, 4, ..., 5, 6, 8], dtype=uint8)),
 (array([[[0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          ...,
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0]],

         [[0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          ...,
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0]],

         [[0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          ...,
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0]],

         ...,

         [[0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          ...,
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0]],

         [[0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          ...,
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0]],

         [[0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          ...,
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0],
          [0, 0, 0, ..., 0, 0, 0]]], dtype=uint8),
  array([7, 2, 1, ..., 4, 5, 6], dtype=uint8)))
```

In [0]:

```
# Splitting MNIST dataset into train and test

(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

In [10]:

```
print("Shape of X_train is", X_train.shape)
print("Shape of y_train is", y_train.shape, '\n')

print("Shape of X_test is", X_test.shape)
print("Shape of y_test is", y_test.shape, '\n')
```

```
print("Number of training examples :", X_train.shape[0])
print("Number of testing examples :", X_test.shape[0], '\n')

print("Each training image is of shape", (X_train.shape[1], X_train.shape[2]))
print("Each testing image is of shape", (X_test.shape[1], X_test.shape[2]))
```

```
Shape of X_train is (60000, 28, 28)
Shape of y_train is (60000,)

Shape of X_test is (10000, 28, 28)
Shape of y_test is (10000,)

Number of training examples : 60000
Number of testing examples : 10000

Each training image is of shape (28, 28)
Each testing image is of shape (28, 28)
```

In [0]:

```
# Vector is 3 dimensional. So converting 3 dimensional vector to 1 dimensional vector i.e 1 * 784

X_train = X_train.reshape(X_train.shape[0], X_train.shape[1]*X_train.shape[2])
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1]*X_test.shape[2])
```

In [12]:

```
# Shape and dimensions after converting from 3 dimension to 1 dimension

print("Shape of X_train is", X_train.shape)
print("Shape of X_test is", X_test.shape, '\n')

print("Number of training examples :", X_train.shape[0])
print("Number of testing examples :", X_test.shape[0], '\n')

print("Each training image is of shape", X_train.shape[1])
print("Each testing image is of shape", X_test.shape[1])
```

```
Shape of X_train is (60000, 784)
Shape of X_test is (10000, 784)

Number of training examples : 60000
Number of testing examples : 10000

Each training image is of shape 784
Each testing image is of shape 784
```

In [0]:

```
# If we observe the above matrix each cell is having a value between 0-255
# Before we move to apply machine learning algorithms lets try to normalize the data
# X => (X - Xmin)/(Xmax-Xmin) = X/255

X_train = X_train/255
X_test = X_test/255
```

In [14]:

```
# Here we are having a class number for each image
print("Class label of first image :", y_train[0])

# Lets convert this into a 10 dimensional vector
# Ex: consider an image is 5 convert it into 5 => [0, 0, 0, 0, 0, 1, 0, 0, 0, 0]
# This conversion needed for MLPs

Y_train = np_utils.to_categorical(y_train, 10)
Y_test = np_utils.to_categorical(y_test, 10)

print("After converting the output into a vector : ",Y_train[0])
```

```
Class label of first image : 5
After converting the output into a vector :  [0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
```

In [0]:

```
# Model parameters

# Output
output_dim = 10

# Input
input_dim = X_train.shape[1]

batch_size = 128

# Number of times to input complete data
nb_epoch = 20

# Defining hidden layers
in_lay = 784
hid_lay_1 = 512
hid_lay_2 = 300
hid_lay_3 = 200
hid_lay_4 = 100
hid_lay_5 = 50
```

In [0]:

```
# Importing libraries

from keras.models import Sequential
from keras.layers import Dense, Activation, Dropout
from keras.layers.normalization import BatchNormalization
```

In [0]:

```
# Defining a function to get train and test loss

def mod(layer):

  # Initializing Sequential()
  model = Sequential()

  if layer == 2:

    print("For hidden layers 2", '\n')

    # Passing in parameters like input data, output data and activation
    model.add(Dense(hid_lay_1, activation='relu', input_shape = (input_dim,)))
    model.add(Dense(hid_lay_2, activation='relu'))
    model.add(Dense(output_dim, activation='relu'))

  if layer == 3:

    print("For hidden layers 3", '\n')

    # Passing in parameters like input data, output data and activation
    model.add(Dense(hid_lay_1, activation='relu', input_shape = (input_dim,)))
    model.add(Dense(hid_lay_2, activation='relu'))
    model.add(Dense(hid_lay_3, activation='relu'))
    model.add(Dense(output_dim, activation='relu'))

  if layer == 5:

    print("For hidden layers 5", '\n')

    # Passing in parameters like input data, output data and activation
    model.add(Dense(hid_lay_1, activation='relu', input_shape=(input_dim,)))
    model.add(Dense(hid_lay_2, activation='relu'))
    model.add(Dense(hid_lay_3, activation='relu'))
    model.add(Dense(hid_lay_4, activation='relu'))
    model.add(Dense(hid_lay_5, activation='relu'))
    model.add(Dense(output_dim, activation='relu'))
```

```
  # Compiling
  model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

  # FIt the model
  history = model.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validati
on_data=(X_test, Y_test))

  return history
```

In [0]:

```
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import time

# https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
# https://stackoverflow.com/a/14434334
# this function is used to update the plots for each epoch and error

def plt_la(x, vy, ty, ax, t, colors=['b']):

  if t == 'loss':
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
    plt.title("Epoch vs Loss")
    plt.legend()
    plt.grid()

  if t == 'acc':
    ax.plot(x, vy, 'b', label="Validation Accuracy")
    ax.plot(x, ty, 'r', label="Train Accuracy")
    plt.title("Epoch vs Accuracy")
    plt.legend()
    plt.grid()
```

In [0]:

```
def plotting(history, t):

  fig,ax = plt.subplots(1,1)
  ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy')

  # list of epoch numbers
  x = list(range(1,nb_epoch+1))

  # print(history.history.keys())
  # dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
  # history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1,
validation_data=(X_test, Y_test))

  # we will get val_loss and val_acc only when you pass the paramter validation_data
  # val_loss : validation loss
  # val_acc : validation accuracy

  # loss : training loss
  # acc : train accuracy
  # for each key in histrory.histrory we will have a list of length equal to number of epochs

  if t == 'loss':
    vy = history.history['val_loss']
    ty = history.history['loss']

    plt_la(x, vy, ty, ax, t)

  if t == 'acc':
    vy = history.history['val_acc']
    ty = history.history['acc']

    plt_la(x, vy, ty, ax, t)

  return vy, ty
```

In [20]:

```
plot_2 = mod(2)
```

```
WARNING: Logging before flag parsing goes to stderr.
W0717 10:36:34.833462 139739433367424 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:74: The name
tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

W0717 10:36:34.860073 139739433367424 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:517: The name
tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

W0717 10:36:34.865509 139739433367424 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:4138: The name
tf.random_uniform is deprecated. Please use tf.random.uniform instead.

W0717 10:36:34.914246 139739433367424 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/optimizers.py:790: The name tf.train.Optimizer is dep
recated. Please use tf.compat.v1.train.Optimizer instead.

W0717 10:36:34.941758 139739433367424 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:3295: The name tf.log i
s deprecated. Please use tf.math.log instead.
```

```
For hidden layers 2
```

