# Lab 4: Data Imputation using an Autoencoder

In this lab, you will build and train an autoencoder to impute (or "fill in") missing data.

We will be using the Adult Data Set provided by the UCI Machine Learning Repository [1], available at https://archive.ics.uci.edu/ml/datasets/adult. The data set contains census record files of adults, including their age, martial status, the type of work they do, and other features.

Normally, people use this data set to build a supervised classification model to classify whether a person is a high income earner. We will not use the dataset for this original intended purpose.

Instead, we will perform the task of imputing (or "filling in") missing values in the dataset. For example, we may be missing one person's martial status, and another person's age, and a third person's level of education. Our model will predict the missing features based on the information that we do have about each person.

We will use a variation of a denoising autoencoder to solve this data imputation problem. Our autoencoder will be trained using inputs that have one categorical feature artificially removed, and the goal of the autoencoder is to correctly reconstruct all features, including the one removed from the input.

In the process, you are expected to learn to:

1. Clean and process continuous and categorical data for machine learning.
2. Implement an autoencoder that takes continuous and categorical (one-hot) inputs.
3. Tune the hyperparameters of an autoencoder.
4. Use baseline models to help interpret model performance.

[1] Dua, D. and Karra Taniskidou, E. (2017). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.

## What to submit

Submit a PDF file containing all your code, outputs, and write-up. You can produce a PDF of your Google Colab file by going to File > Print and then save as PDF. The Colab instructions have more information.

Do not submit any other files produced by your code.

Include a link to your colab file in your submission.

# Colab Link

Include a link to your Colab file here. If you would like the TA to look at your Colab file in case your solutions are cut off, **please make sure that your Colab file is publicly accessible at the time of submission**.

Colab Link: https://colab.research.google.com/drive/1oJ90ueIz-moe9pjXtNYpz0dIz08UBRzP?usp=sharing

In [34]:
```
import csv
import numpy as np
import random
import torch
import torch.utils.data
import time
import matplotlib.pyplot as plt
```

# Part 0

We will be using a package called `pandas` for this assignment.

If you are using Colab, `pandas` should already be available. If you are using your own computer, installation instructions for `pandas` are available here: https://pandas.pydata.org/pandas-docs/stable/install.html

In [2]:
```
import pandas as pd
```

# Part 1. Data Cleaning [15 pt]

The adult.data file is available at `https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data`

The function `pd.read_csv` loads the adult.data file into a pandas dataframe. You can read about the pandas documentation for `pd.read_csv` at https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.read_csv.html

In [3]:
```
header = ['age', 'work', 'fnlwgt', 'edu', 'yredu', 'marriage', 'occupation',
 'relationship', 'race', 'sex', 'capgain', 'caploss', 'workhr', 'country']
df = pd.read_csv(
    "https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.d
    names=header,
    index_col=False)
```

```
<ipython-input-3-037957db2593>:3: ParserWarning: Length of header or names d
oes not match length of data. This leads to a loss of data with index_col=Fa
lse.
  df = pd.read_csv(
```

In [4]:
```
df.shape # there are 32561 rows (records) in the data frame, and 14 columns
```

Out[4]:
```
(32561, 14)
```

## Part (a) Continuous Features [3 pt]

For each of the columns `["age", "yredu", "capgain", "caploss", "workhr"]`, report the minimum, maximum, and average value across the dataset.

Then, normalize each of the features `["age", "yredu", "capgain", "caploss", "workhr"]` so that their values are always between 0 and 1. Make sure that you are actually modifying the dataframe `df`.

Like numpy arrays and torch tensors, pandas data frames can be sliced. For example, we can display the first 3 rows of the data frame (3 records) below.

In [5]:
```
df[:3] # show the first 3 records
```

Out[5]:

| | age | work | fnlwgt | edu | yredu | marriage | occupation | relationship | race | sex |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 39 | State-gov | 77516 | Bachelors | 13 | Never-married | Adm-clerical | Not-in-family | White | Male |
| **1** | 50 | Self-emp-not-inc | 83311 | Bachelors | 13 | Married-civ-spouse | Exec-managerial | Husband | White | Male |
| **2** | 38 | Private | 215646 | HS-grad | 9 | Divorced | Handlers-cleaners | Not-in-family | White | Male |

Alternatively, we can slice based on column names, for example `df["race"]`, `df["hr"]`, or even index multiple columns like below.

In [6]:

```
subdf = df[["age", "yredu", "capgain", "caploss", "workhr"]]
subdf[:3] # show the first 3 records
```

Out[6]:

| | age | yredu | capgain | caploss | workhr |
|---|---|---|---|---|---|
| **0** | 39 | 13 | 2174 | 0 | 40 |
| **1** | 50 | 13 | 0 | 0 | 13 |
| **2** | 38 | 9 | 0 | 0 | 40 |

Numpy works nicely with pandas, like below:

In [7]:

```
np.sum(subdf["caploss"])
```

Out[7]:

```
2842700
```

Just like numpy arrays, you can modify entire columns of data rather than one scalar element at a time. For example, the code

`df["age"] = df["age"] + 1`

would increment everyone's age by 1.

In [211…

```
print("The maximum value at each desired column: \n")
print(subdf.max(), '\n')
print('The minimum value at each desired column: \n')
print(subdf.min(), '\n')
print('The average value at each desired column: \n')
print(subdf.mean())
```

```
The maximum value at each desired column:

age           90
yredu         16
capgain    99999
caploss     4356
workhr        99
dtype: int64

The minimum value at each desired column:

age        17
yredu       1
capgain     0
caploss     0
workhr      1
dtype: int64

The average value at each desired column:

age          38.581647
yredu        10.080679
capgain    1077.648844
caploss      87.303830
workhr       40.437456
dtype: float64
```

In [9]:

```
df[["age", "yredu", "capgain", "caploss", "workhr"]] = (subdf - subdf.min())
print('This is the normalized dataframe: \n')
df[:3]
```

```
This is the normalized dataframe:
```

Out[9]:

| | age | work | fnlwgt | edu | yredu | marriage | occupation | relationship | race |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.301370 | State-gov | 77516 | Bachelors | 0.800000 | Never-married | Adm-clerical | Not-in-family | White |
| **1** | 0.452055 | Self-emp-not-inc | 83311 | Bachelors | 0.800000 | Married-civ-spouse | Exec-managerial | Husband | White |
| **2** | 0.287671 | Private | 215646 | HS-grad | 0.533333 | Divorced | Handlers-cleaners | Not-in-family | White |

## Part (b) Categorical Features [1 pt]

What percentage of people in our data set are male? Note that the data labels all have an unfortunate space in the beginning, e.g. " Male" instead of "Male".

What percentage of people in our data set are female?

In [10]:
```
# hint: you can do something like this in pandas
sum(df["sex"] == " Male")
```

Out[10]:
```
21790
```

In [11]:
```
total_people = df["sex"].size
male_num = sum(df["sex"] == " Male")
female_num = sum(df["sex"] == " Female")

print("The percentage of male in our dataset is: ",
      male_num/total_people*100 ,'%.')
print("The percentage of female in our dataset is: ",
      female_num/total_people*100 ,'%.')
```

```
The percentage of male in our dataset is:  66.92054912318419 %.
The percentage of female in our dataset is:  33.07945087681583 %.
```

## Part (c) [2 pt]

Before proceeding, we will modify our data frame in a couple more ways:

1. We will restrict ourselves to using a subset of the features (to simplify our autoencoder)
2. We will remove any records (rows) already containing missing values, and store them in a second dataframe. We will only use records without missing values to train our autoencoder.

