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/github/GreatArcStudios/APS360/blob/master/Lab%204/Lab4%20Data%20Imputation.ipynb

```
import csv
import numpy as np
import random
import torch
import torch.utils.data
```

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

```
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

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

```
C:\Users\ericz\AppData\Local\Temp\ipykernel_31408\1439901705.py:3: ParserWarning: Length of header or names does not match
length of data. This leads to a loss of data with index_col=False.
  df_full = pd.read_csv(
```

```
df.shape # there are 32561 rows (records) in the data frame, and 14 columns (features)
```

```
(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.

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

	age	work	fnlwgt	edu	yredu	marriage	occupation	relationship	race	sex	capgain	caploss	workhr	country
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States

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

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

	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:

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

```
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.

So we need to first report the min/max/avg of variables of interest (`["age", "yredu", "capgain", "caploss", "workhr"]`) then normalize them. As in we compute the following for normalization:

$$\mathbf{x}_{\text{normalized}} = \frac{(\mathbf{x} - \bar{\mathbf{x}})}{\widehat{\sigma}_{\mathbf{x}}}$$

```
for variable in ["age", "yredu", "capgain", "caploss", "workhr"]:
    print(f"{variable} statistics | min: {min(df[variable])}, max: {max(df[variable])}, average: { np.average(df[variable])}")
    df[variable] = (df[variable] - np.average(df[variable])) / np.std(df[variable])

df.head()
```

```
age statistics | min: -1.5822062886564523, max: 3.769612336743166, average: -2.7059150282317012e-17
yredu statistics | min: -3.5296563996401558, max: 2.3008375546552444, average: 1.4718868439857116e-16
capgain statistics | min: -0.14592048355885345, max: 13.394577908462539, average: 1.3093137233379199e-17
caploss statistics | min: -0.21665952703259014, max: 10.593506563264937, average: 1.0169003251257845e-16
workhr statistics | min: -3.1940303099566942, max: 4.742966730361867, average: -1.5493545726165386e-17
```

	age	work	fnlwgt	edu	yredu	marriage	occupation	relationship	race	sex	capgain	caploss	workhr
0	0.030671	State-gov	77516	Bachelors	1.134739	Never-married	Adm-clerical	Not-in-family	White	Male	0.148453	-0.21666	-0.035429
1	0.837109	Self-emp-not-inc	83311	Bachelors	1.134739	Married-civ-spouse	Exec-managerial	Husband	White	Male	-0.145920	-0.21666	-2.222153
2	-0.042642	Private	215646	HS-grad	-0.420060	Divorced	Handlers-cleaners	Not-in-family	White	Male	-0.145920	-0.21666	-0.035429
3	1.057047	Private	234721	11th	-1.197459	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	-0.145920	-0.21666	-0.035429
4	-0.775768	Private	338409	Bachelors	1.134739	Married-civ-spouse	Prof-specialty	Wife	Black	Female	-0.145920	-0.21666	-0.035429

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?

```
# hint: you can do something like this in pandas
print("Percentage of women in dataset:", sum(df["sex"] == " Female")/len(df["sex"]) * 100)
```

```
Percentage of women in dataset: 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?

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

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

To find the number of samples with missing features, we can simply find the length of the `df_with_missing` dataframe. Then similarly to find the percentage of records, we can simply divide that number by the total number of samples in this dataset.

```
length_missing = len(df_with_missing)
length_total = len(df)

precentage_missing = length_missing/length_total
print(f"Precentage missing: {round(precentage_missing, 4)*100}% | Records with missing features: {length_missing}")
```

```
Precentage missing: 5.66% | Records with missing features: 1843
```

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.

```
set(df_not_missing['work'])
```

```
{' Federal-gov',
 ' Local-gov',
 ' Private',
 ' Self-emp-inc',
 ' Self-emp-not-inc',
 ' State-gov',
 ' Without-pay'}
```

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`.

```
data = pd.get_dummies(df_not_missing)
```

```
data[:3]
```

	age	yredu	capgain	caploss	workhr	work_Federal-gov	work_Local-gov	work_Private	work_Self-emp-inc	work_Self-emp-not-inc	...	edu_Prof-school	edu_Some-college	relationship_Husband	rela Not fam
0	0.030671	1.134739	0.148453	-0.21666	-0.035429	0	0	0	0	0	...	0	0	0	1
1	0.837109	1.134739	-0.145920	-0.21666	-2.222153	0	0	0	0	1	...	0	0	1	0
2	-0.042642	-0.420060	-0.145920	-0.21666	-0.035429	0	0	1	0	0	...	0	0	0	1

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.

```
len(data.columns)
```

```
57
```

This number is the length property of the `data.columns` object, which is an iterable, so it has a length property, meaning we can call `len` on it. Note that `data.columns` gets all of the column names of a dataframe.

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.

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

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

# 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 underscore
        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]

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

    # this is really asking us to retrieve the respective value from
    # cat_values based on the argmax of the respective subarray of the onehot buffer

    # the first example in the doc string since it is the only 1 in position 6
    # which corresponds to 'State-gov' in cat_values

    index = np.argmax(onehot)
    feature_values = cat_values[feature]
    return feature_values[index]
```

```
# clearly works as expected
print(get_categorical_value(np.array([0., 0., 0., 0., 0., 1., 0.]), "work"), get_categorical_value(np.array([0.1, 0., 1.1, 0
```

```
State-gov Private
```

```
# 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.

```
# set the numpy seed for reproducibility
# https://docs.scipy.org/doc/numpy/reference/generated/numpy.random.seed.html
np.random.seed(50)

# todo

# seems like we want to perform the splitting in numpy if we are seeting the seed using numpy
# so first shuffle the data
# then slice 70%, 15%, and 15%
data_shuffled = datanp[:]
np.random.shuffle(data_shuffled)
train_end, val_end = int(len(data_shuffled)*0.7), int(len(data_shuffled)*0.85) # make sure to floor them
data_train, data_val, data_test = data_shuffled[:train_end], data_shuffled[train_end: val_end], data_shuffled[val_end: ]
print(len(data_train), len(data_val), len(data_test))
```

```
21502 4608 4608
```

As we can see from the block above, the train set has 21502 samples, 4608 samples in the validation set, and finally 4608 samples in the test set.

```
# create the Pytorch datasets and dataloaders for training
from torch.utils.data import TensorDataset, DataLoader
from torchinfo import summary

train_set = TensorDataset(torch.from_numpy(data_train))
val_set = TensorDataset(torch.from_numpy(data_val))
test_set = TensorDataset(torch.from_numpy(data_test))

train_loader, val_loader, test_loader = DataLoader(train_set, 128), DataLoader(val_set, len(data_val)), DataLoader(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.

```
from torch import nn

class AutoEncoder(nn.Module):
    def __init__(self):
        super(AutoEncoder, self).__init__()
        self.encoder = nn.Sequential(
            nn.Linear(57, 57), # TODO -- FILL OUT THE CODE HERE!
            nn.Linear(57, 47),
            nn.Linear(47, 37),
            nn.Linear(37, 30),
            nn.Linear(30, 20),
            nn.Linear(20, 12),
        )
        self.decoder = nn.Sequential(
            nn.Linear(12, 20),
            nn.Linear(20, 28),
            nn.Linear(28, 40),
            nn.Linear(40, 50),
            nn.Linear(50, 57),
            nn.Linear(57, 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.)

The sigmoid function allow us to output values between 0 and 1 (on the interval $[0,\ 1]$), and since we are creating an imputation model for categorical features that are learning the one-hot encodings that are either 0 and 1, we need the use the sigmoid function to "clamp" our predictions to be between 0 and 1. Note that while we cannot have exactly 0 or 1 due to the continuous nature of this model or some kind of discretization, we can have the model output on 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.)

```
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 train(model, train_loader, valid_loader, num_epochs=5, learning_rate=1e-4, val_epochs=10, weight_decay=1e-4, acc_func=N
    """ Training loop. You should update this."""
    torch.manual_seed(42)

    # determine if CUDA is available and set Tensor core flags
    if use_cuda and torch.cuda.is_available():
        dev = "cuda:0"
        torch.backends.cuda.matmul.allow_tf32 = True
        torch.backends.cudnn.allow_tf32 = True
    else:
        print("CUDA unavailable, training on CPU")
        dev = "CPU"
    device = torch.device(dev)
    model = model.to(device)
    val_set = None

    best_val_loss = float('inf')

    for _, batch in enumerate(valid_loader):
        val_set = batch[0].to(device)
        summary(model, input_data=val_set, verbose=2, device=device)

    loss_dict = {"config": f"Epochs: {num_epochs}, Lr: {learning_rate}",
                 "epochs": num_epochs,
                 "train_loss": [], "val_loss": [],
                 "train_acc": [], "val_acc": []}

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

    for epoch in range(num_epochs):
        train_loss = 0.0
        batches = 0

        for _, data in enumerate(train_loader):
            data = data[0].to(device)
            # zero out one categorical feature
            datam = zero_out_random_feature(data.clone())
            recon = model(datam)
            loss = criterion(recon, data)
            train_loss += loss
            batches += 1
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()
```

```
        train_loss /= batches

        if epoch % val_epochs == 0:
            with torch.no_grad():
                val_acc = 0.0
                train_acc = 0.0
                preds = model(val_set)
                val_loss = criterion(preds, val_set)
                print(
                    f"epoch: {epoch}, train_loss: {train_loss}, val_loss: {val_loss}")
                if plot_acc:
                    val_acc = acc_func(model, valid_loader)
                    train_acc = acc_func(model, train_loader)
                    print(
                        f"epoch: {epoch}, train_acc: {train_acc}, val_acc: {val_acc}")

                loss_dict["train_loss"].append(train_loss)
                loss_dict["val_loss"].append(val_loss)
                loss_dict["train_acc"].append(train_acc)
                loss_dict["val_acc"].append(val_acc)

                if val_loss < best_val_loss:
                    best_val_loss = val_loss
                    torch.save(model.state_dict(), model_path_prefix +
                               f"valloss-{torch.round(best_val_loss, decimals=4)}-lr_{learning_rate}-epoch_num_{epoch}.mdlc

    return model, loss_dict
```

```
FCAutoEncoder = AutoEncoder()
model, loss_dict = train(FCAutoEncoder, train_loader, val_loader, num_epochs=100, acc_func=get_accuracy, plot_acc=True)
```