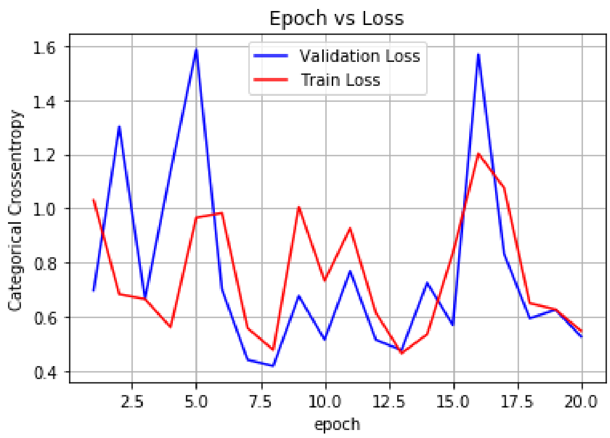
```
W0717 10:36:35.066195 139739433367424 deprecation.py:323] From /usr/local/lib/python3.6/dist-
packages/tensorflow/python/ops/math_grad.py:1250: add_dispatch_support.<locals>.wrapper (from
tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
W0717 10:36:35.131325 139739433367424 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:986: The name
tf.assign_add is deprecated. Please use tf.compat.v1.assign_add instead.
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 66us/step - loss: 1.0303 - acc: 0.7467 -
val_loss: 0.6980 - val_acc: 0.8917
Epoch 2/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.6834 - acc: 0.8517 -
val_loss: 1.3012 - val_acc: 0.4896
Epoch 3/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.6654 - acc: 0.8600 -
val_loss: 0.6658 - val_acc: 0.7872
Epoch 4/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.5612 - acc: 0.8716 -
val_loss: 1.1368 - val_acc: 0.4313
Epoch 5/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.9658 - acc: 0.6388 -
val_loss: 1.5858 - val_acc: 0.1322
Epoch 6/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.9826 - acc: 0.6496 -
val_loss: 0.7014 - val_acc: 0.9017
Epoch 7/20
60000/60000 [==============================] - 3s 51us/step - loss: 0.5582 - acc: 0.8998 -
val_loss: 0.4414 - val_acc: 0.9257
Epoch 8/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.4774 - acc: 0.9133 -
val_loss: 0.4182 - val_acc: 0.9345
Epoch 9/20
60000/60000 [==============================] - 3s 51us/step - loss: 1.0053 - acc: 0.5628 -
val_loss: 0.6766 - val_acc: 0.7826
Epoch 10/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.7324 - acc: 0.8299 -
val_loss: 0.5150 - val_acc: 0.9152
Epoch 11/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.9272 - acc: 0.5608 -
val_loss: 0.7688 - val_acc: 0.7195
Epoch 12/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.6147 - acc: 0.8854 -
```

```
val_loss: 0.5147 - val_acc: 0.9120
Epoch 13/20
60000/60000 [==============================] - 3s 51us/step - loss: 0.4650 - acc: 0.9223 -
val_loss: 0.4765 - val_acc: 0.9340
Epoch 14/20
60000/60000 [==============================] - 3s 51us/step - loss: 0.5351 - acc: 0.8390 -
val_loss: 0.7249 - val_acc: 0.6945
Epoch 15/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.8344 - acc: 0.7137 -
val_loss: 0.5692 - val_acc: 0.8900
Epoch 16/20
60000/60000 [==============================] - 3s 51us/step - loss: 1.2019 - acc: 0.3671 -
val_loss: 1.5678 - val_acc: 0.1488
Epoch 17/20
60000/60000 [==============================] - 3s 51us/step - loss: 1.0751 - acc: 0.5070 -
val_loss: 0.8320 - val_acc: 0.8401
Epoch 18/20
60000/60000 [==============================] - 3s 51us/step - loss: 0.6501 - acc: 0.8554 -
val_loss: 0.5942 - val_acc: 0.8908
Epoch 19/20
60000/60000 [==============================] - 3s 51us/step - loss: 0.6270 - acc: 0.8508 -
val_loss: 0.6260 - val_acc: 0.8990
Epoch 20/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.5478 - acc: 0.9096 -
val_loss: 0.5267 - val_acc: 0.9182
```

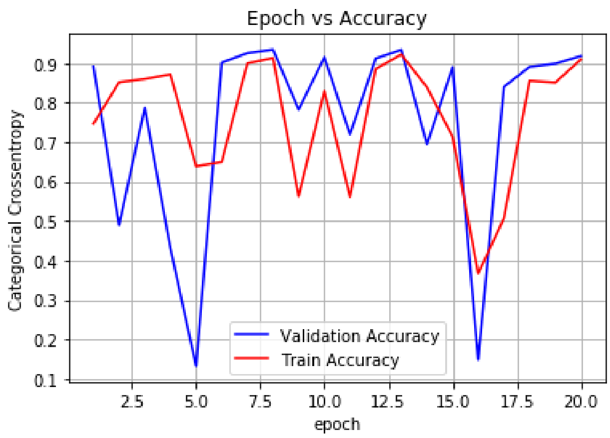
In [21]:

```
v_el_2, t_el_2 = plotting(plot_2, 'loss')
```



In [22]:

```
v_ea_2, t_ea_2 = plotting(plot_2, 'acc')
```



In [23]:

```
va_el_2 = np.round(min(v_el_2), 3)
ta_el_2 = np.round(min(t_el_2),3)

print("Validation loss:", va_el_2)
```

```
print("Train loss:", ta_el_2, '\n')

print('*'*30, '\n')

va_ea_2 = np.round(max(v_ea_2),3)
ta_ea_2 = np.round(max(t_ea_2),3)

print("Validation accuracy:", va_ea_2)
print("Train accuracy:", ta_ea_2)
```

```
Validation loss: 0.418
Train loss: 0.465

******************************

Validation accuracy: 0.934
Train accuracy: 0.922
```

In [24]:

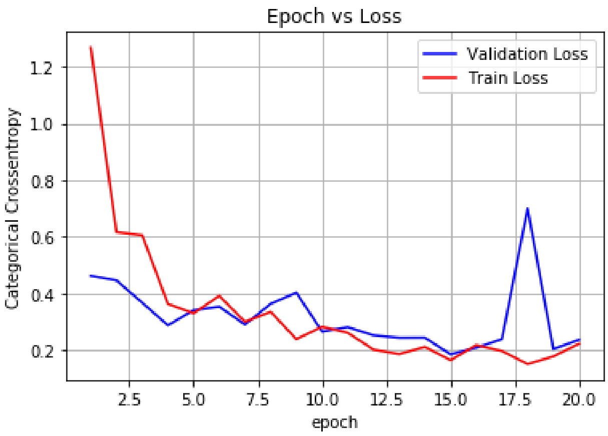
```
plot_3 = mod(3)
```

```
For hidden layers 3

Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 66us/step - loss: 1.2680 - acc: 0.8193 -
val_loss: 0.4619 - val_acc: 0.9143
Epoch 2/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.6163 - acc: 0.8604 -
val_loss: 0.4458 - val_acc: 0.8960
Epoch 3/20
60000/60000 [==============================] - 4s 58us/step - loss: 0.6054 - acc: 0.8495 -
val_loss: 0.3670 - val_acc: 0.9394
Epoch 4/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.3627 - acc: 0.9327 -
val_loss: 0.2869 - val_acc: 0.9415
Epoch 5/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.3297 - acc: 0.9254 -
val_loss: 0.3404 - val_acc: 0.9362
Epoch 6/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.3910 - acc: 0.9160 -
val_loss: 0.3530 - val_acc: 0.9317
Epoch 7/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.2994 - acc: 0.9466 -
val_loss: 0.2896 - val_acc: 0.9577
Epoch 8/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.3347 - acc: 0.9367 -
val_loss: 0.3632 - val_acc: 0.9241
Epoch 9/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.2380 - acc: 0.9523 -
val_loss: 0.4024 - val_acc: 0.8793
Epoch 10/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.2819 - acc: 0.9415 -
val_loss: 0.2648 - val_acc: 0.9540
Epoch 11/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.2608 - acc: 0.9459 -
val_loss: 0.2804 - val_acc: 0.9453
Epoch 12/20
60000/60000 [==============================] - 4s 58us/step - loss: 0.2012 - acc: 0.9630 -
val_loss: 0.2518 - val_acc: 0.9583
Epoch 13/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.1855 - acc: 0.9657 -
val_loss: 0.2428 - val_acc: 0.9527
Epoch 14/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.2107 - acc: 0.9608 -
val_loss: 0.2431 - val_acc: 0.9629
Epoch 15/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1640 - acc: 0.9713 -
val_loss: 0.1847 - val_acc: 0.9692
Epoch 16/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.2169 - acc: 0.9602 -
val_loss: 0.2078 - val_acc: 0.9690
Epoch 17/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.1963 - acc: 0.9620 -
```

```
val_loss: 0.2381 - val_acc: 0.9674
Epoch 18/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.1503 - acc: 0.9749 -
val_loss: 0.6999 - val_acc: 0.8358
Epoch 19/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.1774 - acc: 0.9630 -
val_loss: 0.2032 - val_acc: 0.9691
Epoch 20/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.2216 - acc: 0.9495 -
val_loss: 0.2358 - val_acc: 0.9627
```