Both of these steps are done for you, below.

How many records contained missing features? What percentage of records were removed?

In [12]:
```
contcols = ["age", "yredu", "capgain", "caploss", "workhr"]
catcols = ["work", "marriage", "occupation", "edu", "relationship", "sex"]
features = contcols + catcols
df = df[features]
```

In [13]:
```
missing = pd.concat([df[c] == " ?" for c in catcols], axis=1).any(axis=1)
df_with_missing = df[missing]
df_not_missing = df[~missing]
```

In [14]:
```
print(df_with_missing.shape[0], "records contains missing features.")
print(df_with_missing.shape[0]/df.shape[0]*100, "% of records were removed."
```

```
1843 records contains missing features.
5.660145572924664 % of records were removed.
```

## Part (d) One-Hot Encoding [1 pt]

What are all the possible values of the feature "work" in `df_not_missing`? You may find the Python function `set` useful.

In [15]:
```
work_types = set(df_not_missing["work"])
print("All the possible values of \"work\" are: ")

for type in work_types:
  print(type)
```

```
All the possible values of "work" are:
 Federal-gov
 Local-gov
 Without-pay
 Private
 State-gov
 Self-emp-inc
 Self-emp-not-inc
```

We will be using a one-hot encoding to represent each of the categorical variables. Our autoencoder will be trained using these one-hot encodings.

We will use the pandas function `get_dummies` to produce one-hot encodings for all of the categorical variables in `df_not_missing`.

In [16]:
```
data = pd.get_dummies(df_not_missing)
```

In [17]:
```
data[:3]
```

Out[17]:

| | age | yredu | capgain | caploss | workhr | work_ Federal- gov | work_ Local- gov | work_ Private | work_ Self- emp- inc | work_ Self- emp- not- inc |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.301370 | 0.800000 | 0.02174 | 0.0 | 0.397959 | 0 | 0 | 0 | 0 | 0 |
| **1** | 0.452055 | 0.800000 | 0.00000 | 0.0 | 0.122449 | 0 | 0 | 0 | 0 | 1 |
| **2** | 0.287671 | 0.533333 | 0.00000 | 0.0 | 0.397959 | 0 | 0 | 1 | 0 | 0 |

3 rows × 57 columns

## Part (e) One-Hot Encoding [2 pt]

The dataframe `data` contains the cleaned and normalized data that we will use to train our denoising autoencoder.

How many **columns** (features) are in the dataframe `data`?

Briefly explain where that number come from.

In [18]:

```
print("There are", data.shape[1],"columns in data.")
```

```
There are 57 columns in data.
```

In [19]:

```
#This number comes from the sum of the number of
#all possible values of the categorial features
#and the number of continuous features.

number = len(work_types) + len(set(df_not_missing["marriage"])) + len(set(df
print(number)
```

```
57
```

## Part (f) One-Hot Conversion [3 pt]

We will convert the pandas data frame `data` into numpy, so that it can be further converted into a PyTorch tensor. However, in doing so, we lose the column label information that a panda data frame automatically stores.

Complete the function `get_categorical_value` that will return the named value of a feature given a one-hot embedding. You may find the global variables `cat_index` and `cat_values` useful. (Display them and figure out what they are first.)

We will need this function in the next part of the lab to interpret our autoencoder outputs. So, the input to our function `get_categorical_values` might not actually be "one-hot" -- the input may instead contain real-valued predictions from our neural network.

In [20]:

```
datanp = data.values.astype(np.float32)
```

In [21]:

```
cat_index = {}  # Mapping of feature -> start index of feature in a record
cat_values = {} # Mapping of feature -> list of categorical values the featu

# build up the cat_index and cat_values dictionary
for i, header in enumerate(data.keys()):
    if "_" in header: # categorical header
        feature, value = header.split()
        feature = feature[:-1] # remove the last char; it is always an under
        if feature not in cat_index:
            cat_index[feature] = i
            cat_values[feature] = [value]
        else:
            cat_values[feature].append(value)

def get_onehot(record, feature):
    """
    Return the portion of `record` that is the one-hot encoding
    of `feature`. For example, since the feature "work" is stored
    in the indices [5:12] in each record, calling `get_range(record, "work")
    is equivalent to accessing `record[5:12]`.

    Args:
        - record: a numpy array representing one record, formatted
                  the same way as a row in `data.np`
        - feature: a string, should be an element of `catcols`
    """
    start_index = cat_index[feature]
    stop_index = cat_index[feature] + len(cat_values[feature])
    return record[start_index:stop_index]
```

In [22]:
```
cat_index
```

Out[22]:
```
{'work': 5,
 'marriage': 12,
 'occupation': 19,
 'edu': 33,
 'relationship': 49,
 'sex': 55}
```

In [23]:
```
cat_values
```

Out[23]:
```
{'work': ['Federal-gov',
  'Local-gov',
  'Private',
  'Self-emp-inc',
  'Self-emp-not-inc',
  'State-gov',
  'Without-pay'],
 'marriage': ['Divorced',
  'Married-AF-spouse',
  'Married-civ-spouse',
  'Married-spouse-absent',
  'Never-married',
  'Separated',
  'Widowed'],
 'occupation': ['Adm-clerical',
  'Armed-Forces',
  'Craft-repair',
  'Exec-managerial',
  'Farming-fishing',
  'Handlers-cleaners',
  'Machine-op-inspct',
  'Other-service',
  'Priv-house-serv',
  'Prof-specialty',
  'Protective-serv',
  'Sales',
  'Tech-support',
  'Transport-moving'],
 'edu': ['10th',
  '11th',
  '12th',
  '1st-4th',
  '5th-6th',
  '7th-8th',
  '9th',
  'Assoc-acdm',
  'Assoc-voc',
  'Bachelors',
  'Doctorate',
  'HS-grad',
  'Masters',
  'Preschool',
  'Prof-school',
  'Some-college'],
 'relationship': ['Husband',
  'Not-in-family',
  'Other-relative',
  'Own-child',
  'Unmarried',
  'Wife'],
 'sex': ['Female', 'Male']}
```

In [24]:
```
def get_categorical_value(onehot, feature):
    """
    Return the categorical value name of a feature given
    a one-hot vector representing the feature.

    Args:
        - onehot: a numpy array one-hot representation of the feature
        - feature: a string, should be an element of `catcols`

    Examples:

    >>> get_categorical_value(np.array([0., 0., 0., 0., 0., 1., 0.]), "work"
    'State-gov'
    >>> get_categorical_value(np.array([0.1, 0., 1.1, 0.2, 0., 1., 0.]), "wo
    'Private'
    """
    # <----- TODO: WRITE YOUR CODE HERE ----->
    # You may find the variables `cat_index` and `cat_values`
    # (created above) useful.
    max_index = np.argmax(onehot)
    return cat_values[feature][max_index]
```

In [25]:
```
get_categorical_value(np.array([0., 0., 0., 0., 0., 1., 0.]), "work")
```

Out[25]:
```
'State-gov'
```

In [26]:
```
get_categorical_value(np.array([0.1, 0., 1.1, 0.2, 0., 1., 0.]), "work")
```

Out[26]:
```
'Private'
```

In [27]:
```
# more useful code, used during training, that depends on the function
# you write above

def get_feature(record, feature):
    """
    Return the categorical feature value of a record
    """
    onehot = get_onehot(record, feature)
    return get_categorical_value(onehot, feature)

def get_features(record):
    """
    Return a dictionary of all categorical feature values of a record
    """
    return { f: get_feature(record, f) for f in catcols }
```

### Part (g) Train/Test Split [3 pt]

Randomly split the data into approximately 70% training, 15% validation and 15% test.