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
AutoEncoder                              [4608, 57]                --
├─Sequential: 1-1                        [4608, 12]                --
│    └─0.weight                                                    ├─3,249
│    └─0.bias                                                      ├─57
│    └─1.weight                                                    ├─2,679
│    └─1.bias                                                      ├─47
│    └─2.weight                                                    ├─1,739
│    └─2.bias                                                      ├─37
│    └─3.weight                                                    ├─1,110
│    └─3.bias                                                      ├─30
│    └─4.weight                                                    ├─600
│    └─4.bias                                                      ├─20
│    └─5.weight                                                    ├─240
│    └─5.bias                                                      └─12
│    └─Linear: 2-1                       [4608, 57]                3,306
│    │    └─weight                                                 ├─3,249
│    │    └─bias                                                   └─57
│    └─Linear: 2-2                       [4608, 47]                2,726
│    │    └─weight                                                 ├─2,679
│    │    └─bias                                                   └─47
│    └─Linear: 2-3                       [4608, 37]                1,776
│    │    └─weight                                                 ├─1,739
│    │    └─bias                                                   └─37
│    └─Linear: 2-4                       [4608, 30]                1,140
│    │    └─weight                                                 ├─1,110
│    │    └─bias                                                   └─30
```

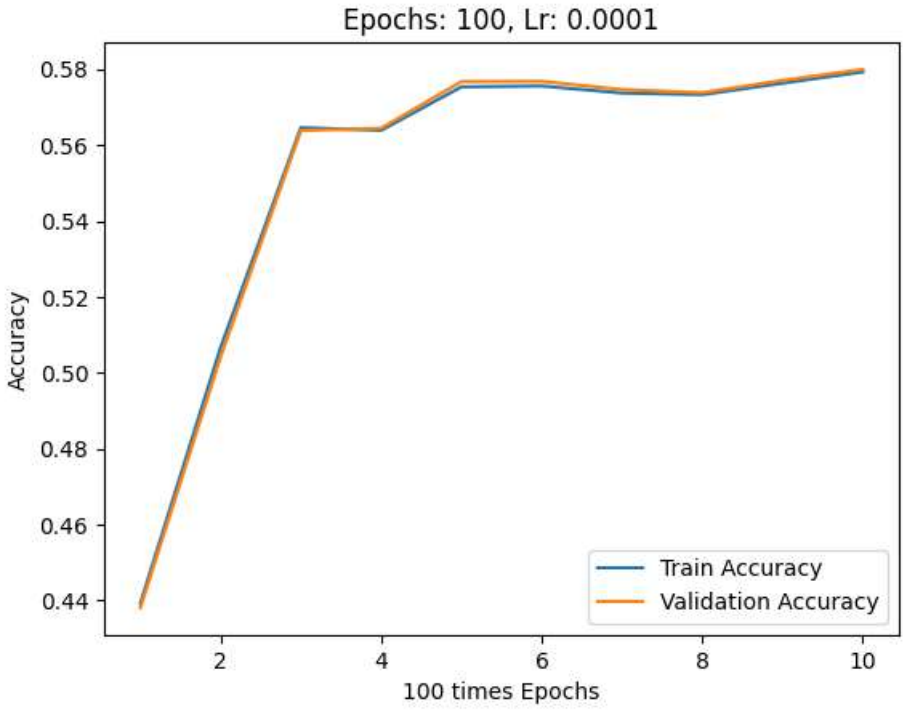
```
│    └─Linear: 2-5                       [4608, 20]                620
│    │    └─weight                                                 ├─600
│    │    └─bias                                                   └─20
│    └─Linear: 2-6                       [4608, 12]                252
│    │    └─weight                                                 ├─240
│    │    └─bias                                                   └─12
├─Sequential: 1-2                        [4608, 57]                --
│    └─0.weight                                                    ├─240
│    └─0.bias                                                      ├─20
│    └─1.weight                                                    ├─560
│    └─1.bias                                                      ├─28
│    └─2.weight                                                    ├─1,120
│    └─2.bias                                                      ├─40
│    └─3.weight                                                    ├─2,000
│    └─3.bias                                                      ├─50
│    └─4.weight                                                    ├─2,850
│    └─4.bias                                                      ├─57
│    └─5.weight                                                    ├─3,249
│    └─5.bias                                                      └─57
│    └─Linear: 2-7                       [4608, 20]                260
│    │    └─weight                                                 ├─240
│    │    └─bias                                                   └─20
│    └─Linear: 2-8                       [4608, 28]                588
│    │    └─weight                                                 ├─560
│    │    └─bias                                                   └─28
│    └─Linear: 2-9                       [4608, 40]                1,160
│    │    └─weight                                                 ├─1,120
│    │    └─bias                                                   └─40
│    └─Linear: 2-10                      [4608, 50]                2,050
│    │    └─weight                                                 ├─2,000
│    │    └─bias                                                   └─50
│    └─Linear: 2-11                      [4608, 57]                2,907
│    │    └─weight                                                 ├─2,850
│    │    └─bias                                                   └─57
│    └─Linear: 2-12                      [4608, 57]                3,306
│    │    └─weight                                                 ├─3,249
│    │    └─bias                                                   └─57
│    └─Sigmoid: 2-13                     [4608, 57]                --
==========================================================================================
Total params: 20,091
Trainable params: 20,091
Non-trainable params: 0
Total mult-adds (M): 92.58
==========================================================================================
Input size (MB): 1.05
Forward/backward pass size (MB): 16.77
Params size (MB): 0.08
Estimated Total Size (MB): 17.90
==========================================================================================
epoch: 0, train_loss: 0.27756449580192566, val_loss: 0.16905611753463745
epoch: 0, train_acc: 0.4391917030973863, val_acc: 0.4380787037037037
epoch: 10, train_loss: 0.1364634931087494, val_loss: 0.13517829775810242
epoch: 10, train_acc: 0.5066815490031935, val_acc: 0.5041956018518519
epoch: 20, train_loss: 0.1276019960641861, val_loss: 0.12661626935005188
epoch: 20, train_acc: 0.5645831395529098, val_acc: 0.5638020833333334
epoch: 30, train_loss: 0.1206154152750969, val_loss: 0.11883264780044556
epoch: 30, train_acc: 0.5638777788112733, val_acc: 0.5644169560185185
epoch: 40, train_loss: 0.11693570762872696, val_loss: 0.11505910754203796
epoch: 40, train_acc: 0.5753263262332187, val_acc: 0.5767144097222222
epoch: 50, train_loss: 0.11512292176485062, val_loss: 0.113580621778965
epoch: 50, train_acc: 0.5755511115245093, val_acc: 0.5767867476851852
epoch: 60, train_loss: 0.11442399024963379, val_loss: 0.11348515748977661
epoch: 60, train_acc: 0.5737063218925371, val_acc: 0.5746166087962963
```

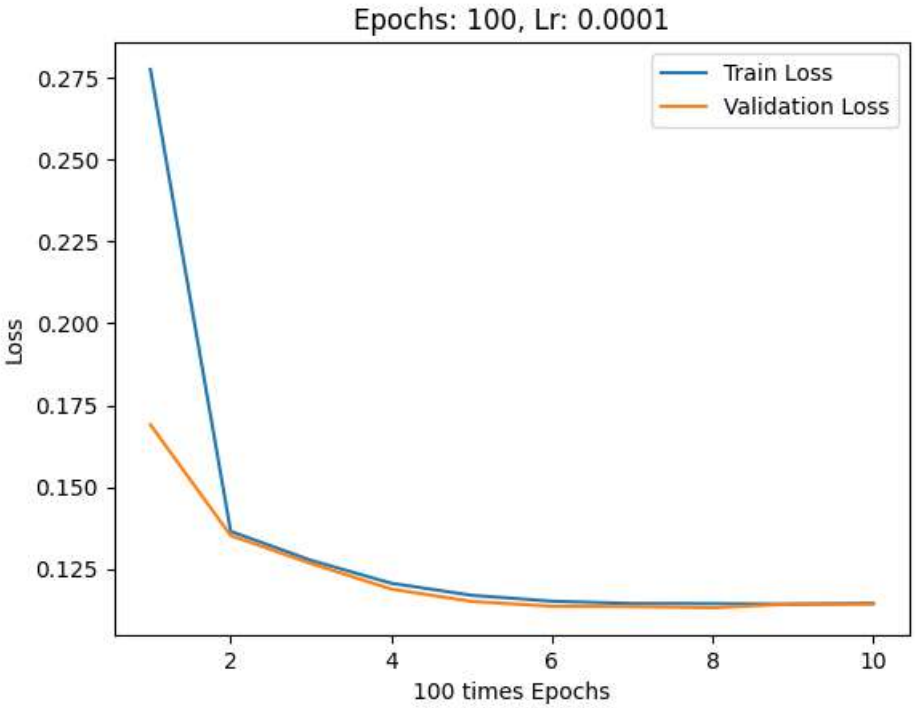
```
epoch: 70, train_loss: 0.11439178138971329, val_loss: 0.11313560605049133
epoch: 70, train_acc: 0.5732645025268968, val_acc: 0.5737847222222222
epoch: 80, train_loss: 0.11422046273946762, val_loss: 0.11427033692598343
epoch: 80, train_acc: 0.57628747713391, val_acc: 0.5770399305555556
epoch: 90, train_loss: 0.1144983321428299, val_loss: 0.11424032598733902
epoch: 90, train_acc: 0.579271695656218, val_acc: 0.5799334490740741
```

```python
from matplotlib import pyplot as plt
def plot_acc_curves(loss_dict):
    plt.title(f"{loss_dict['config']}")
    n = len([value for value in loss_dict["train_acc"]])
    plt.plot(range(1,n+1), [value for value in  loss_dict["train_acc"]], label="Train Accuracy")
    plt.plot(range(1,n+1), [value for value in  loss_dict["val_acc"]], label="Validation Accuracy")
    plt.xlabel(f"{loss_dict['epochs']} times Epochs")
    plt.ylabel("Accuracy")
    plt.legend(loc='best')
    plt.show()

def plot_loss_curves(loss_dict):
    plt.title(f"{loss_dict['config']}")
    n = len([value.cpu().data.numpy() for value in loss_dict["train_loss"]])
    plt.plot(range(1,n+1), [value.cpu().data.numpy() for value in loss_dict["train_loss"]], label="Train Loss")
    plt.plot(range(1,n+1), [value.cpu().data.numpy() for value in loss_dict["val_loss"]], label="Validation Loss")
    plt.xlabel(f"{loss_dict['epochs']} times Epochs")
    plt.ylabel("Loss")
    plt.legend(loc='best')
    plt.show()
```

```python
plot_acc_curves(loss_dict)
plot_loss_curves(loss_dict)
```





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.