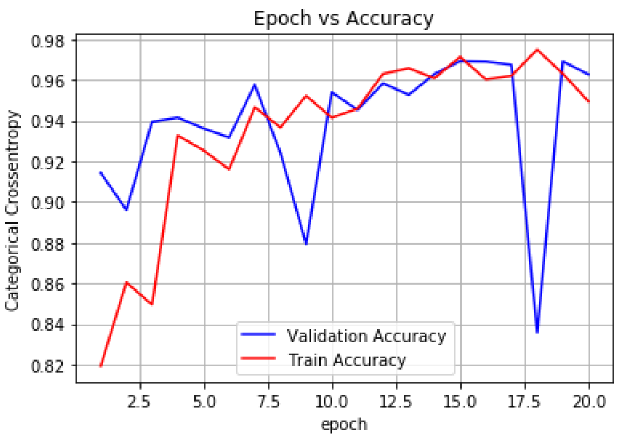
In [25]:

```
v_el_3, t_el_3 = plotting(plot_3, 'loss')
```



In [26]:

```
v_ea_3, t_ea_3 = plotting(plot_3, 'acc')
```



In [27]:

```
va_el_3 = np.round(min(v_el_3), 3)
ta_el_3 = np.round(min(t_el_3),3)

print("Validation loss:", va_el_3)
print("Train loss:", ta_el_3, '\n')

print('*'*30, '\n')

va_ea_3 = np.round(max(v_ea_3),3)
ta_ea_3 = np.round(max(t_ea_3),3)

print("Validation accuracy:", va_ea_3)
print("Train accuracy:", ta_ea_3)
```

```
Validation loss: 0.185
Train loss: 0.15

******************************
```

```
Validation accuracy: 0.969
Train accuracy: 0.975
```

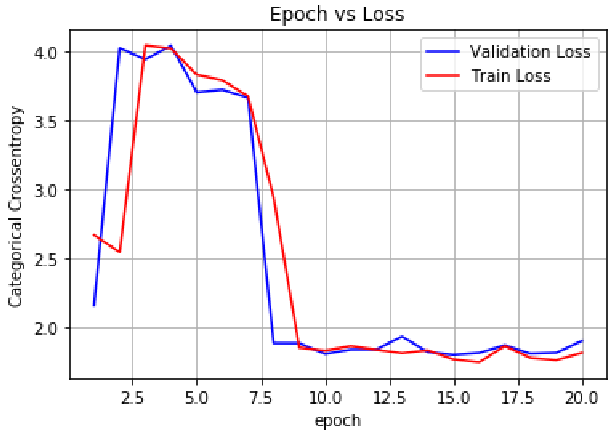
In [28]:

```
plot_5 = mod(5)
```

```
For hidden layers 5

Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 78us/step - loss: 2.6661 - acc: 0.6774 -
val_loss: 2.1556 - val_acc: 0.8120
Epoch 2/20
60000/60000 [==============================] - 4s 70us/step - loss: 2.5416 - acc: 0.7451 -
val_loss: 4.0220 - val_acc: 0.6059
Epoch 3/20
60000/60000 [==============================] - 4s 66us/step - loss: 4.0411 - acc: 0.6686 -
val_loss: 3.9389 - val_acc: 0.7095
Epoch 4/20
60000/60000 [==============================] - 4s 70us/step - loss: 4.0192 - acc: 0.6699 -
val_loss: 4.0392 - val_acc: 0.6216
Epoch 5/20
60000/60000 [==============================] - 4s 69us/step - loss: 3.8282 - acc: 0.7113 -
val_loss: 3.7016 - val_acc: 0.7401
Epoch 6/20
60000/60000 [==============================] - 4s 67us/step - loss: 3.7880 - acc: 0.7074 -
val_loss: 3.7204 - val_acc: 0.7397
Epoch 7/20
60000/60000 [==============================] - 4s 70us/step - loss: 3.6731 - acc: 0.7492 -
val_loss: 3.6614 - val_acc: 0.7508
Epoch 8/20
60000/60000 [==============================] - 4s 68us/step - loss: 2.9369 - acc: 0.7813 -
val_loss: 1.8810 - val_acc: 0.8589
Epoch 9/20
60000/60000 [==============================] - 4s 68us/step - loss: 1.8496 - acc: 0.8628 -
val_loss: 1.8806 - val_acc: 0.8627
Epoch 10/20
60000/60000 [==============================] - 4s 71us/step - loss: 1.8280 - acc: 0.8678 -
val_loss: 1.8039 - val_acc: 0.8671
Epoch 11/20
60000/60000 [==============================] - 4s 67us/step - loss: 1.8612 - acc: 0.8530 -
val_loss: 1.8356 - val_acc: 0.8685
Epoch 12/20
60000/60000 [==============================] - 4s 70us/step - loss: 1.8344 - acc: 0.8651 -
val_loss: 1.8363 - val_acc: 0.8668
Epoch 13/20
60000/60000 [==============================] - 4s 69us/step - loss: 1.8096 - acc: 0.8692 -
val_loss: 1.9295 - val_acc: 0.8171
Epoch 14/20
60000/60000 [==============================] - 4s 66us/step - loss: 1.8304 - acc: 0.8614 -
val_loss: 1.8173 - val_acc: 0.8693
Epoch 15/20
60000/60000 [==============================] - 4s 69us/step - loss: 1.7650 - acc: 0.8775 -
val_loss: 1.7978 - val_acc: 0.8722
Epoch 16/20
60000/60000 [==============================] - 4s 67us/step - loss: 1.7436 - acc: 0.8811 -
val_loss: 1.8116 - val_acc: 0.8746
Epoch 17/20
60000/60000 [==============================] - 4s 69us/step - loss: 1.8614 - acc: 0.8606 -
val_loss: 1.8669 - val_acc: 0.8608
Epoch 18/20
60000/60000 [==============================] - 4s 69us/step - loss: 1.7759 - acc: 0.8748 -
val_loss: 1.8063 - val_acc: 0.8735
Epoch 19/20
60000/60000 [==============================] - 4s 67us/step - loss: 1.7592 - acc: 0.8779 -
val_loss: 1.8124 - val_acc: 0.8750
Epoch 20/20
60000/60000 [==============================] - 4s 70us/step - loss: 1.8121 - acc: 0.8677 -
val_loss: 1.8971 - val_acc: 0.8604
```

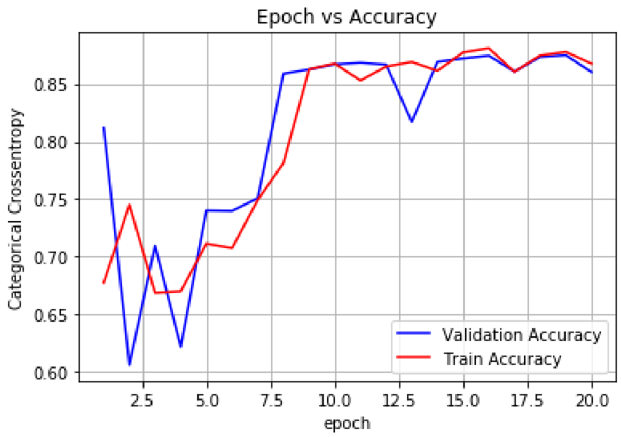
In [29]:

```
v_el_5, t_el_5 = plotting(plot_5, 'loss')
```



In [30]:

```
v_ea_5, t_ea_5 = plotting(plot_5, 'acc')
```



In [31]:

```
va_el_5 = np.round(min(v_el_5), 3)
ta_el_5 = np.round(min(t_el_5),3)

print("Validation loss:", va_el_5)
print("Train loss:", ta_el_5, '\n')

print('*'*30, '\n')

va_ea_5 = np.round(max(v_ea_5),3)
ta_ea_5 = np.round(max(t_ea_5),3)

print("Validation accuracy:", va_ea_5)
print("Train accuracy:", ta_ea_5)
```

```
Validation loss: 1.798
Train loss: 1.744

******************************

Validation accuracy: 0.875
Train accuracy: 0.881
```