Report the number of items in your training, validation, and test set.

In [28]:
```
# set the numpy seed for reproducibility
# https://docs.scipy.org/doc/numpy/reference/generated/numpy.random.seed.htm
np.random.seed(50)

# todo
np.random.shuffle(datanp)

#indicate split points
split_1 = int(len(datanp) * 0.7)
split_2 = int(len(datanp) * 0.85)

train_data= datanp[:split_1]
val_data = datanp[split_1:split_2]
test_data = datanp[split_2:]

print("There are ", len(train_data), "items in training set.")
print("There are ", len(val_data), "items in validation set.")
print("There are ", len(test_data), "items in test set.")
```

```
There are  21502 items in training set.
There are  4608 items in validation set.
There are  4608 items in test set.
```

## Part 2. Model Setup [5 pt]

### Part (a) [4 pt]

Design a fully-connected autoencoder by modifying the `encoder` and `decoder` below.

The input to this autoencoder will be the features of the `data`, with one categorical feature recorded as "missing". The output of the autoencoder should be the reconstruction of the same features, but with the missing value filled in.

**Note**: Do not reduce the dimensionality of the input too much! The output of your embedding is expected to contain information about ~11 features.

In [185…

```
from torch import nn

class AutoEncoder(nn.Module):
    def __init__(self):
        super(AutoEncoder, self).__init__()
        self.name = "AutoEncoder"
        self.encoder = nn.Sequential(
            nn.Linear(57, 40), # TODO -- FILL OUT THE CODE HERE!
            nn.ReLU(),
            nn.Linear(40,20),
            nn.ReLU()
        )
        self.decoder = nn.Sequential(
            nn.Linear(20,40),
            nn.ReLU(),
            nn.Linear(40, 57), # TODO -- FILL OUT THE CODE HERE!
            nn.Sigmoid() # get to the range (0, 1)
        )

    def forward(self, x):
        x = self.encoder(x)
        x = self.decoder(x)
        return x
```

## Part (b) [1 pt]

Explain why there is a sigmoid activation in the last step of the decoder.

(**Note**: the values inside the data frame `data` and the training code in Part 3 might be helpful.)

In [30]:

```
#Sigmoid function forces the output to be
#in the range of [0,1] since the values in the dataframe
#data is normalized to the range of [0,1]
```

# Part 3. Training [18]

## Part (a) [6 pt]

We will train our autoencoder in the following way:

- In each iteration, we will hide one of the categorical features using the `zero_out_random_features` function
- We will pass the data with one missing feature through the autoencoder, and obtain a reconstruction
- We will check how close the reconstruction is compared to the original data -- including the value of the missing feature

Complete the code to train the autoencoder, and plot the training and validation loss every few iterations. You may also want to plot training and validation "accuracy" every few iterations, as we will define in part (b). You may also want to checkpoint your model every few iterations or epochs.

Use `nn.MSELoss()` as your loss function. (Side note: you might recognize that this loss function is not ideal for this problem, but we will use it anyway.)

In [178…

```
def zero_out_feature(records, feature):
    """ Set the feature missing in records, by setting the appropriate
    columns of records to 0
    """
    start_index = cat_index[feature]
    stop_index = cat_index[feature] + len(cat_values[feature])
    records[:, start_index:stop_index] = 0
    return records

def zero_out_random_feature(records):
    """ Set one random feature missing in records, by setting the
    appropriate columns of records to 0
    """
    return zero_out_feature(records, random.choice(catcols))

def get_model_name(name, batch_size, learning_rate, epoch):
    path = "model_{0}_bs{1}_lr{2}_epoch{3}".format(name,
                                                    batch_size,
                                                    learning_rate,
                                                   epoch)
    return path

def train(model, train_data, valid_data, batch_size = 64, num_epochs=5, lear
    """ Training loop. You should update this."""
    train_loader = torch.utils.data.DataLoader(train_data, batch_size=64, sh
```

```
    val_loader = torch.utils.data.DataLoader(val_data, batch_size=64, shuffl

    torch.manual_seed(42)
    criterion = nn.MSELoss()
    optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)

    iters, train_losses, val_losses, train_acc, val_acc = [], [], [], [], []

    start_time = time.time()
    n = 0
    for epoch in range(num_epochs):
        for data in train_loader:
            datam = zero_out_random_feature(data.clone()) # zero out one cat
            recon = model(datam)
            train_loss = criterion(recon, data)
            train_loss.backward()
            optimizer.step()
            optimizer.zero_grad()

        total_val_loss = 0.0
        i = 0

        for data in val_loader:
            datam = zero_out_random_feature(data.clone()) # zero out one cat
            recon = model(datam)
            loss = criterion(recon, data)
            total_val_loss += loss.item()
            i += 1

        val_loss = float(total_val_loss)/(i + 1)

        iters.append(n)
        train_losses.append(float(train_loss) / batch_size) # compute *avera
        val_losses.append(float(val_loss)/batch_size)
        n += 1
        # Save the current model (checkpoint) to a file
        model_path = get_model_name(model.name, batch_size, learning_rate, e
        torch.save(model.state_dict(), model_path)

        train_acc.append(get_accuracy(model, train_loader))  # compute trair
        val_acc.append(get_accuracy(model, val_loader))    #compute validati
        print(("Epoch {}: Train accuracy: {} |" +
               "Validation accuracy: {} ").format(
                epoch +1,
                train_acc[epoch],
                val_acc[epoch]))

    print("Finish Training")
    end_time = time.time()
    elapsed_time = end_time - start_time
    print("Total time elapsed: {:.2f} seconds".format(elapsed_time))

    # plotting
```

```
    plt.title("Training Curve")
    plt.plot(iters, train_losses, label="Train")
    plt.plot(iters, val_losses, label="Validation")
    plt.xlabel("Iterations")
    plt.ylabel("Loss")
    plt.show()

    plt.title("Training Curve")
    plt.plot(range(1, num_epochs+1), train_acc, label="Train")
    plt.plot(range(1, num_epochs+1), val_acc, label="Validation")
    plt.xlabel("Iterations")
    plt.ylabel("Training Accuracy")
    plt.legend(loc='best')
    plt.show()

    print("Final Training Accuracy: {}".format(train_acc[-1]))
    print("Final Validation Accuracy: {}".format(val_acc[-1]))
```

## Part (b) [3 pt]

While plotting training and validation loss is valuable, loss values are harder to compare than accuracy percentages. It would be nice to have a measure of "accuracy" in this problem.

Since we will only be imputing missing categorical values, we will define an accuracy measure. For each record and for each categorical feature, we determine whether the model can predict the categorical feature given all the other features of the record.

A function `get_accuracy` is written for you. It is up to you to figure out how to use the function. **You don't need to submit anything in this part.** To earn the marks, correctly plot the training and validation accuracy every few iterations as part of your training curve.