```
def get_accuracy(model, data_loader, baseline_model = False):
    """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, shuffle=True)
        >>> get_accuracy(model, vdl)
    """
    total = 0
    acc = 0
    for col in catcols:
        for item in data_loader: # minibatches
            item = item[0]
            inp = item.detach().numpy()
```

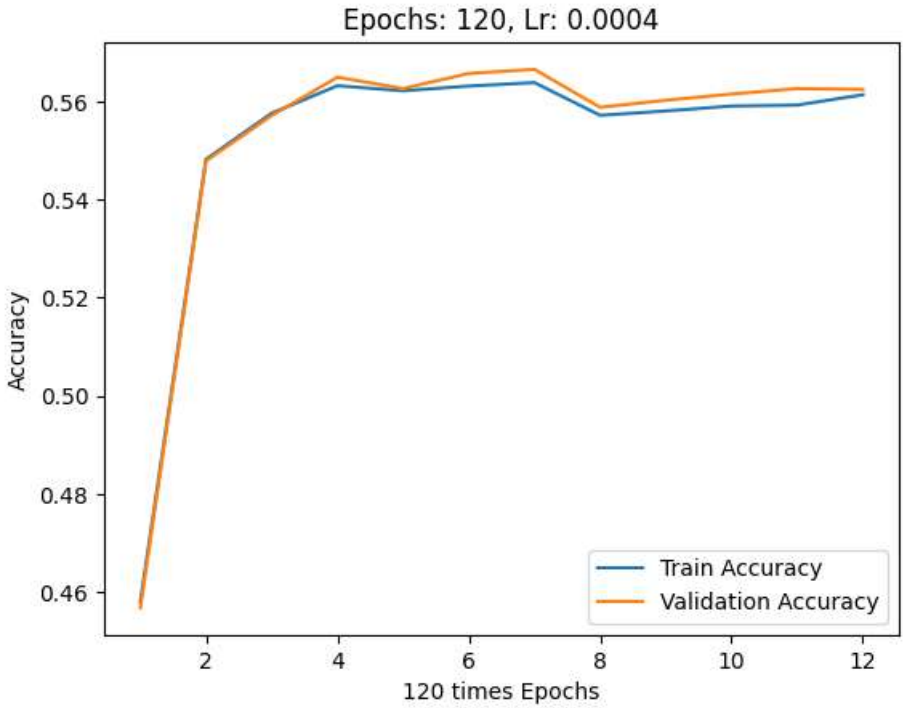
```
            if baseline_model:
                missing_cols = set(range(cat_index[col], cat_index[col] + len(cat_values[col])))
                out = model(zero_out_feature(item.clone(), col), missing_cols).detach().numpy()
            else:
                out = model(zero_out_feature(item.clone(), col).to("cuda:0")).cpu().detach().numpy()
            for i in range(out.shape[0]): # record in minibatch
                acc += int(get_feature(out[i], col) == get_feature(inp[i], col))
                total += 1
    return acc / total
```

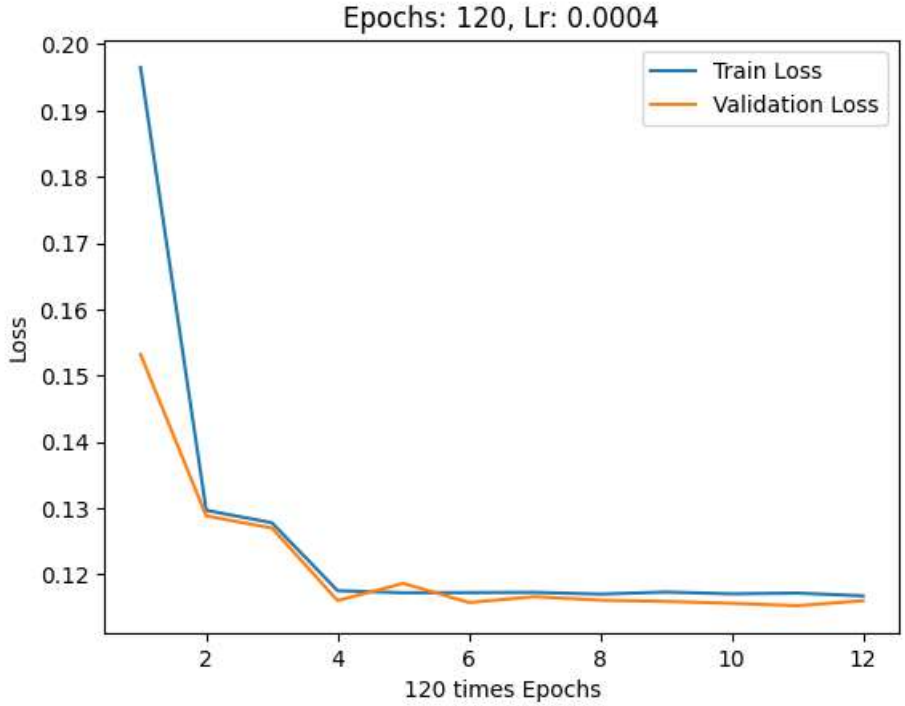
```
FCAutoEncoder = AutoEncoder()
model, loss_dict = train(FCAutoEncoder, train_loader, val_loader, num_epochs=120, learning_rate=4e-4, acc_func=get_accuracy
```

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
AutoEncoder                              [4608, 57]                --
├─Sequential: 1-1                        [4608, 12]                --
│    └─0.weight                                                    ├─3,249
│    └─0.bias                                                      ├─57
│    └─1.weight                                                    ├─2,679
│    └─1.bias                                                      ├─47
│    └─2.weight                                                    ├─1,739
│    └─2.bias                                                      ├─37
│    └─3.weight                                                    ├─1,110
│    └─3.bias                                                      ├─30
│    └─4.weight                                                    ├─600
│    └─4.bias                                                      ├─20
│    └─5.weight                                                    ├─240
│    └─5.bias                                                      └─12
│    └─Linear: 2-1                       [4608, 57]                3,306
│    │    └─weight                                                 ├─3,249
│    │    └─bias                                                   └─57
│    └─Linear: 2-2                       [4608, 47]                2,726
│    │    └─weight                                                 ├─2,679
│    │    └─bias                                                   └─47
│    └─Linear: 2-3                       [4608, 37]                1,776
│    │    └─weight                                                 ├─1,739
│    │    └─bias                                                   └─37
│    └─Linear: 2-4                       [4608, 30]                1,140
│    │    └─weight                                                 ├─1,110
│    │    └─bias                                                   └─30
│    └─Linear: 2-5                       [4608, 20]                620
│    │    └─weight                                                 ├─600
│    │    └─bias                                                   └─20
│    └─Linear: 2-6                       [4608, 12]                252
│    │    └─weight                                                 ├─240
│    │    └─bias                                                   └─12
├─Sequential: 1-2                        [4608, 57]                --
│    └─0.weight                                                    ├─240
│    └─0.bias                                                      ├─20
│    └─1.weight                                                    ├─560
│    └─1.bias                                                      ├─28
│    └─2.weight                                                    ├─1,120
│    └─2.bias                                                      ├─40
│    └─3.weight                                                    ├─2,000
│    └─3.bias                                                      ├─50
│    └─4.weight                                                    ├─2,850
│    └─4.bias                                                      ├─57
│    └─5.weight                                                    ├─3,249
│    └─5.bias                                                      └─57
```

```
│    └─Linear: 2-7                       [4608, 20]                260
│    │    └─weight                                                ├─240
│    │    └─bias                                                  └─20
│    └─Linear: 2-8                       [4608, 28]                588
│    │    └─weight                                                ├─560
│    │    └─bias                                                  └─28
│    └─Linear: 2-9                       [4608, 40]                1,160
│    │    └─weight                                                ├─1,120
│    │    └─bias                                                  └─40
│    └─Linear: 2-10                      [4608, 50]                2,050
│    │    └─weight                                                ├─2,000
│    │    └─bias                                                  └─50
│    └─Linear: 2-11                      [4608, 57]                2,907
│    │    └─weight                                                ├─2,850
│    │    └─bias                                                  └─57
│    └─Linear: 2-12                      [4608, 57]                3,306
│    │    └─weight                                                ├─3,249
│    │    └─bias                                                  └─57
│    └─Sigmoid: 2-13                     [4608, 57]                --
==========================================================================================
Total params: 20,091
Trainable params: 20,091
Non-trainable params: 0
Total mult-adds (M): 92.58
==========================================================================================
Input size (MB): 1.05
Forward/backward pass size (MB): 16.77
Params size (MB): 0.08
Estimated Total Size (MB): 17.90
==========================================================================================
epoch: 0, train_loss: 0.19650046527385712, val_loss: 0.15320537984371185
epoch: 0, train_acc: 0.4579806529625151, val_acc: 0.4568142361111111
epoch: 10, train_loss: 0.1296728402376175, val_loss: 0.12882983684539795
epoch: 10, train_acc: 0.5482203205903327, val_acc: 0.5478877314814815
epoch: 20, train_loss: 0.12780451774597168, val_loss: 0.12700356543064117
epoch: 20, train_acc: 0.557614795522897, val_acc: 0.5571469907407407
epoch: 30, train_loss: 0.11755353212356567, val_loss: 0.11606036126613617
epoch: 30, train_acc: 0.5632111741543422, val_acc: 0.5649594907407407
epoch: 40, train_loss: 0.11723577976226807, val_loss: 0.11865691095590591
epoch: 40, train_acc: 0.5621957647350634, val_acc: 0.5626446759259259
epoch: 50, train_loss: 0.11725984513759613, val_loss: 0.11577272415161133
epoch: 50, train_acc: 0.5631491644188138, val_acc: 0.5657190393518519
epoch: 60, train_loss: 0.11730127036571503, val_loss: 0.11664751172065735
epoch: 60, train_acc: 0.5638545251604502, val_acc: 0.5665509259259259
epoch: 70, train_loss: 0.11703629046678543, val_loss: 0.1161196231842041
epoch: 70, train_acc: 0.5571807273741978, val_acc: 0.5588107638888888
epoch: 80, train_loss: 0.11734554171562195, val_loss: 0.11593350023031235
epoch: 80, train_acc: 0.5580721173224196, val_acc: 0.5602575231481481
epoch: 90, train_loss: 0.11707903444766998, val_loss: 0.11565212160348892
epoch: 90, train_acc: 0.5590797755247574, val_acc: 0.5615234375
epoch: 100, train_loss: 0.11719189584255219, val_loss: 0.11528501659631729
epoch: 100, train_acc: 0.5592735559482839, val_acc: 0.5626446759259259
epoch: 110, train_loss: 0.11677169054746628, val_loss: 0.11604857444763184
epoch: 110, train_acc: 0.5613818869562521, val_acc: 0.5624638310185185
```

```
plot_acc_curves(loss_dict)
plot_loss_curves(loss_dict)
```





Part (c) [4 pt]

Run your updated training code, using reasonable initial hyperparameters.

Include your training curve in your submission.

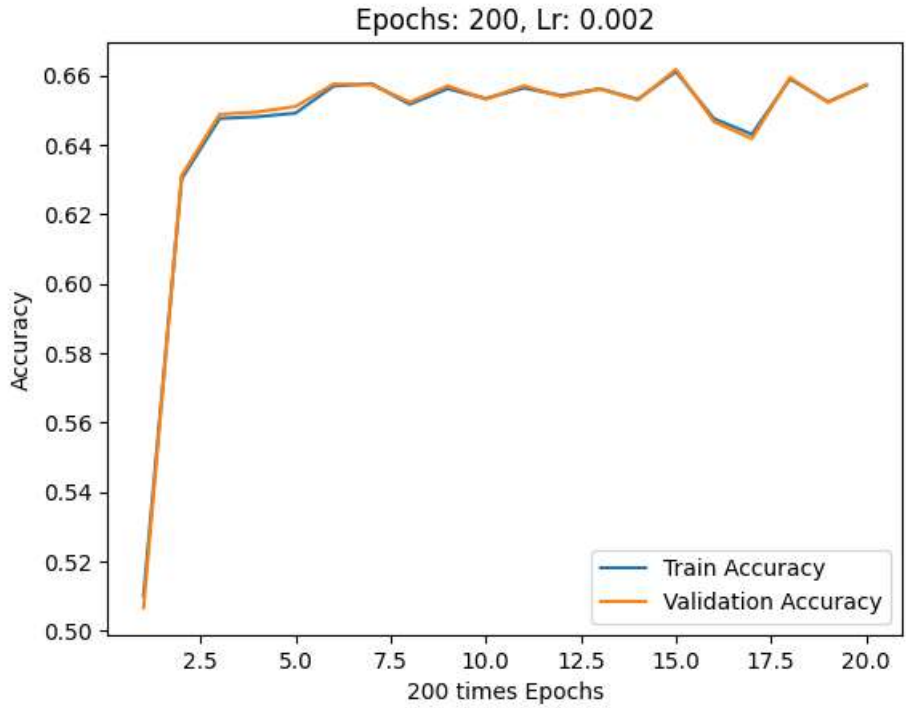
```
FCAutoEncoder = AutoEncoder()
model, loss_dict = train(FCAutoEncoder, train_loader, val_loader, num_epochs=200, learning_rate=2e-3, weight_decay=1e-5, ac
```