In [0]:

```
# Defining a function to get train and test loss

def mod_drop(layer_drop, drop_rate):

  # Initializing Sequential()
  model = Sequential()

  if layer_drop == 2:
```

```
    print("For hidden layers 2", '\n')

    # Passing in parameters like input data, output data and activation
    model.add(Dense(hid_lay_1, activation='relu', input_shape=(input_dim,)))
    model.add(Dropout(drop_rate))
    model.add(Dense(hid_lay_2, activation='relu'))
    model.add(Dropout(drop_rate))
    model.add(Dense(output_dim, activation='relu'))

  if layer_drop == 3:

    print("For hidden layers 3", '\n')

    # Passing in parameters like input data, output data and activation
    model.add(Dense(hid_lay_1, activation='relu', input_shape=(input_dim,)))
    model.add(Dropout(drop_rate))
    model.add(Dense(hid_lay_2, activation='relu'))
    model.add(Dropout(drop_rate))
    model.add(Dense(hid_lay_3, activation='relu'))
    model.add(Dropout(drop_rate))
    model.add(Dense(output_dim, activation='relu'))

  if layer_drop == 5:

    print("For hidden layers 5", '\n')

    # Passing in parameters like input data, output data and activation
    model.add(Dense(hid_lay_1, activation='relu', input_shape=(input_dim,)))
    model.add(Dropout(drop_rate))
    model.add(Dense(hid_lay_2, activation='relu'))
    model.add(Dropout(drop_rate))
    model.add(Dense(hid_lay_3, activation='relu'))
    model.add(Dropout(drop_rate))
    model.add(Dense(hid_lay_4, activation='relu'))
    model.add(Dropout(drop_rate))
    model.add(Dense(hid_lay_5, activation='relu'))
    model.add(Dropout(drop_rate))
    model.add(Dense(output_dim, activation='relu'))


  # Compiling
  model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

  # FIt the model
  history = model.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validati
on_data=(X_test, Y_test))

  return history
```

In [33]:

```
d_plot_2 = mod_drop(2, 0.25)
```

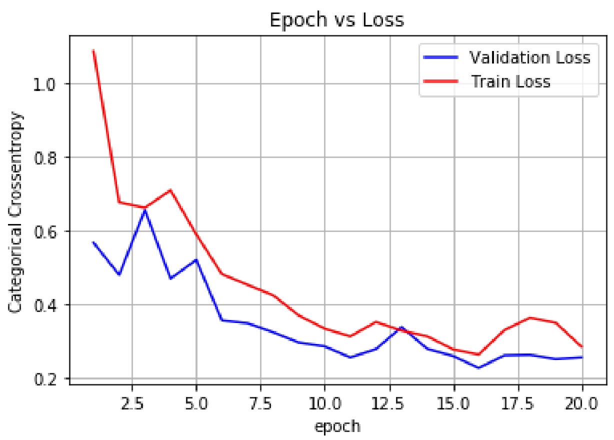
```
W0717 10:40:54.943426 139739433367424 deprecation.py:506] From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:3445: calling dropout (from
tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future
version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
```

```
For hidden layers 2

Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 63us/step - loss: 1.0854 - acc: 0.7995 -
val_loss: 0.5659 - val_acc: 0.9150
Epoch 2/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.6754 - acc: 0.8788 -
val_loss: 0.4785 - val_acc: 0.9076
Epoch 3/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.6606 - acc: 0.8634 -
val_loss: 0.6546 - val_acc: 0.7746
Epoch 4/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.7083 - acc: 0.8639 -
```

```
val_loss: 0.4685 - val_acc: 0.9181
Epoch 5/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.5885 - acc: 0.8885 -
val_loss: 0.5192 - val_acc: 0.9037
Epoch 6/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.4805 - acc: 0.9126 -
val_loss: 0.3552 - val_acc: 0.9380
Epoch 7/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.4518 - acc: 0.9126 -
val_loss: 0.3476 - val_acc: 0.9412
Epoch 8/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.4233 - acc: 0.9205 -
val_loss: 0.3229 - val_acc: 0.9378
Epoch 9/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.3684 - acc: 0.9371 -
val_loss: 0.2950 - val_acc: 0.9466
Epoch 10/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.3328 - acc: 0.9429 -
val_loss: 0.2847 - val_acc: 0.9513
Epoch 11/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.3118 - acc: 0.9478 -
val_loss: 0.2548 - val_acc: 0.9535
Epoch 12/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.3509 - acc: 0.9359 -
val_loss: 0.2773 - val_acc: 0.9533
Epoch 13/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.3274 - acc: 0.9463 -
val_loss: 0.3371 - val_acc: 0.9472
Epoch 14/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.3120 - acc: 0.9459 -
val_loss: 0.2779 - val_acc: 0.9556
Epoch 15/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.2766 - acc: 0.9525 -
val_loss: 0.2588 - val_acc: 0.9499
Epoch 16/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.2627 - acc: 0.9553 -
val_loss: 0.2262 - val_acc: 0.9623
Epoch 17/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.3288 - acc: 0.9395 -
val_loss: 0.2604 - val_acc: 0.9617
Epoch 18/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.3625 - acc: 0.9362 -
val_loss: 0.2619 - val_acc: 0.9579
Epoch 19/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.3488 - acc: 0.9360 -
val_loss: 0.2504 - val_acc: 0.9613
Epoch 20/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.2841 - acc: 0.9549 -
val_loss: 0.2550 - val_acc: 0.9625
```

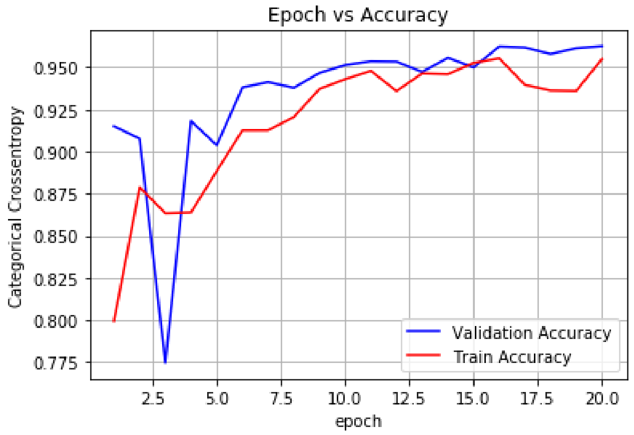
In [34]:

```
d_v_el_2, d_t_el_2 = plotting(d_plot_2, 'loss')
```



In [35]:

```
d_v_ea_2, d_t_ea_2 = plotting(d_plot_2, 'acc')
```



In [36]:

```
d_va_el_2 = np.round(min(d_v_el_2), 3)
d_ta_el_2 = np.round(min(d_t_el_2),3)

print("Validation loss:", d_va_el_2)
print("Train loss:", d_ta_el_2, '\n')

print('*'*30, '\n')

d_va_ea_2 = np.round(max(d_v_ea_2),3)
d_ta_ea_2 = np.round(max(d_t_ea_2),3)

print("Validation accuracy:", d_va_ea_2)
print("Train accuracy:", d_ta_ea_2)
```

```
Validation loss: 0.226
Train loss: 0.263

******************************

Validation accuracy: 0.962
Train accuracy: 0.955
```

In [37]:

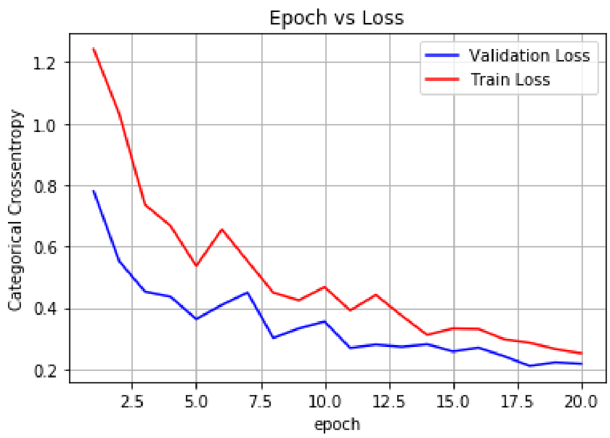
```
d_plot_3 = mod_drop(3, 0.25)
```

```
For hidden layers 3

Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 75us/step - loss: 1.2423 - acc: 0.7449 -
val_loss: 0.7797 - val_acc: 0.8940
Epoch 2/20
60000/60000 [==============================] - 4s 61us/step - loss: 1.0313 - acc: 0.7695 -
val_loss: 0.5514 - val_acc: 0.9033
Epoch 3/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.7357 - acc: 0.8580 -
val_loss: 0.4527 - val_acc: 0.9228
Epoch 4/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.6666 - acc: 0.8677 -
val_loss: 0.4361 - val_acc: 0.9209
Epoch 5/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.5365 - acc: 0.9015 -
val_loss: 0.3631 - val_acc: 0.9309
Epoch 6/20
60000/60000 [==============================] - 4s 64us/step - loss: 0.6555 - acc: 0.8638 -
val_loss: 0.4097 - val_acc: 0.9098
Epoch 7/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.5522 - acc: 0.8839 -
val_loss: 0.4498 - val_acc: 0.8804
Epoch 8/20
60000/60000 [==============================] - 4s 64us/step - loss: 0.4497 - acc: 0.9202 -
val_loss: 0.3018 - val_acc: 0.9445
Epoch 9/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.4245 - acc: 0.9200 -
```

```
val_loss: 0.3328 - val_acc: 0.9199
Epoch 10/20
60000/60000 [==============================] - 4s 65us/step - loss: 0.4677 - acc: 0.9035 -
val_loss: 0.3552 - val_acc: 0.9366
Epoch 11/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.3914 - acc: 0.9285 -
val_loss: 0.2688 - val_acc: 0.9506
Epoch 12/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.4422 - acc: 0.9043 -
val_loss: 0.2803 - val_acc: 0.9448
Epoch 13/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.3748 - acc: 0.9319 -
val_loss: 0.2724 - val_acc: 0.9530
Epoch 14/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.3117 - acc: 0.9427 -
val_loss: 0.2812 - val_acc: 0.9460
Epoch 15/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.3325 - acc: 0.9381 -
val_loss: 0.2580 - val_acc: 0.9579
Epoch 16/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.3310 - acc: 0.9359 -
val_loss: 0.2700 - val_acc: 0.9598
Epoch 17/20
60000/60000 [==============================] - 4s 64us/step - loss: 0.2974 - acc: 0.9475 -
val_loss: 0.2425 - val_acc: 0.9617
Epoch 18/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.2860 - acc: 0.9505 -
val_loss: 0.2106 - val_acc: 0.9629
Epoch 19/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.2656 - acc: 0.9549 -
val_loss: 0.2226 - val_acc: 0.9633
Epoch 20/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.2519 - acc: 0.9563 -
val_loss: 0.2178 - val_acc: 0.9657
```

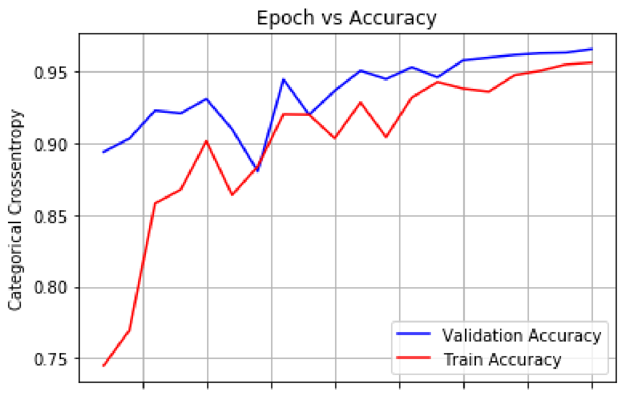
In [38]:

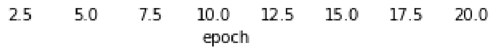
```
d_v_el_3, d_t_el_3 = plotting(d_plot_3, 'loss')
```



In [42]:

```
d_v_ea_3, d_t_ea_3 = plotting(d_plot_3, 'acc')
```





In [43]:

```
d_va_el_3 = np.round(min(d_v_el_3), 3)
d_ta_el_3 = np.round(min(d_t_el_3),3)

print("Validation loss:", d_va_el_3)
print("Train loss:", d_ta_el_3, '\n')

print('*'*30, '\n')

d_va_ea_3 = np.round(max(d_v_ea_3),3)
d_ta_ea_3 = np.round(max(d_t_ea_3),3)

print("Validation accuracy:", d_va_ea_3)
print("Train accuracy:", d_ta_ea_3)
```

```
Validation loss: 0.211
Train loss: 0.252

******************************

Validation accuracy: 0.966
Train accuracy: 0.956
```

In [44]:

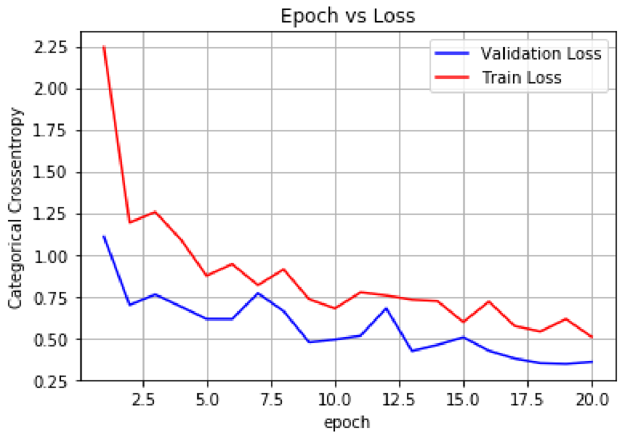
```
d_plot_5 = mod_drop(5, 0.25)
```

```
For hidden layers 5

Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 87us/step - loss: 2.2429 - acc: 0.4461 -
val_loss: 1.1078 - val_acc: 0.7453
Epoch 2/20
60000/60000 [==============================] - 4s 72us/step - loss: 1.1910 - acc: 0.7068 -
val_loss: 0.6980 - val_acc: 0.8591
Epoch 3/20
60000/60000 [==============================] - 5s 75us/step - loss: 1.2555 - acc: 0.7153 -
val_loss: 0.7612 - val_acc: 0.8528
Epoch 4/20
60000/60000 [==============================] - 4s 73us/step - loss: 1.0899 - acc: 0.7553 -
val_loss: 0.6881 - val_acc: 0.8721
Epoch 5/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.8731 - acc: 0.8244 -
val_loss: 0.6142 - val_acc: 0.9024
Epoch 6/20
60000/60000 [==============================] - 4s 75us/step - loss: 0.9427 - acc: 0.8089 -
val_loss: 0.6139 - val_acc: 0.8991
Epoch 7/20
60000/60000 [==============================] - 4s 73us/step - loss: 0.8167 - acc: 0.8288 -
val_loss: 0.7685 - val_acc: 0.8584
Epoch 8/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.9111 - acc: 0.8277 -
val_loss: 0.6616 - val_acc: 0.8905
Epoch 9/20
60000/60000 [==============================] - 5s 75us/step - loss: 0.7326 - acc: 0.8682 -
val_loss: 0.4738 - val_acc: 0.9288
Epoch 10/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.6773 - acc: 0.8880 -
val_loss: 0.4906 - val_acc: 0.9165
Epoch 11/20
60000/60000 [==============================] - 4s 73us/step - loss: 0.7741 - acc: 0.8747 -
val_loss: 0.5135 - val_acc: 0.9171
Epoch 12/20
60000/60000 [==============================] - 5s 76us/step - loss: 0.7555 - acc: 0.8854 -
val_loss: 0.6779 - val_acc: 0.9058
Epoch 13/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.7297 - acc: 0.8841 -
val_loss: 0.4222 - val_acc: 0.9336
Epoch 14/20
60000/60000 [==============================] - 4s 73us/step - loss: 0.7213 - acc: 0.8775 -
```

```
val_loss: 0.4586 - val_acc: 0.9225
Epoch 15/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.5960 - acc: 0.9026 -
val_loss: 0.5041 - val_acc: 0.9186
Epoch 16/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.7184 - acc: 0.8729 -
val_loss: 0.4238 - val_acc: 0.9335
Epoch 17/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.5728 - acc: 0.9041 -
val_loss: 0.3777 - val_acc: 0.9430
Epoch 18/20
60000/60000 [==============================] - 4s 73us/step - loss: 0.5387 - acc: 0.9172 -
val_loss: 0.3496 - val_acc: 0.9457
Epoch 19/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.6138 - acc: 0.8990 -
val_loss: 0.3446 - val_acc: 0.9432
Epoch 20/20
60000/60000 [==============================] - 5s 75us/step - loss: 0.5072 - acc: 0.9234 -
val_loss: 0.3571 - val_acc: 0.9416
```