In [179…

```
def get_accuracy(model, data_loader):
    """Return the "accuracy" of the autoencoder model across a data set.
    That is, for each record and for each categorical feature,
    we determine whether the model can successfully predict the value
    of the categorical feature given all the other features of the
    record. The returned "accuracy" measure is the percentage of times
    that our model is successful.

    Args:
       - model: the autoencoder model, an instance of nn.Module
       - data_loader: an instance of torch.utils.data.DataLoader

    Example (to illustrate how get_accuracy is intended to be called.
             Depending on your variable naming this code might require
             modification.)

        >>> model = AutoEncoder()
        >>> vdl = torch.utils.data.DataLoader(data_valid, batch_size=256, sh
        >>> get_accuracy(model, vdl)
    """
    total = 0
    acc = 0
    for col in catcols:
        for item in data_loader: # minibatches
            inp = item.detach().numpy()
            out = model(zero_out_feature(item.clone(), col)).detach().numpy(
            for i in range(out.shape[0]): # record in minibatch
                acc += int(get_feature(out[i], col) == get_feature(inp[i], c
                total += 1
    return acc / total
```

## Part (c) [4 pt]

Run your updated training code, using reasonable initial hyperparameters.

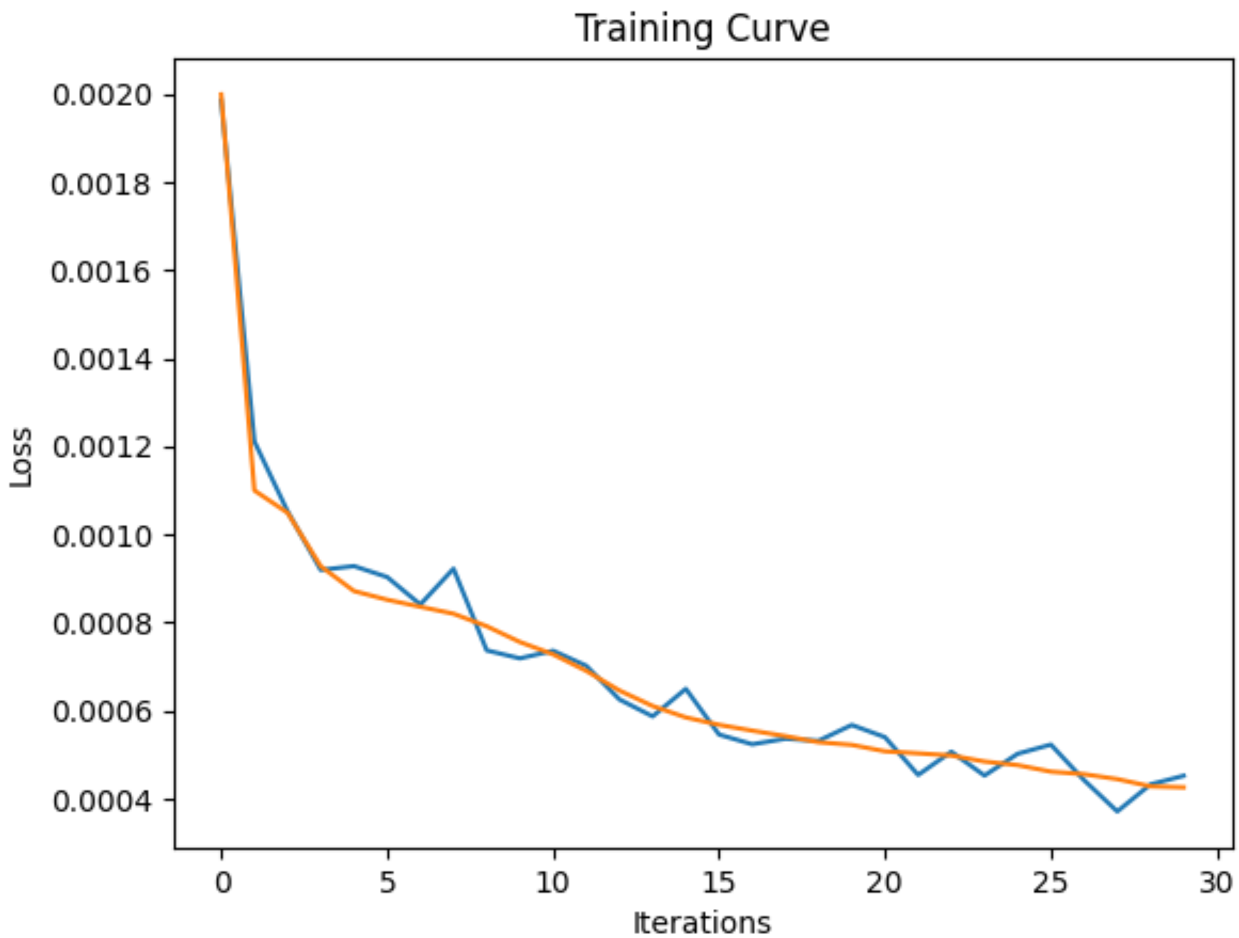
Include your training curve in your submission.