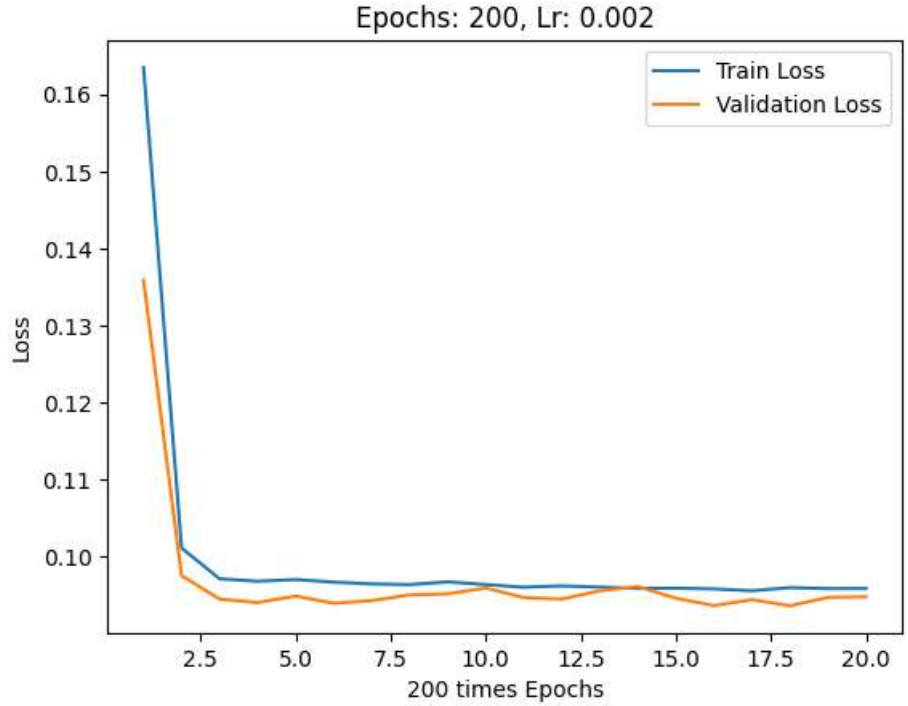
```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
```

```
AutoEncoder                              [4608, 57]                --
├─Sequential: 1-1                        [4608, 12]                --
│    └─0.weight                                                    ├─3,249
│    └─0.bias                                                      ├─57
│    └─1.weight                                                    ├─2,679
│    └─1.bias                                                      ├─47
│    └─2.weight                                                    ├─1,739
│    └─2.bias                                                      ├─37
│    └─3.weight                                                    ├─1,110
│    └─3.bias                                                      ├─30
│    └─4.weight                                                    ├─600
│    └─4.bias                                                      ├─20
│    └─5.weight                                                    ├─240
│    └─5.bias                                                      └─12
│    └─Linear: 2-1                       [4608, 57]                3,306
│    │    └─weight                                                 ├─3,249
│    │    └─bias                                                   └─57
│    └─Linear: 2-2                       [4608, 47]                2,726
│    │    └─weight                                                 ├─2,679
│    │    └─bias                                                   └─47
│    └─Linear: 2-3                       [4608, 37]                1,776
│    │    └─weight                                                 ├─1,739
│    │    └─bias                                                   └─37
│    └─Linear: 2-4                       [4608, 30]                1,140
│    │    └─weight                                                 ├─1,110
│    │    └─bias                                                   └─30
│    └─Linear: 2-5                       [4608, 20]                620
│    │    └─weight                                                 ├─600
│    │    └─bias                                                   └─20
│    └─Linear: 2-6                       [4608, 12]                252
│    │    └─weight                                                 ├─240
│    │    └─bias                                                   └─12
├─Sequential: 1-2                        [4608, 57]                --
│    └─0.weight                                                    ├─240
│    └─0.bias                                                      ├─20
│    └─1.weight                                                    ├─560
│    └─1.bias                                                      ├─28
│    └─2.weight                                                    ├─1,120
│    └─2.bias                                                      ├─40
│    └─3.weight                                                    ├─2,000
│    └─3.bias                                                      ├─50
│    └─4.weight                                                    ├─2,850
│    └─4.bias                                                      ├─57
│    └─5.weight                                                    ├─3,249
│    └─5.bias                                                      └─57
│    └─Linear: 2-7                       [4608, 20]                260
│    │    └─weight                                                 ├─240
│    │    └─bias                                                   └─20
│    └─Linear: 2-8                       [4608, 28]                588
│    │    └─weight                                                 ├─560
│    │    └─bias                                                   └─28
│    └─Linear: 2-9                       [4608, 40]                1,160
│    │    └─weight                                                 ├─1,120
│    │    └─bias                                                   └─40
│    └─Linear: 2-10                      [4608, 50]                2,050
│    │    └─weight                                                 ├─2,000
│    │    └─bias                                                   └─50
│    └─Linear: 2-11                      [4608, 57]                2,907
│    │    └─weight                                                 ├─2,850
│    │    └─bias                                                   └─57
│    └─Linear: 2-12                      [4608, 57]                3,306
│    │    └─weight                                                 ├─3,249
│    │    └─bias                                                   └─57
```

```
│    └─Sigmoid: 2-13                     [4608, 57]                --
==========================================================================================
Total params: 20,091
Trainable params: 20,091
Non-trainable params: 0
Total mult-adds (M): 92.58
==========================================================================================
Input size (MB): 1.05
Forward/backward pass size (MB): 16.77
Params size (MB): 0.08
Estimated Total Size (MB): 17.90
==========================================================================================
epoch: 0, train_loss: 0.16350798308849335, val_loss: 0.13589662313461304
epoch: 0, train_acc: 0.5098750503829101, val_acc: 0.5065827546296297
epoch: 10, train_loss: 0.10111326724290848, val_loss: 0.09753181785345078
epoch: 10, train_acc: 0.6301971909589805, val_acc: 0.6311848958333334
epoch: 20, train_loss: 0.09710381180047989, val_loss: 0.09447476267814636
epoch: 20, train_acc: 0.6476141754255418, val_acc: 0.6488353587962963
epoch: 30, train_loss: 0.09679349511861801, val_loss: 0.09402942657470703
epoch: 30, train_acc: 0.6481412581775339, val_acc: 0.6495225694444444
epoch: 40, train_loss: 0.09701282531023026, val_loss: 0.09486211091279984
epoch: 40, train_acc: 0.6491799212476359, val_acc: 0.6510778356481481
epoch: 50, train_loss: 0.09667780250310898, val_loss: 0.09393224865198135
epoch: 50, train_acc: 0.656977645490342, val_acc: 0.6575520833333334
epoch: 60, train_loss: 0.0964442566037178, val_loss: 0.09427308291196823
epoch: 60, train_acc: 0.657636498930332, val_acc: 0.6573712384259259
epoch: 70, train_loss: 0.0963512733578682, val_loss: 0.09502405673265457
epoch: 70, train_acc: 0.6517223204043034, val_acc: 0.65234375
epoch: 80, train_loss: 0.09671428054571152, val_loss: 0.09514930099248886
epoch: 80, train_acc: 0.6562180262301182, val_acc: 0.6570095486111112
epoch: 90, train_loss: 0.09635379165410995, val_loss: 0.09591325372457504
epoch: 90, train_acc: 0.6533810808296903, val_acc: 0.6532118055555556
epoch: 100, train_loss: 0.09602594375610352, val_loss: 0.09466587752103806
epoch: 100, train_acc: 0.6564195578705857, val_acc: 0.6570457175925926
epoch: 110, train_loss: 0.09618617594242096, val_loss: 0.09448018670082092
epoch: 110, train_acc: 0.6542104610423837, val_acc: 0.6539351851851852
epoch: 120, train_loss: 0.09603038430213928, val_loss: 0.09555862843990326
epoch: 120, train_acc: 0.6561792701454129, val_acc: 0.6561776620370371
epoch: 130, train_loss: 0.09586621820926666, val_loss: 0.09610024839639664
epoch: 130, train_acc: 0.6531640467553406, val_acc: 0.6529586226851852
epoch: 140, train_loss: 0.095892995595932, val_loss: 0.09459006786346436
epoch: 140, train_acc: 0.6611400489876911, val_acc: 0.6617838541666666
epoch: 150, train_loss: 0.09579801559448242, val_loss: 0.0936271995306015
epoch: 150, train_acc: 0.6475676681238954, val_acc: 0.6467013888888888
epoch: 160, train_loss: 0.09555616229772568, val_loss: 0.09440086036920547
epoch: 160, train_acc: 0.6430797135150219, val_acc: 0.6418185763888888
epoch: 170, train_loss: 0.09596523642539978, val_loss: 0.09361530095338821
epoch: 170, train_acc: 0.6590317179797228, val_acc: 0.6594328703703703
epoch: 180, train_loss: 0.09583473205566406, val_loss: 0.09469461441040039
epoch: 180, train_acc: 0.6524586860137042, val_acc: 0.6522714120370371
epoch: 190, train_loss: 0.09584932029247284, val_loss: 0.09477134048938751
epoch: 190, train_acc: 0.6572179332155148, val_acc: 0.6573712384259259
```

```
plot_acc_curves(loss_dict)
plot_loss_curves(loss_dict)
```





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.

We will try the four following sets of hyperparameters: 1. A high learning rate with a high weight decay 2. A high learning rate with a lower weight decay 3. A lower learning rate with a high weight decay 4. A lower learning rate with a lower weight decay 5. Based on the above, we will try a larger epoch count

This will essentially allow for us to perform a grid search over the available hyperparameters that I have coded. And then choose the combination, e.g., high learning rate and high weight decay, using a binary search strategy. This will be the main thinking for model 5

where we select the hyperparameters that we train over more epochs.

```
# high learning rate, high WD
FCAutoEncoder = AutoEncoder()
model, loss_dict = train(FCAutoEncoder, train_loader, val_loader, num_epochs=100, learning_rate=6e-2, weight_decay=1e-3, ac
```