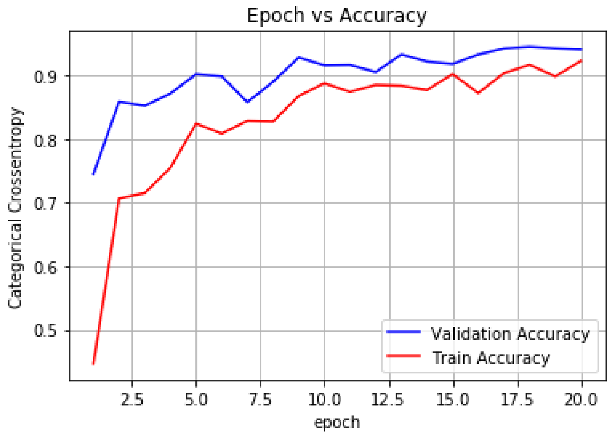
In [45]:

```
d_v_el_5, d_t_el_5 = plotting(d_plot_5, 'loss')
```



In [46]:

```
d_v_ea_5, d_t_ea_5 = plotting(d_plot_5, 'acc')
```



In [47]:

```
d_va_el_5 = np.round(min(d_v_el_5), 3)
d_ta_el_5 = np.round(min(d_t_el_5),3)

print("Validation loss:", d_va_el_5)
print("Train loss:", d_ta_el_5, '\n')

print('*'*30, '\n')

d_va_ea_5 = np.round(max(d_v_ea_5),3)
d_ta_ea_5 = np.round(max(d_t_ea_5),3)
```

```
print("Validation accuracy:", d_va_ea_5)
print("Train accuracy:", d_ta_ea_5)
```

```
Validation loss: 0.345
Train loss: 0.507

******************************

Validation accuracy: 0.946
Train accuracy: 0.923
```

In [0]:

```
# Defining a function to get train and test loss

def mod_batch(layer_batch):

  # Initializing Sequential()
  model_batch = Sequential()

  if layer_batch == 2:

    print("For hidden layers 2", '\n')

    # Passing in parameters like input data, output data and activation
    model_batch.add(Dense(hid_lay_1, activation='relu', input_shape=(input_dim,),
kernel_initializer=RandomNormal(mean=0.0, stddev=0.125, seed=None)))
    model_batch.add(BatchNormalization())
    model_batch.add(Dense(hid_lay_2, activation='relu', kernel_initializer=RandomNormal(mean=0.0, s
tddev=0.125, seed=None)))
    model_batch.add(BatchNormalization())
    model_batch.add(Dense(output_dim, activation='relu'))

  if layer_batch == 3:

    print("For hidden layers 3", '\n')

    # Passing in parameters like input data, output data and activation
    model_batch.add(Dense(hid_lay_1, activation='relu', input_shape=(input_dim,),
kernel_initializer=RandomNormal(mean=0.0, stddev=0.125, seed=None)))
    model_batch.add(BatchNormalization())
    model_batch.add(Dense(hid_lay_2, activation='relu', kernel_initializer=RandomNormal(mean=0.0, s
tddev=0.125, seed=None)))
    model_batch.add(BatchNormalization())
    model_batch.add(Dense(hid_lay_3, activation='relu', kernel_initializer=RandomNormal(mean=0.0, s
tddev=0.125, seed=None)))
    model_batch.add(BatchNormalization())
    model_batch.add(Dense(output_dim, activation='relu'))

  if layer_batch == 5:

    print("For hidden layers 5", '\n')

    # Passing in parameters like input data, output data and activation
    model_batch.add(Dense(hid_lay_1, activation='relu', input_shape=(input_dim,),
kernel_initializer=RandomNormal(mean=0.0, stddev=0.125, seed=None)))
    model_batch.add(BatchNormalization())
    model_batch.add(Dense(hid_lay_2, activation='relu', kernel_initializer=RandomNormal(mean=0.0, s
tddev=0.125, seed=None)))
    model_batch.add(BatchNormalization())
    model_batch.add(Dense(hid_lay_3, activation='relu', kernel_initializer=RandomNormal(mean=0.0, s
tddev=0.125, seed=None)))
    model_batch.add(BatchNormalization())
    model_batch.add(Dense(hid_lay_4, activation='relu', kernel_initializer=RandomNormal(mean=0.0, s
tddev=0.125, seed=None)))
    model_batch.add(BatchNormalization())
    model_batch.add(Dense(hid_lay_5, activation='relu', kernel_initializer=RandomNormal(mean=0.0, s
tddev=0.125, seed=None)))
    model_batch.add(BatchNormalization())
    model_batch.add(Dense(output_dim, activation='relu'))


  # Compiling
  model_batch.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
  # FIt the model
  history = model_batch.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

  return history
```

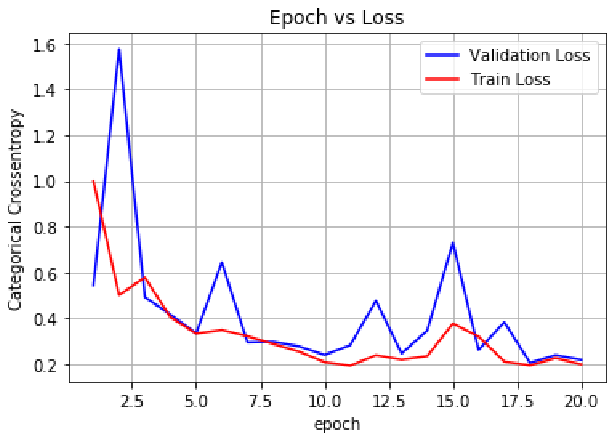
In [49]:

```
b_plot_2 = mod_batch(2)
```

```
For hidden layers 2

Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.9991 - acc: 0.8124 -
val_loss: 0.5446 - val_acc: 0.8979
Epoch 2/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.5026 - acc: 0.8902 -
val_loss: 1.5758 - val_acc: 0.8158
Epoch 3/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.5790 - acc: 0.8375 -
val_loss: 0.4939 - val_acc: 0.8909
Epoch 4/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.4056 - acc: 0.9171 -
val_loss: 0.4172 - val_acc: 0.9368
Epoch 5/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.3347 - acc: 0.9332 -
val_loss: 0.3358 - val_acc: 0.9432
Epoch 6/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.3502 - acc: 0.9222 -
val_loss: 0.6448 - val_acc: 0.8934
Epoch 7/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.3233 - acc: 0.9354 -
val_loss: 0.2960 - val_acc: 0.9482
Epoch 8/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.2892 - acc: 0.9375 -
val_loss: 0.2987 - val_acc: 0.9437
Epoch 9/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.2561 - acc: 0.9428 -
val_loss: 0.2789 - val_acc: 0.9483
Epoch 10/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.2101 - acc: 0.9589 -
val_loss: 0.2414 - val_acc: 0.9616
Epoch 11/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.1944 - acc: 0.9625 -
val_loss: 0.2837 - val_acc: 0.9592
Epoch 12/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.2401 - acc: 0.9479 -
val_loss: 0.4781 - val_acc: 0.9176
Epoch 13/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.2208 - acc: 0.9511 -
val_loss: 0.2475 - val_acc: 0.9632
Epoch 14/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.2362 - acc: 0.9435 -
val_loss: 0.3483 - val_acc: 0.9339
Epoch 15/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.3784 - acc: 0.9009 -
val_loss: 0.7307 - val_acc: 0.8782
Epoch 16/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.3218 - acc: 0.9209 -
val_loss: 0.2633 - val_acc: 0.9459
Epoch 17/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.2121 - acc: 0.9555 -
val_loss: 0.3846 - val_acc: 0.9221
Epoch 18/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.1957 - acc: 0.9575 -
val_loss: 0.2068 - val_acc: 0.9668
Epoch 19/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.2275 - acc: 0.9443 -
val_loss: 0.2407 - val_acc: 0.9539
Epoch 20/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.2001 - acc: 0.9591 -
val_loss: 0.2200 - val_acc: 0.9612
```