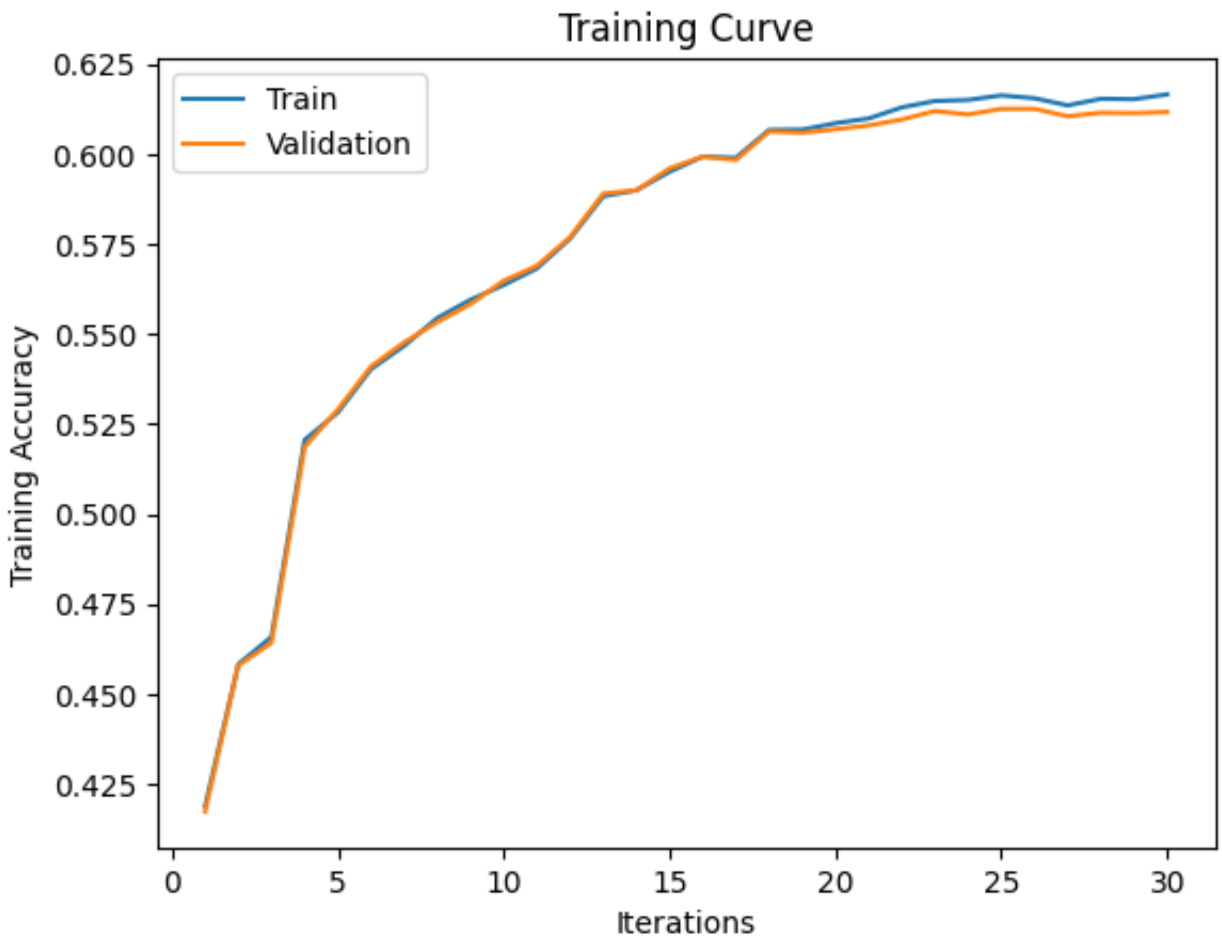
In [186…

```
AE = AutoEncoder()
train(AE, train_data, val_data, num_epochs= 30)
```

```
Epoch 1: Train accuracy: 0.41884475862710446 |Validation accuracy: 0.4173538
773148148
Epoch 2: Train accuracy: 0.45828295042321643 |Validation accuracy: 0.4579354
7453703703
Epoch 3: Train accuracy: 0.4658558893746318 |Validation accuracy: 0.46419270
83333333
Epoch 4: Train accuracy: 0.5206259882801599 |Validation accuracy: 0.51862702
54629629
Epoch 5: Train accuracy: 0.5282454345332217 |Validation accuracy: 0.52904369
21296297
Epoch 6: Train accuracy: 0.5402675720088054 |Validation accuracy: 0.54101562
```

```
5
Epoch 7: Train accuracy: 0.5467398381545903 |Validation accuracy: 0.54770688
65740741
Epoch 8: Train accuracy: 0.5544833038787089 |Validation accuracy: 0.55334924
76851852
Epoch 9: Train accuracy: 0.5595370973242799 |Validation accuracy: 0.55834056
71296297
Epoch 10: Train accuracy: 0.5636529935199827 |Validation accuracy: 0.5648148
148148148
Epoch 11: Train accuracy: 0.56824171394909 |Validation accuracy: 0.568974247
6851852
Epoch 12: Train accuracy: 0.5765355160760239 |Validation accuracy: 0.5769314
236111112
Epoch 13: Train accuracy: 0.5882941121756116 |Validation accuracy: 0.5890480
324074074
Epoch 14: Train accuracy: 0.5899761262518215 |Validation accuracy: 0.5899522
569444444
Epoch 15: Train accuracy: 0.5951229343006852 |Validation accuracy: 0.5960648
148148148
Epoch 16: Train accuracy: 0.5993395963166217 |Validation accuracy: 0.5993200
231481481
Epoch 17: Train accuracy: 0.598983040337333 |Validation accuracy: 0.59837962
96296297
Epoch 18: Train accuracy: 0.6067420084953338 |Validation accuracy: 0.6063006
365740741
Epoch 19: Train accuracy: 0.6068117694478034 |Validation accuracy: 0.6059751
157407407
Epoch 20: Train accuracy: 0.6086100517781292 |Validation accuracy: 0.6069155
092592593
Epoch 21: Train accuracy: 0.6099122562242272 |Validation accuracy: 0.6079644
097222222
Epoch 22: Train accuracy: 0.61300499178371 |Validation accuracy: 0.609628182
8703703
Epoch 23: Train accuracy: 0.6147722692462717 |Validation accuracy: 0.6119791
666666666
Epoch 24: Train accuracy: 0.615066815490032 |Validation accuracy: 0.61103877
31481481
Epoch 25: Train accuracy: 0.6163380150683657 |Validation accuracy: 0.6125940
393518519
Epoch 26: Train accuracy: 0.6155318885064955 |Validation accuracy: 0.6125940
393518519
Epoch 27: Train accuracy: 0.6135553281865253 |Validation accuracy: 0.6105324
074074074
Epoch 28: Train accuracy: 0.6153768641676743 |Validation accuracy: 0.6115089
699074074
Epoch 29: Train accuracy: 0.6152838495643816 |Validation accuracy: 0.6114004
629629629
Epoch 30: Train accuracy: 0.6166093076613028 |Validation accuracy: 0.6117259
837962963
Finish Training
Total time elapsed: 75.02 seconds
```


Training Curve
0.0020
0.0018
0.0016
0.0014
0.0012
0.0010
0.0008
0.0006
0.0004
Loss
0
5
10
15
20
25
30
Iterations




```
Final Training Accuracy: 0.6166093076613028
Final Validation Accuracy: 0.6117259837962963
```

## Part (d) [5 pt]

Tune your hyperparameters, training at least 4 different models (4 sets of hyperparameters).

Do not include all your training curves. Instead, explain what hyperparameters you tried, what their effect was, and what your thought process was as you chose the next set of hyperparameters to try.

In [183…

```
def no_plot_train(model, train_data, valid_data, batch_size = 64, num_epochs
    """ Training loop. You should update this."""
    train_loader = torch.utils.data.DataLoader(train_data, batch_size=64, sh
    val_loader = torch.utils.data.DataLoader(val_data, batch_size=64, shuffl

    torch.manual_seed(42)
    criterion = nn.MSELoss()
    optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)

    iters, train_losses, val_losses, train_acc, val_acc = [], [], [], [], []

    start_time = time.time()
    n = 0
    for epoch in range(num_epochs):
        for data in train_loader:
            datam = zero_out_random_feature(data.clone()) # zero out one cat
            recon = model(datam)
            train_loss = criterion(recon, data)
            train_loss.backward()
            optimizer.step()
            optimizer.zero_grad()

        total_val_loss = 0.0
        i = 0

        for data in val_loader:
            datam = zero_out_random_feature(data.clone()) # zero out one cat
            recon = model(datam)
            loss = criterion(recon, data)
            total_val_loss += loss.item()
            i += 1

        val_loss = float(total_val_loss)/(i + 1)

        iters.append(n)
        train_losses.append(float(train_loss) / batch_size) # compute *avera
        val_losses.append(float(val_loss)/batch_size)
        n += 1
        # Save the current model (checkpoint) to a file
        model_path = get_model_name(model.name, batch_size, learning_rate, e
        torch.save(model.state_dict(), model_path)

        train_acc.append(get_accuracy(model, train_loader))  # compute trair
        val_acc.append(get_accuracy(model, val_loader))    #compute validati

    print("Finish Training")
    end_time = time.time()
    elapsed_time = end_time - start_time
    print("Total time elapsed: {:.2f} seconds".format(elapsed_time))
    print(("Final training accuracy: {}").format(train_acc[-1]))
    print(("Final validation accuracy: {}").format(val_acc[-1]))
```

In [187…

```
model_1 = AutoEncoder()
no_plot_train(model_1, train_data, val_data, num_epochs = 50, learning_rate=

#Hyperparameter set 1:

#batch_size = 64
#num_epochs = 50
#learning_rate = 0.001

#I kept the batch_size the same because I
#think the epoch is too short and the
#learning rate is too small.
#By increasing epochs and learning rate,
#the model will faster converge to its
#minimum loss.
```

```
Finish Training
Total time elapsed: 122.91 seconds
Final training accuracy: 0.6530322760673426
Final validation accuracy: 0.6509693287037037
```

In [188…

```
model_2 = AutoEncoder()
no_plot_train(model_2, train_data, val_data,
              batch_size = 128, num_epochs = 50,
              learning_rate = 0.007)

#Hyperparameter set 2:

#batch_size = 128
#num_epochs = 50
#learning_rate = 0.007

#Based on the last training, I increases the batch_size
#because the dataset is very large, larger batch_size
#will help increase training efficiency.
#I also increase the learning_rate a bit more to 0.007
#to see if the model can converge more than the last
#training.
```

```
Finish Training
Total time elapsed: 122.28 seconds
Final training accuracy: 0.6938734381297864
Final validation accuracy: 0.6915147569444444
```