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
AutoEncoder                              [4608, 57]                --
├─Sequential: 1-1                        [4608, 12]                --
│    └─0.weight                                                    ├─3,249
│    └─0.bias                                                      ├─57
│    └─1.weight                                                    ├─2,679
│    └─1.bias                                                      ├─47
│    └─2.weight                                                    ├─1,739
│    └─2.bias                                                      ├─37
│    └─3.weight                                                    ├─1,110
│    └─3.bias                                                      ├─30
│    └─4.weight                                                    ├─600
│    └─4.bias                                                      ├─20
│    └─5.weight                                                    ├─240
│    └─5.bias                                                      └─12
│    └─Linear: 2-1                       [4608, 57]                3,306
│    │    └─weight                                                 ├─3,249
│    │    └─bias                                                   └─57
│    └─Linear: 2-2                       [4608, 47]                2,726
│    │    └─weight                                                 ├─2,679
│    │    └─bias                                                   └─47
│    └─Linear: 2-3                       [4608, 37]                1,776
│    │    └─weight                                                 ├─1,739
│    │    └─bias                                                   └─37
│    └─Linear: 2-4                       [4608, 30]                1,140
│    │    └─weight                                                 ├─1,110
│    │    └─bias                                                   └─30
│    └─Linear: 2-5                       [4608, 20]                620
│    │    └─weight                                                 ├─600
│    │    └─bias                                                   └─20
│    └─Linear: 2-6                       [4608, 12]                252
│    │    └─weight                                                 ├─240
│    │    └─bias                                                   └─12
├─Sequential: 1-2                        [4608, 57]                --
│    └─0.weight                                                    ├─240
│    └─0.bias                                                      ├─20
│    └─1.weight                                                    ├─560
│    └─1.bias                                                      ├─28
│    └─2.weight                                                    ├─1,120
│    └─2.bias                                                      ├─40
│    └─3.weight                                                    ├─2,000
│    └─3.bias                                                      ├─50
│    └─4.weight                                                    ├─2,850
│    └─4.bias                                                      ├─57
│    └─5.weight                                                    ├─3,249
│    └─5.bias                                                      └─57
│    └─Linear: 2-7                       [4608, 20]                260
│    │    └─weight                                                 ├─240
│    │    └─bias                                                   └─20
│    └─Linear: 2-8                       [4608, 28]                588
│    │    └─weight                                                 ├─560
│    │    └─bias                                                   └─28
│    └─Linear: 2-9                       [4608, 40]                1,160
```

```
│    │    └─weight                                            ├─1,120
│    │    └─bias                                              └─40
│    └─Linear: 2-10                      [4608, 50]            2,050
│    │    └─weight                                            ├─2,000
│    │    └─bias                                              └─50
│    └─Linear: 2-11                      [4608, 57]            2,907
│    │    └─weight                                            ├─2,850
│    │    └─bias                                              └─57
│    └─Linear: 2-12                      [4608, 57]            3,306
│    │    └─weight                                            ├─3,249
│    │    └─bias                                              └─57
│    └─Sigmoid: 2-13                     [4608, 57]            --
==========================================================================================
Total params: 20,091
Trainable params: 20,091
Non-trainable params: 0
Total mult-adds (M): 92.58
==========================================================================================
Input size (MB): 1.05
Forward/backward pass size (MB): 16.77
Params size (MB): 0.08
Estimated Total Size (MB): 17.90
==========================================================================================
epoch: 0, train_loss: 0.5030332207679749, val_loss: 0.5977501273155212
epoch: 0, train_acc: 0.1250116268254116, val_acc: 0.12507233796296297
epoch: 10, train_loss: 0.4942972958087921, val_loss: 0.7176238894462585
epoch: 10, train_acc: 0.23252100579791027, val_acc: 0.23328993055555555
epoch: 20, train_loss: 0.5574783682823181, val_loss: 0.5407599806785583
epoch: 20, train_acc: 0.2727963290236567, val_acc: 0.2742332175925926
epoch: 30, train_loss: 0.8430361151695251, val_loss: 0.8313632011413574
epoch: 30, train_acc: 0.2104842960344774, val_acc: 0.2105034722222222
epoch: 40, train_loss: 0.27510350942611694, val_loss: 0.23407931625843048
epoch: 40, train_acc: 0.19185037050816978, val_acc: 0.19223813657407407
epoch: 50, train_loss: 0.19435147941112518, val_loss: 0.18663515150547028
epoch: 50, train_acc: 0.4062645335317645, val_acc: 0.40346498842592593
epoch: 60, train_loss: 0.16892503201961517, val_loss: 0.15700899064540863
epoch: 60, train_acc: 0.45718227761758595, val_acc: 0.4545355902777778
epoch: 70, train_loss: 0.1565491259098053, val_loss: 0.15707500278949738
epoch: 70, train_acc: 0.45907357455120457, val_acc: 0.4580078125
epoch: 80, train_loss: 0.1565597653388977, val_loss: 0.15672360360622406
epoch: 80, train_acc: 0.45907357455120457, val_acc: 0.4580078125
epoch: 90, train_loss: 0.15645688772201538, val_loss: 0.15681621432304382
epoch: 90, train_acc: 0.45907357455120457, val_acc: 0.4580078125
```

```
# high learning rate, low WD
FCAutoEncoder = AutoEncoder()
model, loss_dict = train(FCAutoEncoder, train_loader, val_loader, num_epochs=100, learning_rate=6e-2, weight_decay=1e-5, ac
```

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
AutoEncoder                              [4608, 57]                --
├─Sequential: 1-1                        [4608, 12]                --
│    └─0.weight                                                    ├─3,249
│    └─0.bias                                                      ├─57
│    └─1.weight                                                    ├─2,679
│    └─1.bias                                                      ├─47
│    └─2.weight                                                    ├─1,739
│    └─2.bias                                                      ├─37
│    └─3.weight                                                    ├─1,110
│    └─3.bias                                                      ├─30
```

```
│    └─4.weight                                                  ├─600
│    └─4.bias                                                    ├─20
│    └─5.weight                                                  ├─240
│    └─5.bias                                                    └─12
│    └─Linear: 2-1                       [4608, 57]              3,306
│    │    └─weight                                               ├─3,249
│    │    └─bias                                                 └─57
│    └─Linear: 2-2                       [4608, 47]              2,726
│    │    └─weight                                               ├─2,679
│    │    └─bias                                                 └─47
│    └─Linear: 2-3                       [4608, 37]              1,776
│    │    └─weight                                               ├─1,739
│    │    └─bias                                                 └─37
│    └─Linear: 2-4                       [4608, 30]              1,140
│    │    └─weight                                               ├─1,110
│    │    └─bias                                                 └─30
│    └─Linear: 2-5                       [4608, 20]              620
│    │    └─weight                                               ├─600
│    │    └─bias                                                 └─20
│    └─Linear: 2-6                       [4608, 12]              252
│    │    └─weight                                               ├─240
│    │    └─bias                                                 └─12
├─Sequential: 1-2                        [4608, 57]              --
│    └─0.weight                                                  ├─240
│    └─0.bias                                                    ├─20
│    └─1.weight                                                  ├─560
│    └─1.bias                                                    ├─28
│    └─2.weight                                                  ├─1,120
│    └─2.bias                                                    ├─40
│    └─3.weight                                                  ├─2,000
│    └─3.bias                                                    ├─50
│    └─4.weight                                                  ├─2,850
│    └─4.bias                                                    ├─57
│    └─5.weight                                                  ├─3,249
│    └─5.bias                                                    └─57
│    └─Linear: 2-7                       [4608, 20]              260
│    │    └─weight                                               ├─240
│    │    └─bias                                                 └─20
│    └─Linear: 2-8                       [4608, 28]              588
│    │    └─weight                                               ├─560
│    │    └─bias                                                 └─28
│    └─Linear: 2-9                       [4608, 40]              1,160
│    │    └─weight                                               ├─1,120
│    │    └─bias                                                 └─40
│    └─Linear: 2-10                      [4608, 50]              2,050
│    │    └─weight                                               ├─2,000
│    │    └─bias                                                 └─50
│    └─Linear: 2-11                      [4608, 57]              2,907
│    │    └─weight                                               ├─2,850
│    │    └─bias                                                 └─57
│    └─Linear: 2-12                      [4608, 57]              3,306
│    │    └─weight                                               ├─3,249
│    │    └─bias                                                 └─57
│    └─Sigmoid: 2-13                     [4608, 57]              --
==========================================================================================
Total params: 20,091
Trainable params: 20,091
Non-trainable params: 0
Total mult-adds (M): 92.58
==========================================================================================
Input size (MB): 1.05
Forward/backward pass size (MB): 16.77
Params size (MB): 0.08
```

```
Estimated Total Size (MB): 17.90
==========================================================================================
epoch: 0, train_loss: 0.2868417501449585, val_loss: 0.22494566440582275
epoch: 0, train_acc: 0.3187455430502589, val_acc: 0.31984230324074076
epoch: 10, train_loss: 0.9014258980751038, val_loss: 0.8849048614501953
epoch: 10, train_acc: 0.0911388087929805, val_acc: 0.09241174768518519
epoch: 20, train_loss: 0.559620201587677, val_loss: 0.5531684160232544
epoch: 20, train_acc: 0.1595898055994791, val_acc: 0.16120515046296297
epoch: 30, train_loss: 0.6714227199554443, val_loss: 0.5306887030601501
epoch: 30, train_acc: 0.14635847828109014, val_acc: 0.14872685185185186
epoch: 40, train_loss: 0.5203275084495544, val_loss: 0.517612874507904
epoch: 40, train_acc: 0.1563187920503519, val_acc: 0.1576244212962963
epoch: 50, train_loss: 0.6175085306167603, val_loss: 0.6094297170639038
epoch: 50, train_acc: 0.1830837441478312, val_acc: 0.18395543981481483
epoch: 60, train_loss: 0.586700439453125, val_loss: 0.5914342403411865
epoch: 60, train_acc: 0.3002433882119493, val_acc: 0.3013599537037037
epoch: 70, train_loss: 0.6224239468574524, val_loss: 0.6555841565132141
epoch: 70, train_acc: 0.18219235419960933, val_acc: 0.18160445601851852
epoch: 80, train_loss: 0.5891613364219666, val_loss: 0.5598772764205933
epoch: 80, train_acc: 0.1650621647598673, val_acc: 0.16608796296296297
epoch: 90, train_loss: 0.48640769720077515, val_loss: 0.4906626045703888
epoch: 90, train_acc: 0.23662139955973088, val_acc: 0.23509837962962962
```

```
# Lower learning rate, high WD
FCAutoEncoder = AutoEncoder()
model, loss_dict = train(FCAutoEncoder, train_loader, val_loader, num_epochs=100, learning_rate=2e-4, weight_decay=1e-3, ac
```

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
AutoEncoder                              [4608, 57]                --
├─Sequential: 1-1                        [4608, 12]                --
│    └─0.weight                                                    ├─3,249
│    └─0.bias                                                      ├─57
│    └─1.weight                                                    ├─2,679
│    └─1.bias                                                      ├─47
│    └─2.weight                                                    ├─1,739
│    └─2.bias                                                      ├─37
│    └─3.weight                                                    ├─1,110
│    └─3.bias                                                      ├─30
│    └─4.weight                                                    ├─600
│    └─4.bias                                                      ├─20
│    └─5.weight                                                    ├─240
│    └─5.bias                                                      └─12
│    └─Linear: 2-1                       [4608, 57]                3,306
│    │    └─weight                                                 ├─3,249
│    │    └─bias                                                   └─57
│    └─Linear: 2-2                       [4608, 47]                2,726
│    │    └─weight                                                 ├─2,679
│    │    └─bias                                                   └─47
│    └─Linear: 2-3                       [4608, 37]                1,776
│    │    └─weight                                                 ├─1,739
│    │    └─bias                                                   └─37
│    └─Linear: 2-4                       [4608, 30]                1,140
│    │    └─weight                                                 ├─1,110
│    │    └─bias                                                   └─30
│    └─Linear: 2-5                       [4608, 20]                620
│    │    └─weight                                                 ├─600
│    │    └─bias                                                   └─20
│    └─Linear: 2-6                       [4608, 12]                252
│    │    └─weight                                                 ├─240
```