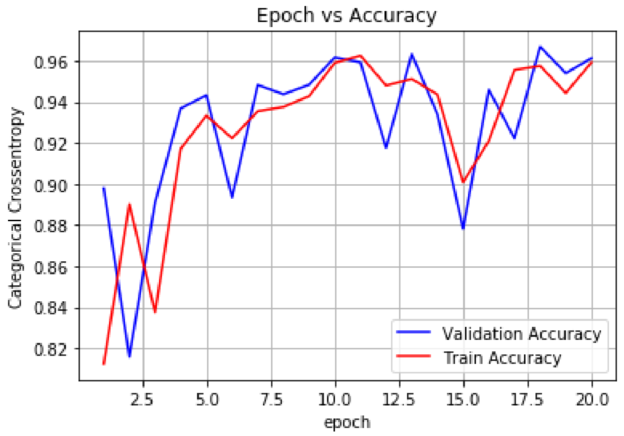
In [50]:

```
b_v_el_2, b_t_el_2 = plotting(b_plot_2, 'loss')
```



In [51]:

```
b_v_ea_2, b_t_ea_2 = plotting(b_plot_2, 'acc')
```



In [52]:

```
b_va_el_2 = np.round(min(b_v_el_2), 3)
b_ta_el_2 = np.round(min(b_t_el_2),3)

print("Validation loss:", b_va_el_2)
print("Train loss:", b_ta_el_2, '\n')

print('*'*30, '\n')

b_va_ea_2 = np.round(max(b_v_ea_2),3)
b_ta_ea_2 = np.round(max(b_t_ea_2),3)

print("Validation accuracy:", b_va_ea_2)
print("Train accuracy:", b_ta_ea_2)
```

```
Validation loss: 0.207
Train loss: 0.194

******************************

Validation accuracy: 0.967
Train accuracy: 0.962
```

In [54]:

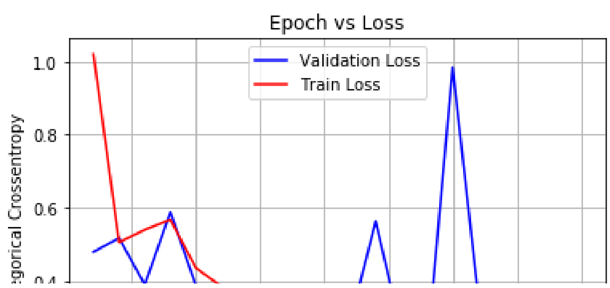
```
b_plot_3 = mod_batch(3)
```

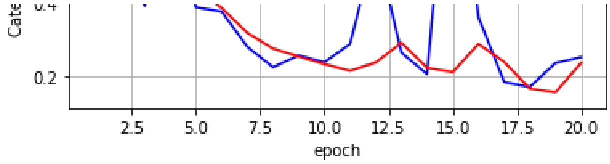
```
For hidden layers 3

Train on 60000 samples, validate on 10000 samples
```

```
Epoch 1/20
60000/60000 [==============================] - 8s 135us/step - loss: 1.0194 - acc: 0.8171 -
val_loss: 0.4800 - val_acc: 0.9129
Epoch 2/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.5061 - acc: 0.8800 -
val_loss: 0.5178 - val_acc: 0.8924
Epoch 3/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.5404 - acc: 0.8745 -
val_loss: 0.3903 - val_acc: 0.9235
Epoch 4/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.5678 - acc: 0.8535 -
val_loss: 0.5888 - val_acc: 0.8377
Epoch 5/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.4355 - acc: 0.8851 -
val_loss: 0.3867 - val_acc: 0.9182
Epoch 6/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.3851 - acc: 0.9109 -
val_loss: 0.3753 - val_acc: 0.9039
Epoch 7/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.3170 - acc: 0.9264 -
val_loss: 0.2790 - val_acc: 0.9435
Epoch 8/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.2741 - acc: 0.9400 -
val_loss: 0.2233 - val_acc: 0.9524
Epoch 9/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.2526 - acc: 0.9418 -
val_loss: 0.2555 - val_acc: 0.9484
Epoch 10/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.2320 - acc: 0.9463 -
val_loss: 0.2369 - val_acc: 0.9513
Epoch 11/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.2137 - acc: 0.9527 -
val_loss: 0.2864 - val_acc: 0.9410
Epoch 12/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.2363 - acc: 0.9422 -
val_loss: 0.5636 - val_acc: 0.9009
Epoch 13/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.2899 - acc: 0.9205 -
val_loss: 0.2629 - val_acc: 0.9404
Epoch 14/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.2218 - acc: 0.9527 -
val_loss: 0.2044 - val_acc: 0.9612
Epoch 15/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.2102 - acc: 0.9523 -
val_loss: 0.9831 - val_acc: 0.8655
Epoch 16/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.2866 - acc: 0.9349 -
val_loss: 0.3600 - val_acc: 0.9121
Epoch 17/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.2379 - acc: 0.9450 -
val_loss: 0.1828 - val_acc: 0.9626
Epoch 18/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.1652 - acc: 0.9648 -
val_loss: 0.1697 - val_acc: 0.9679
Epoch 19/20
60000/60000 [==============================] - 7s 108us/step - loss: 0.1552 - acc: 0.9682 -
val_loss: 0.2348 - val_acc: 0.9475
Epoch 20/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.2352 - acc: 0.9452 -
val_loss: 0.2507 - val_acc: 0.9478
```

In [55]:

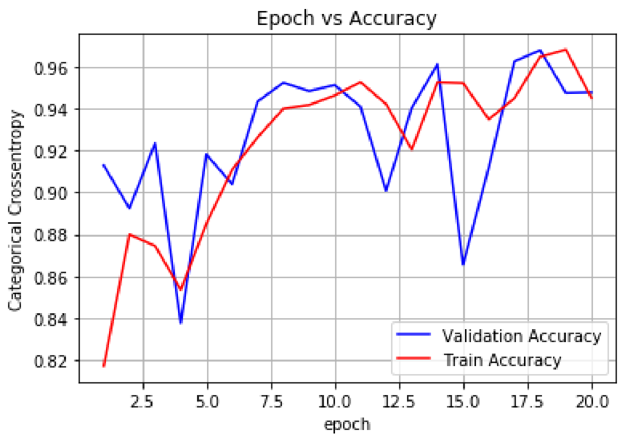
```
b_v_el_3, b_t_el_3 = plotting(b_plot_3, 'loss')
```





In [56]:

```
b_v_ea_3, b_t_ea_3 = plotting(b_plot_3, 'acc')
```



In [57]:

```
b_va_el_3 = np.round(min(b_v_el_3), 3)
b_ta_el_3 = np.round(min(b_t_el_3),3)

print("Validation loss:", b_va_el_3)
print("Train loss:", b_ta_el_3, '\n')

print('*'*30, '\n')

b_va_ea_3 = np.round(max(b_v_ea_3),3)
b_ta_ea_3 = np.round(max(b_t_ea_3),3)

print("Validation accuracy:", b_va_ea_3)
print("Train accuracy:", b_ta_ea_3)
```

```
Validation loss: 0.17
Train loss: 0.155

******************************

Validation accuracy: 0.968
Train accuracy: 0.968
```

In [58]:

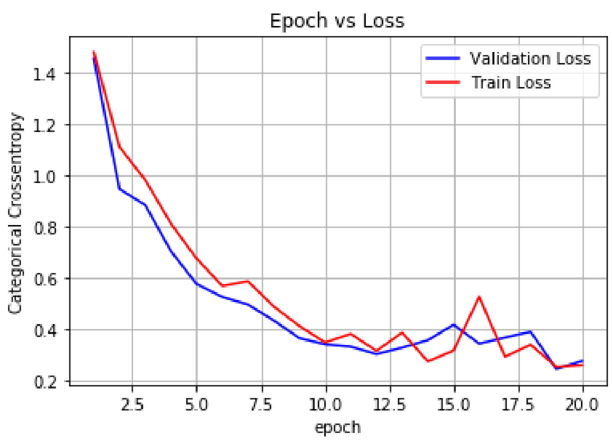
```
b_plot_5 = mod_batch(5)
```

```
For hidden layers 5

Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 11s 191us/step - loss: 1.4800 - acc: 0.7048 - val_l
oss: 1.4548 - val_acc: 0.6643
Epoch 2/20
60000/60000 [==============================] - 9s 149us/step - loss: 1.1101 - acc: 0.7169 -
val_loss: 0.9456 - val_acc: 0.7740
Epoch 3/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.9810 - acc: 0.7525 -
val_loss: 0.8830 - val_acc: 0.7671
Epoch 4/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.8108 - acc: 0.7942 -
val_loss: 0.7032 - val_acc: 0.8403
Epoch 5/20
60000/60000 [==============================] - 9s 150us/step - loss: 0.6740 - acc: 0.8475 -
val_loss: 0.5745 - val_acc: 0.8830
```

```
Epoch 6/20
60000/60000 [==============================] - 9s 150us/step - loss: 0.5670 - acc: 0.8787 -
val_loss: 0.5243 - val_acc: 0.8945
Epoch 7/20
60000/60000 [==============================] - 9s 149us/step - loss: 0.5852 - acc: 0.8559 -
val_loss: 0.4946 - val_acc: 0.8974
Epoch 8/20
60000/60000 [==============================] - 9s 148us/step - loss: 0.4871 - acc: 0.8959 -
val_loss: 0.4324 - val_acc: 0.9159
Epoch 9/20
60000/60000 [==============================] - 9s 150us/step - loss: 0.4106 - acc: 0.9153 -
val_loss: 0.3632 - val_acc: 0.9261
Epoch 10/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.3463 - acc: 0.9276 -
val_loss: 0.3390 - val_acc: 0.9354
Epoch 11/20
60000/60000 [==============================] - 9s 147us/step - loss: 0.3796 - acc: 0.9182 -
val_loss: 0.3300 - val_acc: 0.9380
Epoch 12/20
60000/60000 [==============================] - 9s 150us/step - loss: 0.3135 - acc: 0.9353 -
val_loss: 0.3010 - val_acc: 0.9448
Epoch 13/20
60000/60000 [==============================] - 9s 149us/step - loss: 0.3846 - acc: 0.9174 -
val_loss: 0.3262 - val_acc: 0.9386
Epoch 14/20
60000/60000 [==============================] - 9s 146us/step - loss: 0.2727 - acc: 0.9453 -
val_loss: 0.3551 - val_acc: 0.9312
Epoch 15/20
60000/60000 [==============================] - 9s 146us/step - loss: 0.3144 - acc: 0.9327 -
val_loss: 0.4156 - val_acc: 0.9145
Epoch 16/20
60000/60000 [==============================] - 9s 150us/step - loss: 0.5244 - acc: 0.8814 -
val_loss: 0.3416 - val_acc: 0.9290
Epoch 17/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.2909 - acc: 0.9364 -
val_loss: 0.3653 - val_acc: 0.8967
Epoch 18/20
60000/60000 [==============================] - 9s 148us/step - loss: 0.3375 - acc: 0.9198 -
val_loss: 0.3880 - val_acc: 0.9231
Epoch 19/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.2511 - acc: 0.9459 -
val_loss: 0.2429 - val_acc: 0.9540
Epoch 20/20
60000/60000 [==============================] - 9s 152us/step - loss: 0.2583 - acc: 0.9405 -
val_loss: 0.2742 - val_acc: 0.9435
```

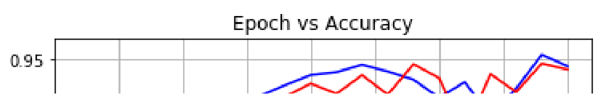
In [59]:

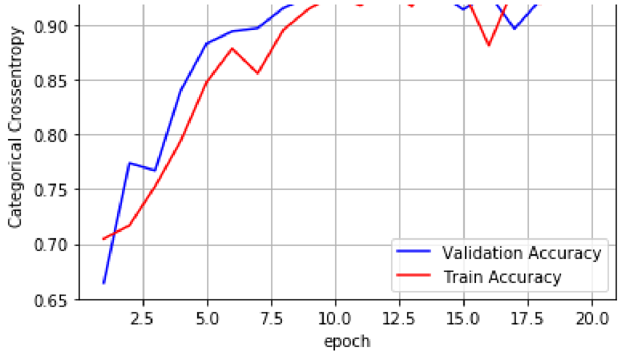
```
b_v_el_5, b_t_el_5 = plotting(b_plot_5, 'loss')
```



In [60]:

```
b_v_ea_5, b_t_ea_5 = plotting(b_plot_5, 'acc')
```





In [61]:

```
b_va_el_5 = np.round(min(b_v_el_5), 3)
b_ta_el_5 = np.round(min(b_t_el_5),3)

print("Validation loss:", b_va_el_5)
print("Train loss:", b_ta_el_5, '\n')

print('*'*30, '\n')

b_va_ea_5 = np.round(max(b_v_ea_5),3)
b_ta_ea_5 = np.round(max(b_t_ea_5),3)

print("Validation accuracy:", b_va_ea_5)
print("Train accuracy:", b_ta_ea_5)
```

```
Validation loss: 0.243
Train loss: 0.251

******************************

Validation accuracy: 0.954
Train accuracy: 0.946
```

In [62]:

```
from prettytable import PrettyTable

a = PrettyTable()

a.field_names = ['S.No', 'Layers', 'Activation', 'Optimizer', 'Regularization', 'Test Loss', 'Test
Accuracy']

a.add_row([1, 2, 'relu', 'adam', 'None', va_el_2, va_ea_2])
a.add_row([2, 3, 'relu', 'adam', 'None', va_el_3, va_ea_3])
a.add_row([3, 5, 'relu', 'adam', 'None', va_el_5, va_ea_5])

print(a.get_string(title = 'Table for activation - relu and optimizer - adam'))

print('\n')

from prettytable import PrettyTable

b = PrettyTable()

b.field_names = ['S.No', 'Layers', 'Activation', 'Optimizer', 'Regularization', 'Test Loss', 'Test
Accuracy']

b.add_row([1, 2, 'relu', 'adam', 'Dropout', d_va_el_2, d_va_ea_2])
b.add_row([2, 3, 'relu', 'adam', 'Dropout', d_va_el_3, d_va_ea_3])
b.add_row([3, 5, 'relu', 'adam', 'Dropout', d_va_el_5, d_va_ea_5])

print(b.get_string(title = 'Table for Activation - Relu and Optimizer - Adam, regularization-
Dropout'))

print('\n')

from prettytable import PrettyTable

c = PrettyTable()

c.field_names = ['S.No', 'Layers', 'Activation', 'Optimizer', 'Regularization', 'Test Loss', 'Test
```

```
c.field_names = ['S.No', 'Layers', 'Activation', 'Optimizer', 'Regularization', 'Test Loss', 'Test Accuracy']

c.add_row([1, 2, 'relu', 'adam', 'Batch Normalization', b_va_el_2, b_va_ea_2])
c.add_row([2, 3, 'relu', 'adam', 'Batch Normalization', b_va_el_3, b_va_ea_3])
c.add_row([3, 5, 'relu', 'adam', 'Batch Normalization', b_va_el_5, b_va_ea_5])

print(c.get_string(title = 'Table for Activation - Relu and Optimizer - Adam, regularization-BatchNormalization'))
```

S.No	Layers	Activation	Optimizer	Regularization	Test Loss	Test Accuracy
1	2	relu	adam	None	0.418	0.934
2	3	relu	adam	None	0.185	0.969
3	5	relu	adam	None	1.798	0.875

S.No	Layers	Activation	Optimizer	Regularization	Test Loss	Test Accuracy
1	2	relu	adam	Dropout	0.226	0.962
2	3	relu	adam	Dropout	0.211	0.966
3	5	relu	adam	Dropout	0.345	0.946

S.No	Layers	Activation	Optimizer	Regularization	Test Loss	Test Accuracy
1	2	relu	adam	Batch Normalization	0.207	0.967
2	3	relu	adam	Batch Normalization	0.17	0.968
3	5	relu	adam	Batch Normalization	0.243	0.954