In [190…

```
model_3 = AutoEncoder()
no_plot_train(model_3, train_data, val_data,
              batch_size = 128, num_epochs = 80,
              learning_rate = 0.007)

#Hyperparameter set 3:

#batch_size = 128
#num_epochs = 80
#learning_rate = 0.007

#Model_2 did outperform the model_1, so
#in model_3, I will keep the same batch_size and
#learning_rate.
#I increase the epochs to 80 because the
#model's accuracy still seems to be increasing
#at the end of the last training.
```

```
Finish Training
Total time elapsed: 195.79 seconds
Final training accuracy: 0.6997798654388739
Final validation accuracy: 0.6951678240740741
```

In [194…

```
model_4 = AutoEncoder()
train(model_4, train_data, val_data,
              batch_size = 128, num_epochs = 90,
              learning_rate = 0.0065)

#Hyperparameter set 4:

#batch_size = 128
#num_epochs = 90
#learning_rate = 0.007

#Model_3 performed better than model_2,
#so batch_size remain unchanged.
#But for the learning_rate, I will decrease
#it to 0.0065 to check if it can reach its
#minimum loss more slowly but accurately.
#The number of epochs is increased to 90 to
#see if the model's accuracy can still increase because
#in the last training, it seemed to be increasing in the
#end.
```

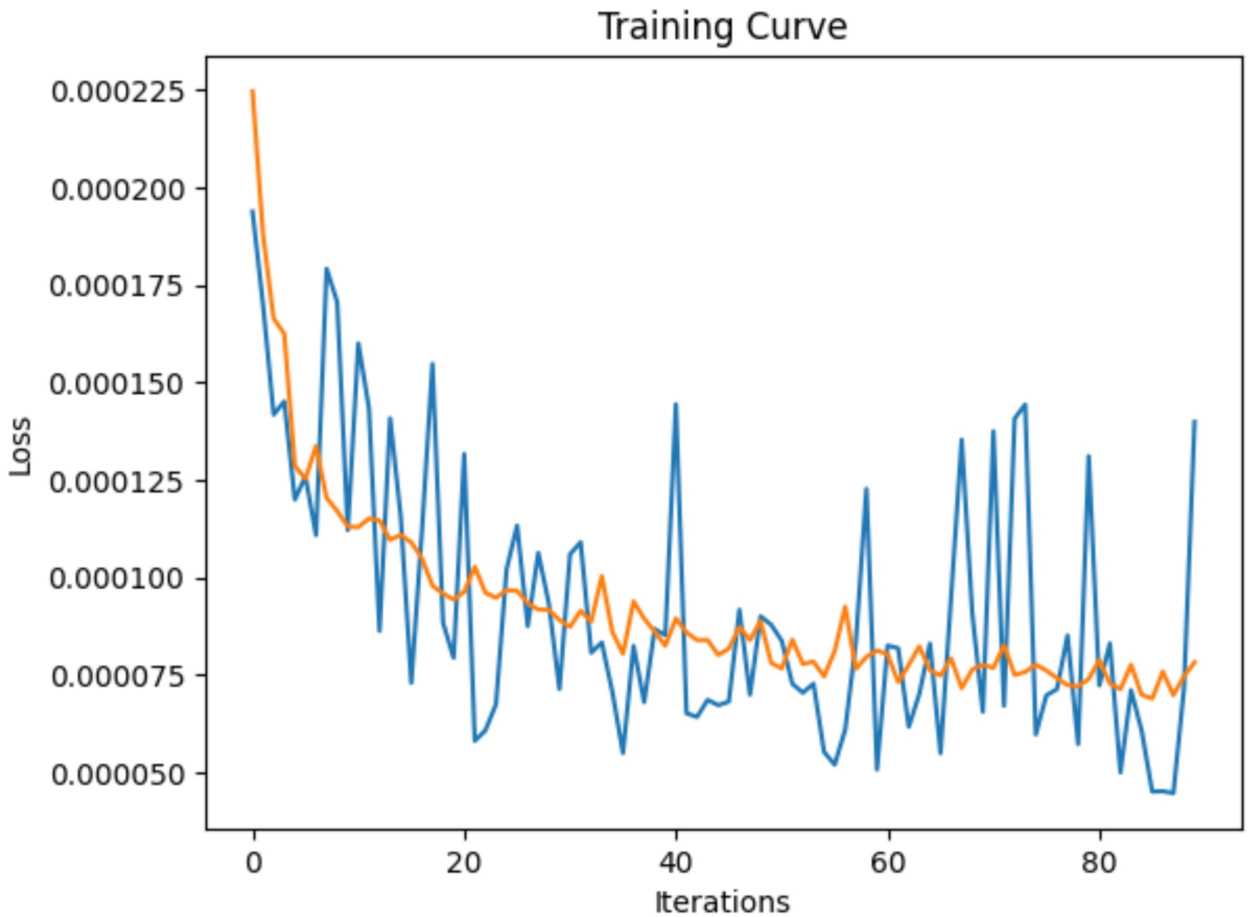
```
Epoch 1: Train accuracy: 0.6103385731559855 |Validation accuracy: 0.60611979
16666666
Epoch 2: Train accuracy: 0.6171363904132949 |Validation accuracy: 0.61089409
72222222
Epoch 3: Train accuracy: 0.6183843363408055 |Validation accuracy: 0.61103877
31481481
Epoch 4: Train accuracy: 0.6173921805723499 |Validation accuracy: 0.61469184
02777778
Epoch 5: Train accuracy: 0.6297708740272223 |Validation accuracy: 0.62528935
```