```
│    │    └─bias                                                 └─12
├─Sequential: 1-2                       [4608, 57]                --
│    └─0.weight                                                   ├─240
│    └─0.bias                                                     ├─20
│    └─1.weight                                                   ├─560
│    └─1.bias                                                     ├─28
│    └─2.weight                                                   ├─1,120
│    └─2.bias                                                     ├─40
│    └─3.weight                                                   ├─2,000
│    └─3.bias                                                     ├─50
│    └─4.weight                                                   ├─2,850
│    └─4.bias                                                     ├─57
│    └─5.weight                                                   ├─3,249
│    └─5.bias                                                     └─57
│    └─Linear: 2-7                      [4608, 20]                260
│    │    └─weight                                                ├─240
│    │    └─bias                                                  └─20
│    └─Linear: 2-8                      [4608, 28]                588
│    │    └─weight                                                ├─560
│    │    └─bias                                                  └─28
│    └─Linear: 2-9                      [4608, 40]                1,160
│    │    └─weight                                                ├─1,120
│    │    └─bias                                                  └─40
│    └─Linear: 2-10                     [4608, 50]                2,050
│    │    └─weight                                                ├─2,000
│    │    └─bias                                                  └─50
│    └─Linear: 2-11                     [4608, 57]                2,907
│    │    └─weight                                                ├─2,850
│    │    └─bias                                                  └─57
│    └─Linear: 2-12                     [4608, 57]                3,306
│    │    └─weight                                                ├─3,249
│    │    └─bias                                                  └─57
│    └─Sigmoid: 2-13                    [4608, 57]                --
==========================================================================================
Total params: 20,091
Trainable params: 20,091
Non-trainable params: 0
Total mult-adds (M): 92.58
==========================================================================================
Input size (MB): 1.05
Forward/backward pass size (MB): 16.77
Params size (MB): 0.08
Estimated Total Size (MB): 17.90
==========================================================================================
epoch: 0, train_loss: 0.23870640993118286, val_loss: 0.1571282148361206
epoch: 0, train_acc: 0.4427495116733327, val_acc: 0.44169560185185186
epoch: 10, train_loss: 0.15597547590732574, val_loss: 0.15605829656124115
epoch: 10, train_acc: 0.45907357455120457, val_acc: 0.4580078125
epoch: 20, train_loss: 0.15595705807209015, val_loss: 0.1560332477092743
epoch: 20, train_acc: 0.45907357455120457, val_acc: 0.4580078125
epoch: 30, train_loss: 0.15595701336860657, val_loss: 0.15602293610572815
epoch: 30, train_acc: 0.45907357455120457, val_acc: 0.4580078125
epoch: 40, train_loss: 0.15595783293247223, val_loss: 0.15601320564746857
epoch: 40, train_acc: 0.45907357455120457, val_acc: 0.4580078125
epoch: 50, train_loss: 0.15595784783363342, val_loss: 0.15600837767124176
epoch: 50, train_acc: 0.45907357455120457, val_acc: 0.4580078125
epoch: 60, train_loss: 0.15595762431621552, val_loss: 0.15600818395614624
epoch: 60, train_acc: 0.45907357455120457, val_acc: 0.4580078125
epoch: 70, train_loss: 0.1559571772813797, val_loss: 0.15600888431072235
epoch: 70, train_acc: 0.45907357455120457, val_acc: 0.4580078125
epoch: 80, train_loss: 0.1559567153453827, val_loss: 0.15600994229316711
epoch: 80, train_acc: 0.45907357455120457, val_acc: 0.4580078125
```

```
epoch: 90, train_loss: 0.1559562385082245, val_loss: 0.15601082146167755
epoch: 90, train_acc: 0.45907357455120457, val_acc: 0.4580078125
```

```
# lower learning rate, low WD
FCAutoEncoder = AutoEncoder()
model, loss_dict = train(FCAutoEncoder, train_loader, val_loader, num_epochs=100, learning_rate=2e-4, weight_decay=1e-5, ac
```

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
AutoEncoder                              [4608, 57]                --
├─Sequential: 1-1                        [4608, 12]                --
│    └─0.weight                                                    ├─3,249
│    └─0.bias                                                      ├─57
│    └─1.weight                                                    ├─2,679
│    └─1.bias                                                      ├─47
│    └─2.weight                                                    ├─1,739
│    └─2.bias                                                      ├─37
│    └─3.weight                                                    ├─1,110
│    └─3.bias                                                      ├─30
│    └─4.weight                                                    ├─600
│    └─4.bias                                                      ├─20
│    └─5.weight                                                    ├─240
│    └─5.bias                                                      └─12
│    └─Linear: 2-1                       [4608, 57]                3,306
│    │    └─weight                                                 ├─3,249
│    │    └─bias                                                   └─57
│    └─Linear: 2-2                       [4608, 47]                2,726
│    │    └─weight                                                 ├─2,679
│    │    └─bias                                                   └─47
│    └─Linear: 2-3                       [4608, 37]                1,776
│    │    └─weight                                                 ├─1,739
│    │    └─bias                                                   └─37
│    └─Linear: 2-4                       [4608, 30]                1,140
│    │    └─weight                                                 ├─1,110
│    │    └─bias                                                   └─30
│    └─Linear: 2-5                       [4608, 20]                620
│    │    └─weight                                                 ├─600
│    │    └─bias                                                   └─20
│    └─Linear: 2-6                       [4608, 12]                252
│    │    └─weight                                                 ├─240
│    │    └─bias                                                   └─12
├─Sequential: 1-2                        [4608, 57]                --
│    └─0.weight                                                    ├─240
│    └─0.bias                                                      ├─20
│    └─1.weight                                                    ├─560
│    └─1.bias                                                      ├─28
│    └─2.weight                                                    ├─1,120
│    └─2.bias                                                      ├─40
│    └─3.weight                                                    ├─2,000
│    └─3.bias                                                      ├─50
│    └─4.weight                                                    ├─2,850
│    └─4.bias                                                      ├─57
│    └─5.weight                                                    ├─3,249
│    └─5.bias                                                      └─57
│    └─Linear: 2-7                       [4608, 20]                260
│    │    └─weight                                                 ├─240
│    │    └─bias                                                   └─20
│    └─Linear: 2-8                       [4608, 28]                588
│    │    └─weight                                                 ├─560
│    │    └─bias                                                   └─28
```

```
│    └─Linear: 2-9                       [4608, 40]                1,160
│    │    └─weight                                                 ├─1,120
│    │    └─bias                                                   └─40
│    └─Linear: 2-10                      [4608, 50]                2,050
│    │    └─weight                                                 ├─2,000
│    │    └─bias                                                   └─50
│    └─Linear: 2-11                      [4608, 57]                2,907
│    │    └─weight                                                 ├─2,850
│    │    └─bias                                                   └─57
│    └─Linear: 2-12                      [4608, 57]                3,306
│    │    └─weight                                                 ├─3,249
│    │    └─bias                                                   └─57
│    └─Sigmoid: 2-13                     [4608, 57]                --
==========================================================================================
Total params: 20,091
Trainable params: 20,091
Non-trainable params: 0
Total mult-adds (M): 92.58
==========================================================================================
Input size (MB): 1.05
Forward/backward pass size (MB): 16.77
Params size (MB): 0.08
Estimated Total Size (MB): 17.90
==========================================================================================
epoch: 0, train_loss: 0.22502842545509338, val_loss: 0.1546163260936737
epoch: 0, train_acc: 0.45774036523734224, val_acc: 0.45652488425925924
epoch: 10, train_loss: 0.12747928500175476, val_loss: 0.12583349645137787
epoch: 10, train_acc: 0.5654977831519549, val_acc: 0.5650679976851852
epoch: 20, train_loss: 0.11648808419704437, val_loss: 0.11538629978895187
epoch: 20, train_acc: 0.5700865035810623, val_acc: 0.5715422453703703
epoch: 30, train_loss: 0.11202333122491837, val_loss: 0.10926668345928192
epoch: 30, train_acc: 0.5886661705887825, val_acc: 0.5870587384259259
epoch: 40, train_loss: 0.10487788170576096, val_loss: 0.1019371747970581
epoch: 40, train_acc: 0.5746442191424054, val_acc: 0.5764250578703703
epoch: 50, train_loss: 0.1041886955499649, val_loss: 0.1016688197851181
epoch: 50, train_acc: 0.5975335627693548, val_acc: 0.599609375
epoch: 60, train_loss: 0.10358430445194244, val_loss: 0.10109434276819229
epoch: 60, train_acc: 0.5993550987505039, val_acc: 0.5999348958333334
epoch: 70, train_loss: 0.10308339446783066, val_loss: 0.10160449892282486
epoch: 70, train_acc: 0.6148652838495644, val_acc: 0.6156322337962963
epoch: 80, train_loss: 0.09992983192205429, val_loss: 0.09717097133398056
epoch: 80, train_acc: 0.6119585774966669, val_acc: 0.6130642361111112
epoch: 90, train_loss: 0.09885147958993912, val_loss: 0.09626201540231705
epoch: 90, train_acc: 0.6379019005983939, val_acc: 0.6387803819444444
```

From the 4 models above (4 choices of hyperparameters), we can see that having a lower learning rate with a lower weight decay performed the best, scoring almost 64% accuracy on the validation set. The lowest performing set of hyperparameters was the one with the high learning rate and lower weight decay. So from that view, it seems that for the 5th model, we should choose a set of hyperparameters that is lower on the learning rate and lower on the weight decay. Since we are trying to train the model for longer, we could maintain a similar decay parameter in order to help regularize the model in later epochs. Training the model longer could help the model learn more, i.e., work its way through harder to optimize surfaces, which may be needed with a lower learning rate.

```
# model 5
FCAutoEncoder = AutoEncoder()
model, loss_dict = train(FCAutoEncoder, train_loader, val_loader, num_epochs=500, learning_rate=1.8e-4, weight_decay=1e-5, a
```

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
AutoEncoder                              [4608, 57]                --
├─Sequential: 1-1                        [4608, 12]                --
│    └─0.weight                                                    ├─3,249
```

```
│    └─0.bias                                                  ├─57
│    └─1.weight                                                ├─2,679
│    └─1.bias                                                  ├─47
│    └─2.weight                                                ├─1,739
│    └─2.bias                                                  ├─37
│    └─3.weight                                                ├─1,110
│    └─3.bias                                                  ├─30
│    └─4.weight                                                ├─600
│    └─4.bias                                                  ├─20
│    └─5.weight                                                ├─240
│    └─5.bias                                                  └─12
│    └─Linear: 2-1                      [4608, 57]             3,306
│    │    └─weight                                             ├─3,249
│    │    └─bias                                               └─57
│    └─Linear: 2-2                      [4608, 47]             2,726
│    │    └─weight                                             ├─2,679
│    │    └─bias                                               └─47
│    └─Linear: 2-3                      [4608, 37]             1,776
│    │    └─weight                                             ├─1,739
│    │    └─bias                                               └─37
│    └─Linear: 2-4                      [4608, 30]             1,140
│    │    └─weight                                             ├─1,110
│    │    └─bias                                               └─30
│    └─Linear: 2-5                      [4608, 20]             620
│    │    └─weight                                             ├─600
│    │    └─bias                                               └─20
│    └─Linear: 2-6                      [4608, 12]             252
│    │    └─weight                                             ├─240
│    │    └─bias                                               └─12
├─Sequential: 1-2                       [4608, 57]             --
│    └─0.weight                                                ├─240
│    └─0.bias                                                  ├─20
│    └─1.weight                                                ├─560
│    └─1.bias                                                  ├─28
│    └─2.weight                                                ├─1,120
│    └─2.bias                                                  ├─40
│    └─3.weight                                                ├─2,000
│    └─3.bias                                                  ├─50
│    └─4.weight                                                ├─2,850
│    └─4.bias                                                  ├─57
│    └─5.weight                                                ├─3,249
│    └─5.bias                                                  └─57
│    └─Linear: 2-7                      [4608, 20]             260
│    │    └─weight                                             ├─240
│    │    └─bias                                               └─20
│    └─Linear: 2-8                      [4608, 28]             588
│    │    └─weight                                             ├─560
│    │    └─bias                                               └─28
│    └─Linear: 2-9                      [4608, 40]             1,160
│    │    └─weight                                             ├─1,120
│    │    └─bias                                               └─40
│    └─Linear: 2-10                     [4608, 50]             2,050
│    │    └─weight                                             ├─2,000
│    │    └─bias                                               └─50
│    └─Linear: 2-11                     [4608, 57]             2,907
│    │    └─weight                                             ├─2,850
│    │    └─bias                                               └─57
│    └─Linear: 2-12                     [4608, 57]             3,306
│    │    └─weight                                             ├─3,249
│    │    └─bias                                               └─57
│    └─Sigmoid: 2-13                    [4608, 57]             --
==========================================================================================
Total params: 20,091
```