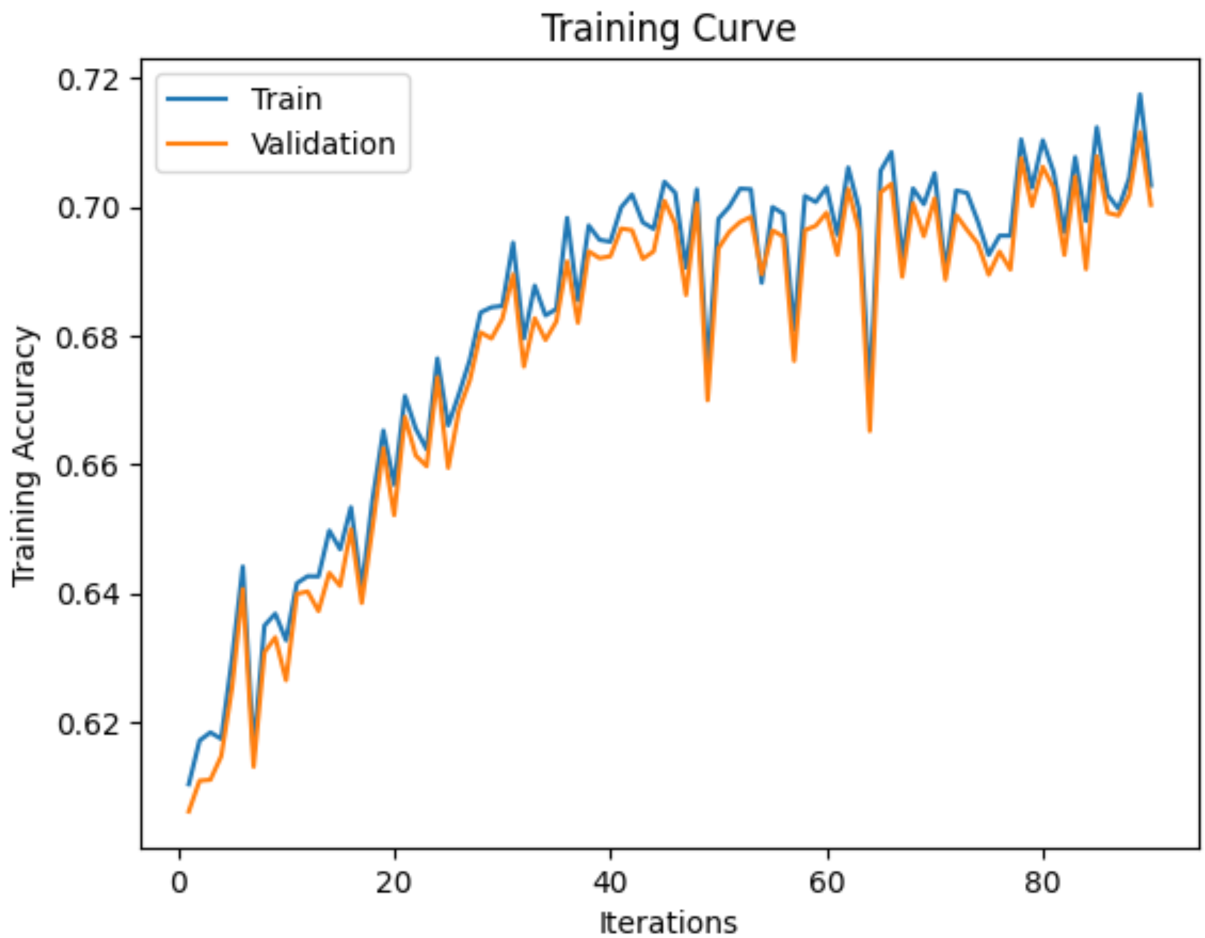
```
18518519
Epoch 6: Train accuracy: 0.6441416302359471 |Validation accuracy: 0.64066116
89814815
Epoch 7: Train accuracy: 0.615725668930022 |Validation accuracy: 0.613064236
1111112
Epoch 8: Train accuracy: 0.6349719405946733 |Validation accuracy: 0.63082320
60185185
Epoch 9: Train accuracy: 0.6368244814435866 |Validation accuracy: 0.63313802
08333334
Epoch 10: Train accuracy: 0.6326930828140018 |Validation accuracy: 0.6264829
282407407
Epoch 11: Train accuracy: 0.6415527237776331 |Validation accuracy: 0.6399016
203703703
Epoch 12: Train accuracy: 0.6426378941493814 |Validation accuracy: 0.6402633
101851852
Epoch 13: Train accuracy: 0.6426068892816172 |Validation accuracy: 0.6372251
157407407
Epoch 14: Train accuracy: 0.64972250643351 |Validation accuracy: 0.643156828
7037037
Epoch 15: Train accuracy: 0.6468235512975538 |Validation accuracy: 0.6411313
657407407
Epoch 16: Train accuracy: 0.653357827178867 |Validation accuracy: 0.64995659
72222222
Epoch 17: Train accuracy: 0.6408008557343503 |Validation accuracy: 0.6384910
300925926
Epoch 18: Train accuracy: 0.6545050072861439 |Validation accuracy: 0.6502459
490740741
Epoch 19: Train accuracy: 0.6652636964003349 |Validation accuracy: 0.6625072
337962963
Epoch 20: Train accuracy: 0.6568613772362261 |Validation accuracy: 0.6521267
361111112
Epoch 21: Train accuracy: 0.6706197873066071 |Validation accuracy: 0.6673538
773148148
Epoch 22: Train accuracy: 0.665542740210213 |Validation accuracy: 0.66138599
53703703
Epoch 23: Train accuracy: 0.6623647412643785 |Validation accuracy: 0.6597222
222222222
Epoch 24: Train accuracy: 0.6764487024462841 |Validation accuracy: 0.6735387
731481481
Epoch 25: Train accuracy: 0.666062071745264 |Validation accuracy: 0.65946903
93518519
Epoch 26: Train accuracy: 0.6709840945028369 |Validation accuracy: 0.6684389
467592593
Epoch 27: Train accuracy: 0.6762471708058165 |Validation accuracy: 0.6730685
763888888
Epoch 28: Train accuracy: 0.6835953244659412 |Validation accuracy: 0.6804832
175925926
Epoch 29: Train accuracy: 0.6843936998108703 |Validation accuracy: 0.6795428
240740741
Epoch 30: Train accuracy: 0.6846029826682789 |Validation accuracy: 0.6825810
185185185
Epoch 31: Train accuracy: 0.6944160233156605 |Validation accuracy: 0.6894892
939814815
```

```
Epoch 32: Train accuracy: 0.6795801940904722 |Validation accuracy: 0.6752025
462962963
Epoch 33: Train accuracy: 0.6877577279632903 |Validation accuracy: 0.6826895
254629629
Epoch 34: Train accuracy: 0.6831302514494776 |Validation accuracy: 0.6793258
101851852
Epoch 35: Train accuracy: 0.6841301584348742 |Validation accuracy: 0.6821831
597222222
Epoch 36: Train accuracy: 0.6982683781353672 |Validation accuracy: 0.6915147
569444444
Epoch 37: Train accuracy: 0.6854711189656776 |Validation accuracy: 0.6820023
148148148
Epoch 38: Train accuracy: 0.6970901931603262 |Validation accuracy: 0.6930700
231481481
Epoch 39: Train accuracy: 0.694865593898242 |Validation accuracy: 0.69202112
26851852
Epoch 40: Train accuracy: 0.6945710476544817 |Validation accuracy: 0.6923104
745370371
Epoch 41: Train accuracy: 0.699919387343813 |Validation accuracy: 0.69661458
33333334
Epoch 42: Train accuracy: 0.7019036988807242 |Validation accuracy: 0.6963614
004629629
Epoch 43: Train accuracy: 0.6975707686106719 |Validation accuracy: 0.6919126
157407407
Epoch 44: Train accuracy: 0.6965786128422162 |Validation accuracy: 0.6930700
231481481
Epoch 45: Train accuracy: 0.7038725079837534 |Validation accuracy: 0.7009186
921296297
Epoch 46: Train accuracy: 0.7021594890397792 |Validation accuracy: 0.6973379
629629629
Epoch 47: Train accuracy: 0.6905636684959539 |Validation accuracy: 0.6863064
236111112
Epoch 48: Train accuracy: 0.7027020742256535 |Validation accuracy: 0.7004846
643518519
Epoch 49: Train accuracy: 0.6751697516510092 |Validation accuracy: 0.6699580
439814815
Epoch 50: Train accuracy: 0.6981211050134871 |Validation accuracy: 0.6935402
199074074
Epoch 51: Train accuracy: 0.7000124019471057 |Validation accuracy: 0.6961082
175925926
Epoch 52: Train accuracy: 0.7028105912628283 |Validation accuracy: 0.6976273
148148148
Epoch 53: Train accuracy: 0.7027175766595355 |Validation accuracy: 0.6984230
324074074
Epoch 54: Train accuracy: 0.6881995473289306 |Validation accuracy: 0.6894892
939814815
Epoch 55: Train accuracy: 0.6999503922115772 |Validation accuracy: 0.6963252
314814815
Epoch 56: Train accuracy: 0.6989272315753573 |Validation accuracy: 0.6953848
379629629
Epoch 57: Train accuracy: 0.6808668961026881 |Validation accuracy: 0.6760706
018518519
Epoch 58: Train accuracy: 0.7016711623724925 |Validation accuracy: 0.6963614
```

```
004629629
Epoch 59: Train accuracy: 0.7007332651226242 |Validation accuracy: 0.6970486
111111112
Epoch 60: Train accuracy: 0.7030276253371779 |Validation accuracy: 0.6990740
740740741
Epoch 61: Train accuracy: 0.6956717204601123 |Validation accuracy: 0.6925274
884259259
Epoch 62: Train accuracy: 0.7061048584627787 |Validation accuracy: 0.7027633
101851852
Epoch 63: Train accuracy: 0.6996480947508759 |Validation accuracy: 0.6962890
625
Epoch 64: Train accuracy: 0.6715886894242397 |Validation accuracy: 0.6651837
384259259
Epoch 65: Train accuracy: 0.7055932781446688 |Validation accuracy: 0.7022207
754629629
Epoch 66: Train accuracy: 0.7084767308467429 |Validation accuracy: 0.7035590
277777778
Epoch 67: Train accuracy: 0.692005394846991 |Validation accuracy: 0.68912760
41666666
Epoch 68: Train accuracy: 0.7028415961305925 |Validation accuracy: 0.7005208
333333334
Epoch 69: Train accuracy: 0.7004077140110997 |Validation accuracy: 0.6954210
069444444
Epoch 70: Train accuracy: 0.7052212197314979 |Validation accuracy: 0.7013165
509259259
Epoch 71: Train accuracy: 0.6899745760084334 |Validation accuracy: 0.6886935
763888888
Epoch 72: Train accuracy: 0.7025392986698912 |Validation accuracy: 0.6987123
842592593
Epoch 73: Train accuracy: 0.7021362353889561 |Validation accuracy: 0.6963975
694444444
Epoch 74: Train accuracy: 0.697718041732552 |Validation accuracy: 0.69426359
95370371
Epoch 75: Train accuracy: 0.6925324775989831 |Validation accuracy: 0.6894531
25
Epoch 76: Train accuracy: 0.69550894490435 |Validation accuracy: 0.693033854
1666666
Epoch 77: Train accuracy: 0.69550894490435 |Validation accuracy: 0.690248842
5925926
Epoch 78: Train accuracy: 0.710437788732831 |Validation accuracy: 0.70753761
57407407
Epoch 79: Train accuracy: 0.7029656156016495 |Validation accuracy: 0.7001229
745370371
Epoch 80: Train accuracy: 0.7103137692617741 |Validation accuracy: 0.7061993
634259259
Epoch 81: Train accuracy: 0.7053917465042011 |Validation accuracy: 0.7029079
861111112
Epoch 82: Train accuracy: 0.6960360276563421 |Validation accuracy: 0.6925274
884259259
Epoch 83: Train accuracy: 0.7076861067187549 |Validation accuracy: 0.7046802
662037037
Epoch 84: Train accuracy: 0.6977955539019626 |Validation accuracy: 0.6903211
805555556
```

```
Epoch 85: Train accuracy: 0.7123290856664496 |Validation accuracy: 0.7078269
675925926
Epoch 86: Train accuracy: 0.70187269401296 |Validation accuracy: 0.699074074
0740741
Epoch 87: Train accuracy: 0.6996868508355811 |Validation accuracy: 0.6986400
462962963
Epoch 88: Train accuracy: 0.704461600471274 |Validation accuracy: 0.70182291
66666666
Epoch 89: Train accuracy: 0.7174448888475491 |Validation accuracy: 0.7115885
416666666
Epoch 90: Train accuracy: 0.7033221715809382 |Validation accuracy: 0.7003038
194444444
Finish Training
Total time elapsed: 228.45 seconds
```






```
Final Training Accuracy: 0.7033221715809382
Final Validation Accuracy: 0.7003038194444444
```

# Part 4. Testing [12 pt]

## Part (a) [2 pt]

Compute and report the test accuracy.

In [195…

```
test_loader = torch.utils.data.DataLoader(test_data, batch_size=64, shuffle=
test_acc = get_accuracy(model_4, test_loader)
print(("Model_4's test accuracy is {} %.").format(test_acc*100))
```

```
Model_4's test accuracy is 69.76634837962963 %.
```

## Part (b) [4 pt]

Based on the test accuracy alone, it is difficult to assess whether our model is actually performing well. We don't know whether a high accuracy is due to the simplicity of the problem, or if a poor accuracy is a result of the inherent difficulty of the problem.

It is therefore very important to be able to compare our model to at least one alternative. In particular, we consider a simple **baseline** model that is not very computationally expensive. Our neural network should at least outperform this baseline model. If our network is not much better than the baseline, then it is not doing well.

For our data imputation problem, consider the following baseline model: to predict a missing feature, the baseline model will look at the **most common value** of the feature in the training set.

For example, if the feature "marriage" is missing, then this model's prediction will be the most common value for "marriage" in the training set, which happens to be "Married-civ-spouse".

What would be the test accuracy of this baseline model?

In [157…

```
baseline_mod = {}
for col in df_not_missing.columns:
  # get the most common value for each column
  baseline_mod[col] = df_not_missing[col].value_counts().idxmax()

count = 0
for val in df_not_missing["marriage"]:
  if val == baseline_mod['marriage']:
    count += 1

baseline_acc = count/len(df_not_missing) * 100
print("The test accuracy of this baseline model on \"marriage\" is ", baseli
```

```
The test accuracy of this baseline model on "marriage" is  46.67947131974738
%
```

## Part (c) [1 pt]

How does your test accuracy from part (a) compared to your basline test accuracy in part (b)?

In [ ]:
```
#Accuracy from part(a): 69.766%
#Accuracy from part(b): 46.679%

#My test accuracy from part(a) is much
#higher than the accuracy we see in part(b).
#This is because the model is not simply predicting
#the most common value for an input. Instead, it is
#learning to predict through the embeddings we construct
#that place importance on all features so that the model
#will have more comprehensive prediction.
```

## Part (d) [1 pt]

Look at the first item in your test data. Do you think it is reasonable for a human to be able to guess this person's education level based on their other features? Explain.

In [155…
```
get_features(test_data[0])

#Yes, I think it is reasonable for a human
#to guess this person's education level based on
#other features. This person is a professional
#specialty, which requires professional
#knowledge and training on the specific area that
#he is working in, so it is reasonable to guess
#that he has a least completed a Bachelor's
#degree.
```

Out[155]:
```
{'work': 'Private',
 'marriage': 'Divorced',
 'occupation': 'Prof-specialty',
 'edu': 'Bachelors',
 'relationship': 'Not-in-family',
 'sex': 'Male'}
```

## Part (e) [2 pt]

What is your model's prediction of this person's education level, given their other features?

In [209…
```
edu_hidden = zero_out_feature(test_data[:1],"edu")[0]
prediction = model_4(torch.from_numpy(edu_hidden))
pred_val = get_feature(prediction.detach().numpy(),"edu")
print(pred_val)

#The predicted education level of this person
#is Masters, which is incorrect. The model
#overestimates the person's education level.
```

```
Masters
```

## Part (f) [2 pt]

What is the baseline model's prediction of this person's education level?

In [160…

```
print("The baseline model's prediction of this person's education leverl is"
      baseline_mod["edu"], '.')
```

```
The baseline model's prediction of this person's education leverl is  HS-gra
d .
```