```
Trainable params: 20,091
Non-trainable params: 0
Total mult-adds (M): 92.58
==========================================================================================
Input size (MB): 1.05
Forward/backward pass size (MB): 16.77
Params size (MB): 0.08
Estimated Total Size (MB): 17.90
==========================================================================================
epoch: 0, train_loss: 0.2254471629858017, val_loss: 0.15538588166236877
epoch: 0, train_acc: 0.45905032090038134, val_acc: 0.45797164351851855
epoch: 10, train_loss: 0.11843421310186386, val_loss: 0.11669634282588959
epoch: 10, train_acc: 0.5842789818001426, val_acc: 0.5829716435185185
epoch: 20, train_loss: 0.10681932419538498, val_loss: 0.10516973584890366
epoch: 20, train_acc: 0.6202058723219546, val_acc: 0.6207320601851852
epoch: 30, train_loss: 0.10572078078985214, val_loss: 0.10456246137619019
epoch: 30, train_acc: 0.6416922456825722, val_acc: 0.6398654513888888
epoch: 40, train_loss: 0.1044655442237854, val_loss: 0.10341266542673111
epoch: 40, train_acc: 0.6429014355253775, val_acc: 0.6436993634259259
epoch: 50, train_loss: 0.10351486504077911, val_loss: 0.10352227091789246
epoch: 50, train_acc: 0.6424363625089139, val_acc: 0.6440610532407407
epoch: 60, train_loss: 0.10307517647743225, val_loss: 0.10230877995491028
epoch: 60, train_acc: 0.6425526307630298, val_acc: 0.6439525462962963
epoch: 70, train_loss: 0.10198158770799637, val_loss: 0.10177503526210785
epoch: 70, train_acc: 0.6461646978575636, val_acc: 0.6472077546296297
epoch: 80, train_loss: 0.09806124866008759, val_loss: 0.09809142351150513
epoch: 80, train_acc: 0.6549003193501379, val_acc: 0.6564308449074074
epoch: 90, train_loss: 0.09745107591152191, val_loss: 0.09793883562088013
epoch: 90, train_acc: 0.6619849316342665, val_acc: 0.6622178819444444
epoch: 100, train_loss: 0.09709273278713226, val_loss: 0.09882154315710068
epoch: 100, train_acc: 0.6553188850649552, val_acc: 0.6555989583333334
epoch: 110, train_loss: 0.09725150465965271, val_loss: 0.09778803586959839
epoch: 110, train_acc: 0.6623104827457911, val_acc: 0.6641348379629629
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epoch: 120, train_acc: 0.66230273152885, val_acc: 0.6634837962962963
epoch: 130, train_loss: 0.09715887904167175, val_loss: 0.09824740141630173
epoch: 130, train_acc: 0.6623414876135554, val_acc: 0.6646412037037037
epoch: 140, train_loss: 0.096817247569561, val_loss: 0.09793438017368317
epoch: 140, train_acc: 0.6598998542771215, val_acc: 0.6614583333333334
epoch: 150, train_loss: 0.09696105867624283, val_loss: 0.09832189977169037
epoch: 150, train_acc: 0.6618764145970918, val_acc: 0.6636646412037037
epoch: 160, train_loss: 0.09696127474308014, val_loss: 0.09839270263910294
epoch: 160, train_acc: 0.663597184758007, val_acc: 0.6636284722222222
epoch: 170, train_loss: 0.09719936549663544, val_loss: 0.09910765290260315
epoch: 170, train_acc: 0.660612966235699, val_acc: 0.6619285300925926
epoch: 180, train_loss: 0.09681446105241776, val_loss: 0.09929074347019196
epoch: 180, train_acc: 0.6544584999844976, val_acc: 0.6548032407407407
epoch: 190, train_loss: 0.0969424918293953, val_loss: 0.09905363619327545
epoch: 190, train_acc: 0.662039190152854, val_acc: 0.6632667824074074
epoch: 200, train_loss: 0.09714095294475555, val_loss: 0.09907418489456177
epoch: 200, train_acc: 0.6581170743806778, val_acc: 0.6591796875
epoch: 210, train_loss: 0.09705800563097, val_loss: 0.10034964233636856
epoch: 210, train_acc: 0.6596053080333613, val_acc: 0.6607711226851852
epoch: 220, train_loss: 0.09695859253406525, val_loss: 0.09988068044185638
epoch: 220, train_acc: 0.6587294205190215, val_acc: 0.6598668981481481
epoch: 230, train_loss: 0.09670357406139374, val_loss: 0.09817198663949966
epoch: 230, train_acc: 0.6615818683533314, val_acc: 0.6620732060185185
epoch: 240, train_loss: 0.09708560258150101, val_loss: 0.09781837463378906
epoch: 240, train_acc: 0.6612253123740427, val_acc: 0.6619285300925926
epoch: 250, train_loss: 0.09659237414598465, val_loss: 0.1001768410205841
epoch: 250, train_acc: 0.6616826341735652, val_acc: 0.6628327546296297
epoch: 260, train_loss: 0.09681931138038635, val_loss: 0.09763730317354202
epoch: 260, train_acc: 0.6662403497349084, val_acc: 0.6665219907407407
```

```
epoch: 270, train_loss: 0.09685008227825165, val_loss: 0.09854917228221893
epoch: 270, train_acc: 0.6614423464483924, val_acc: 0.6623263888888888
epoch: 280, train_loss: 0.09660748392343521, val_loss: 0.09804457426071167
epoch: 280, train_acc: 0.6637057017951818, val_acc: 0.6631221064814815
epoch: 290, train_loss: 0.09688956290483475, val_loss: 0.09863342344760895
epoch: 290, train_acc: 0.6618376585123864, val_acc: 0.6620370370370371
epoch: 300, train_loss: 0.09680263698101044, val_loss: 0.0979376882314682
epoch: 300, train_acc: 0.6594812885623043, val_acc: 0.6598307291666666
epoch: 310, train_loss: 0.0966748297214508, val_loss: 0.09821777790784836
epoch: 310, train_acc: 0.6618221560785044, val_acc: 0.6626519097222222
epoch: 320, train_loss: 0.09689101576805115, val_loss: 0.09942574799060822
epoch: 320, train_acc: 0.6625120143862586, val_acc: 0.6636646412037037
epoch: 330, train_loss: 0.09700945764780045, val_loss: 0.10032179206609726
epoch: 330, train_acc: 0.6631011068737792, val_acc: 0.6638093171296297
epoch: 340, train_loss: 0.09689013659954071, val_loss: 0.09960387647151947
epoch: 340, train_acc: 0.6637987163984745, val_acc: 0.6650390625
epoch: 350, train_loss: 0.09699040651321411, val_loss: 0.0991879552602768
epoch: 350, train_acc: 0.6630545995721329, val_acc: 0.6624710648148148
epoch: 360, train_loss: 0.09686235338449478, val_loss: 0.09735877811908722
epoch: 360, train_acc: 0.6584193718413791, val_acc: 0.6581669560185185
epoch: 370, train_loss: 0.09722639620304108, val_loss: 0.0991189032793045
epoch: 370, train_acc: 0.6636746969274177, val_acc: 0.6646773726851852
epoch: 380, train_loss: 0.09724511951208115, val_loss: 0.09898320585489273
epoch: 380, train_acc: 0.6608067466592255, val_acc: 0.6595052083333334
epoch: 390, train_loss: 0.09686034172773361, val_loss: 0.0990271344780922
epoch: 390, train_acc: 0.6581713328992652, val_acc: 0.6605179398148148
epoch: 400, train_loss: 0.09682028740644455, val_loss: 0.09851497411727905
epoch: 400, train_acc: 0.6628995752333117, val_acc: 0.6633752893518519
epoch: 410, train_loss: 0.09679175913333893, val_loss: 0.09874965250492096
epoch: 410, train_acc: 0.6623414876135554, val_acc: 0.6623987268518519
epoch: 420, train_loss: 0.09686528146266937, val_loss: 0.09876633435487747
epoch: 420, train_acc: 0.6622717266610858, val_acc: 0.6616030092592593
epoch: 430, train_loss: 0.09716001152992249, val_loss: 0.0984620675444603
epoch: 430, train_acc: 0.6646513502619912, val_acc: 0.6657986111111112
epoch: 440, train_loss: 0.0969218984246254, val_loss: 0.09732034802436829
epoch: 440, train_acc: 0.6631011068737792, val_acc: 0.6627604166666666
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epoch: 450, train_acc: 0.663721204229064, val_acc: 0.6645688657407407
epoch: 460, train_loss: 0.09696398675441742, val_loss: 0.09888863563537598
epoch: 460, train_acc: 0.6611555514215732, val_acc: 0.6624348958333334
epoch: 470, train_loss: 0.09700309485197067, val_loss: 0.09944615513086319
epoch: 470, train_acc: 0.6600238737481785, val_acc: 0.6612774884259259
epoch: 480, train_loss: 0.09692465513944626, val_loss: 0.09799867868423462
epoch: 480, train_acc: 0.6649691501565745, val_acc: 0.6630859375
epoch: 490, train_loss: 0.09688393771648407, val_loss: 0.09835939109325409
epoch: 490, train_acc: 0.6619461755495613, val_acc: 0.6613136574074074
```
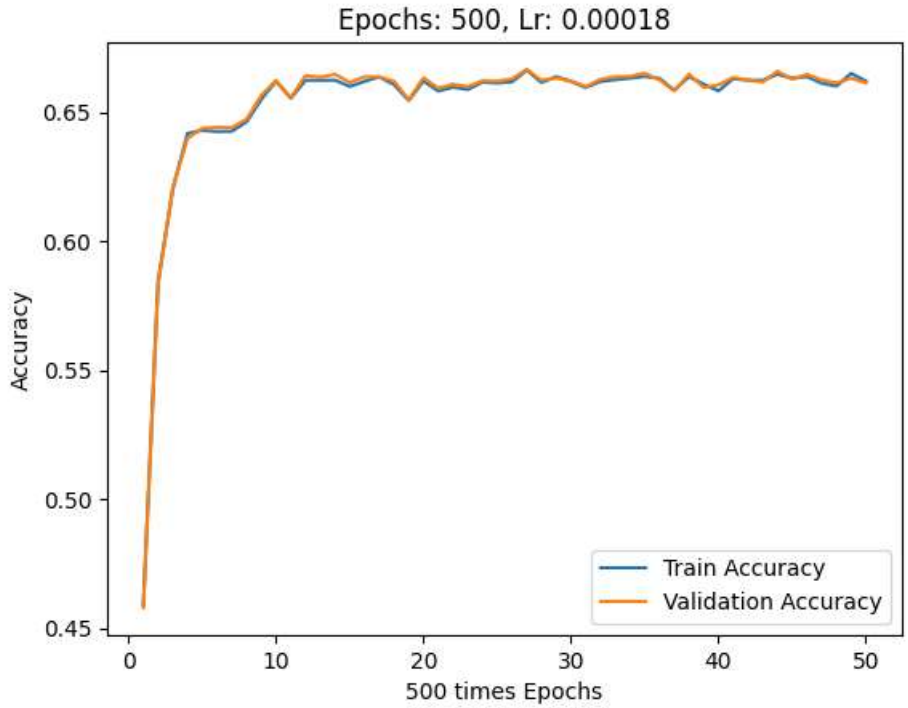
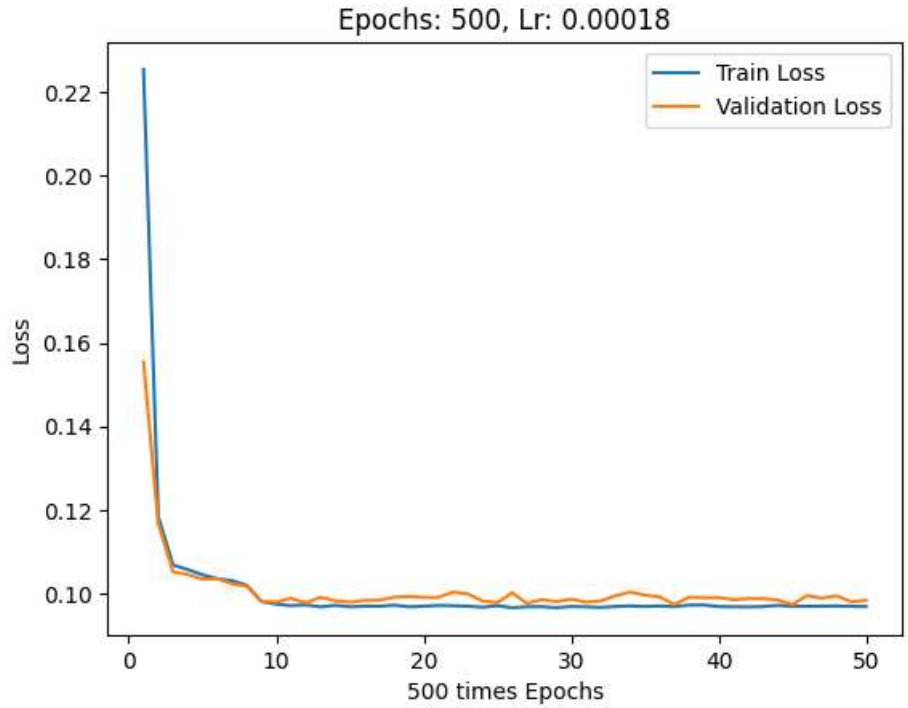

```
plot_acc_curves(loss_dict)
plot_loss_curves(loss_dict)
```





As the above plots show, the final set of hyperparameters improve upon the previous ones, and while the improvement isn't large, it is still a few percent better in terms of validation accuracy which is nice.

Part 4. Testing [12 pt]

Part (a) [2 pt]

Compute and report the test accuracy.

```
get_accuracy(model, test_loader)
```

```
0.6646412037037037
```

So the autoencoder scores a 66.5% accuracy on the test set, which is consistent with the accuracy scores for the train and validation sets.

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?

```
# loop over columns of data_train
# find the most common values per column
# impute values for each features
# this is a bit weird, but I essentially
# wrapped the baseline model in a pytorch model
# it has better compatibility with the get_accuracy function
categorical_features = pd.get_dummies(df_not_missing[catcols]).values.astype(np.int64)
# most common values of one-hot encoded categorical features
most_common = [np.argmax(np.bincount(feature)) for feature in categorical_features.T]

# need a mapping between the actual feature vector that includes contin features
# gets the categorical feature indexes
cat_features_indexes = [(cat_index[feature], cat_index[feature] + len(cat_values[feature])) for feature in catcols]
# a mapping from cat_features_indexes to the most_common list
index_mapping = {}
curr_ptr = 0
for i in range(len(catcols)):
    # has start and finish
    feature_indexes = cat_features_indexes[i]
    length = feature_indexes[1] - feature_indexes[0]
    most_common_subset = most_common[curr_ptr : curr_ptr + length]

    # store the respective values into the dict
    for j in range(length):
        index_mapping[j+feature_indexes[0]] = most_common_subset[j]

    curr_ptr += length

class BaselineModel(nn.Module):
    def __init__(self, index_mapping):
        super(BaselineModel, self).__init__()
        self.most_common = index_mapping

    def forward(self, x, missing_indexes):
        output = []
        for row in x:
            row_preds = []
            for i in range(len(row)):
                if i in self.most_common:
                    pred = self.most_common[i]
                    # if we are supposed to predict these features
                    if i in missing_indexes:
                        row_preds.append(pred)
```

```
                    else:
                        row_preds.append(row[i])
                else:
                    row_preds.append(row[i])
            output.append(row_preds)
        output = torch.from_numpy(np.array(output))
        return output
```

```
baseline_model= BaselineModel(index_mapping)
get_accuracy(baseline_model, test_loader, True)
```

```
0.35366030092592593
```

Part (c) [1 pt]

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

The test accuracy from the autoencoder is roughly 1.9 times as good as the test accuracy from the baseline model. In particular, the baseline model achieved approximately 35.4% test set accuracy, while the autoencoder achieved a test accuracy of approximately 66.5%.

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.

Putting the data back into a pandas dataframe to get the column (feature) names, we have:

```
test_df = pd.DataFrame(data_test, columns=list(data.columns))
test_df.iloc[0]
```

```
age                              1.936798
yredu                            1.134739
capgain                          0.764416
caploss                         -0.216660
workhr                          -0.035429
work_ Federal-gov                0.000000
work_ Local-gov                  0.000000
work_ Private                    1.000000
work_ Self-emp-inc               0.000000
work_ Self-emp-not-inc           0.000000
work_ State-gov                  0.000000
work_ Without-pay                0.000000
marriage_ Divorced               1.000000
marriage_ Married-AF-spouse      0.000000
marriage_ Married-civ-spouse     0.000000
marriage_ Married-spouse-absent  0.000000
marriage_ Never-married          0.000000
marriage_ Separated              0.000000
marriage_ Widowed                0.000000
occupation_ Adm-clerical         0.000000
occupation_ Armed-Forces         0.000000
occupation_ Craft-repair         0.000000
occupation_ Exec-managerial      0.000000
occupation_ Farming-fishing      0.000000
occupation_ Handlers-cleaners    0.000000
occupation_ Machine-op-inspct    0.000000
occupation_ Other-service        0.000000
occupation_ Priv-house-serv      0.000000
occupation_ Prof-specialty       1.000000
occupation_ Protective-serv      0.000000
occupation_ Sales                0.000000
```

```
occupation_ Tech-support          0.000000
occupation_ Transport-moving      0.000000
edu_ 10th                         0.000000
edu_ 11th                         0.000000
edu_ 12th                         0.000000
edu_ 1st-4th                      0.000000
edu_ 5th-6th                      0.000000
edu_ 7th-8th                      0.000000
edu_ 9th                          0.000000
edu_ Assoc-acdm                   0.000000
edu_ Assoc-voc                    0.000000
edu_ Bachelors                    1.000000
edu_ Doctorate                    0.000000
edu_ HS-grad                      0.000000
edu_ Masters                      0.000000
edu_ Preschool                    0.000000
edu_ Prof-school                  0.000000
edu_ Some-college                 0.000000
relationship_ Husband             0.000000
relationship_ Not-in-family       1.000000
relationship_ Other-relative      0.000000
relationship_ Own-child           0.000000
relationship_ Unmarried           0.000000
relationship_ Wife                0.000000
sex_ Female                       0.000000
sex_ Male                         1.000000
Name: 0, dtype: float32
```

It is somewhat predictable about the level of education that this person has. In particular, the `occupation_*` features are fairly good proxies of the education level since those columns are quite descriptive of the occupation, and most occupations have certain levels of education required. Further, other features like `yredu` are also directly related to the education level, e.g., those with a PhD would have a much higher normalized value for `yredu` than anyone else. While the capital gains and losses are not directly indicative of education level, they can be informative, on some level, of education since learning math/economics could help you in an area that would net you capital gains (e.g., investments). Finally, the `work_*` features can be informative in certain cases too if the person works in certain sectors, e.g., the government since some of those positions require some level of education, e.g., certain bureaucratic positions requires at least a bachelors.

Part (e) [2 pt]

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

```
person_of_interest_edu_zerod = torch.from_numpy(zero_out_feature(data_test[:], "edu")[0])
out = model(person_of_interest_edu_zerod.to("cuda:0")).cpu().detach().numpy()
data_frame_cols = list(data.columns)
out_df = pd.DataFrame(out.reshape(1, -1), columns=data_frame_cols)
out_df.filter(regex="edu_*")
```

	yredu	edu_ 10th	edu_ 11th	edu_ 12th	edu_ 1st-4th	edu_ 5th-6th	edu_ 7th-8th	edu_ 9th	edu_ Assoc-acdm	edu_ Assoc-voc	edu_ Bachelors	edu_ Doctorate	edu_ HS grad
0	0.999998	0.014633	0.014967	0.007034	0.000408	0.001515	0.019362	0.007476	0.047725	0.053316	0.999989	0.026379	3.703797 19

```
get_feature(out, "edu")
```

```
'Bachelors'
```

As we can see the autoencoder output predicts correctly that this person has a Bachelor's degree since they had the highest score of `edu_bachelors`. Further, the `get_feature` function also outputs "Bachelors" provided the model predictions.

Part (f) [2 pt]

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

```
person_of_interest_edu_zerod = torch.from_numpy(zero_out_feature(data_test[:], "edu")[0]).reshape(1, -1)
missing_cols = set(range(cat_index["edu"], cat_index["edu"] + len(cat_values["edu"])))
out_baseline = baseline_model(person_of_interest_edu_zerod, missing_cols).detach().numpy()
data_frame_cols = list(data.columns)
out_baseline_df = pd.DataFrame(out_baseline, columns=data_frame_cols)
out_baseline_df.filter(regex="edu_*")
```

	yredu	edu_ 10th	edu_ 11th	edu_ 12th	edu_ 1st-4th	edu_ 5th-6th	edu_ 7th-8th	edu_ 9th	edu_ Assoc-acdm	edu_ Assoc-voc	edu_ Bachelors	edu_ Doctorate	edu_ HS-grad	edu_ Masters	edu_ Preschool	edu_ Prof-school	edu_ Some colleg
0	1.134739	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

```
get_feature(out_baseline.reshape(-1, 1), "edu")
```

```
'10th'
```

The baseline model predicts an education level of 10th grade as indicated by the `get_feature` call shown in the above code cell, which not correct.