Lab 4: Data Imputation using an Autoencoder

Deadline: Mon, March 01, 5:00pm

Late Penalty: There is a penalty-free grace period of one hour past the deadline. Any work that is submitted between 1 hour and 24 hours past the deadline will receive a 20% grade deduction. No other late work is accepted. Quercus submission time will be used, not your local computer time. You can submit your labs as many times as you want before the deadline, so please submit often and early.

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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 (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 (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 (.html files are also acceptable).

Do not submit any other files produced by your code.

Include a link to your colab file in your submission.

Colab Link

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

Colab Link:https://colab.research.google.com/drive/1n0b7tOzwX9BkvrvNYEga8EQmM5Q8tm9v?usp=sharing (https://colab.research.google.com/drive/1n0b7tOzwX9BkvrvNYEga8EQmM5Q8tm9v?usp=sharing)

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

Part 0

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

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

In [ ]:
```
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 (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.read_csv.html)](https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.read_csv.html)

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

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

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

Part (a) Continuous Features [3 pt]

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

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

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

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

Out[ ]:

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

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

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

Out[ ]:

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

Numpy works nicely with pandas, like below:

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

Out[ ]: 2842700

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

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

would increment everyone's age by 1.

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

Out[ ]:
```
0        40
1        51
2        39
3        54
4        29
         ..
32556    28
32557    41
32558    59
32559    23
32560    53
Name: age, Length: 32561, dtype: int64
```

In [ ]:
```
print('The max value of age:', (df['age']).max())
print('The min value of age:', (df['age']).min())
print('The avg value of age:', (df['age']).mean())
```

```
The max value of age: 90
The min value of age: 17
The avg value of age: 38.58164675532078
```

In [208]:
```
print('The max value of yredu:', (df['yredu']).max())
print('The min value of yredu:', (df['yredu']).min())
print('The avg value of yredu:', (df['yredu']).mean())
```

```
The max value of yredu: 1.0
The min value of yredu: 0.0
The avg value of yredu: 0.6053786226875428
```

In [207]:
```
print('The max value of capgain:', (df['capgain']).max())
print('The min value of capgain:', (df['capgain']).min())
print('The avg value of capgain:', (df['capgain']).mean())
```

```
The max value of capgain: 1.0
The min value of capgain: 0.0
The avg value of capgain: 0.010776596203049367
```

In [206]:
```
print('The max value of caploss:', (df['caploss']).max())
print('The min value of caploss:', (df['caploss']).min())
print('The avg value of caploss:', (df['caploss']).mean())
```

```
The max value of caploss: 1.0
The min value of caploss: 0.0
The avg value of caploss: 0.020042201500222017
```

In [205]:
```
print('The max value of workhr:', (df['workhr']).max())
print('The min value of workhr:', (df['workhr']).min())
print('The avg value of workhr:', (df['workhr']).mean())
```

```
The max value of workhr: 1.0
The min value of workhr: 0.0
The avg value of workhr: 0.4024230188989772
```

In [209]:
```
df["age"] = (df["age"]-(df['age']).min()) / ((df['age']).max() - (df['
age']).min())
df["yredu"] = (df["yredu"]-(df['yredu']).min()) / ((df['yredu']).max()
- (df['yredu']).min())
df["capgain"] = (df["capgain"]-(df['capgain']).min()) / ((df['capgain'
]).max() - (df['capgain']).min())
df["caploss"] = (df["caploss"]-(df['caploss']).min()) / ((df['caploss'
]).max() - (df['caploss']).min())
df["workhr"] = (df["workhr"]-(df['workhr']).min()) / ((df['workhr']).m
ax() - (df['workhr']).min())
```

Part (b) Categorical Features [1 pt]

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

What percentage of people in our data set are female?

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

Out[ ]: 21790

In [ ]:
```
print("percentage of people in our data set are males are:", sum(df["s
ex"] == " Male")/32561*100, "%")
```

```
percentage of people in our data set are males are: 66.9205491231841
9 %
```

In [ ]:
```
print("percentage of people in our data set are females are:", sum(df[
"sex"] == " Female")/32561*100, "%")
```

```
percentage of people in our data set are females are: 33.07945087681
583 %
```

Part (c) [2 pt]

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

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

Both of these steps are done for you, below.

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

In [210]:
```
contcols = ["age", "yredu", "capgain", "caploss", "workhr"]
catcols = ["work", "marriage", "occupation", "edu", "relationship", "s
ex"]
features = contcols + catcols
df = df[features]
```

In [211]:
```
missing = pd.concat([df[c] == " ?" for c in catcols], axis=1).any(axis
=1)
df_with_missing = df[missing]
df_not_missing = df[~missing]
```

In [213]:
```
print("number of records with missing features:", len(df_with_missing)
)
print('percentage of records being removed:',(df_with_missing.shape[0]
/len(df)*100),'%')
```

```
number of records with missing features: 1843
percentage of records being removed: 5.660145572924664 %
```

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

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

In [ ]:
```
print(set(df_not_missing["work"]))
```

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

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

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

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

In [214]:
```
data
```

Out[214]:

	age	yredu	capgain	caploss	workhr	work_ Federal-gov	work_ Local-gov	work_ Private	work_ Self-emp-inc	wor Se em nc i
0	0.301370	0.800000	0.021740	0.0	0.397959	0	0	0	0	
1	0.452055	0.800000	0.000000	0.0	0.122449	0	0	0	0	
2	0.287671	0.533333	0.000000	0.0	0.397959	0	0	1	0	
3	0.493151	0.400000	0.000000	0.0	0.397959	0	0	1	0	
4	0.150685	0.800000	0.000000	0.0	0.397959	0	0	1	0	
...	...	...	...	...	...	...	...	...	...	
32556	0.136986	0.733333	0.000000	0.0	0.377551	0	0	1	0	
32557	0.315068	0.533333	0.000000	0.0	0.397959	0	0	1	0	
32558	0.561644	0.533333	0.000000	0.0	0.397959	0	0	1	0	
32559	0.068493	0.533333	0.000000	0.0	0.193878	0	0	1	0	
32560	0.479452	0.533333	0.150242	0.0	0.397959	0	0	0	1	

30718 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.

Answer There are 57 columns are in the dataframe data.

The number comes from original 14 column with string value, plus their expanded categorical values that represented by a one-hot encoding. For example, the columns work expaned to 7 columns.

In [ ]:
```
print("There are",len(data.columns),"columns in the datafram data")
```

```
There are 57 columns in the datafram data
```

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

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

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

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

In [ ]:
```
datanp = data.values.astype(np.float32)
```

In [ ]:
```
cat_index = {}  # Mapping of feature -> start index of feature in a re
cord
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., 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.

    max_pos = np.argmax(onehot)
    category = cat_values[feature]
    return cat_values[feature][max_pos]
```

In [ ]:

```
print(get_categorical_value(np.array([0., 0., 0., 0., 0., 1., 0.]), "w
ork"))
print(get_categorical_value(np.array([0.1, 0., 1.1, 0.2, 0., 1., 0.]),
"work"))
```

```
State-gov
Private
```

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

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

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

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

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

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

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

# todo
random.shuffle(datanp) # randomly shuffle the data

train_index = int(datanp.shape[0]*0.7)
val_index = train_index + int(datanp.shape[0]*0.15)

train_data = datanp[:train_index]
val_data = datanp[train_index:val_index+1]
test_data = datanp[val_index+1:]

print("number of items in training set:", len(train_data))
print("number of items in validation set:", len(val_data))
print("number of items in test set:", len(test_data))
```

```
number of items in training set: 21502
number of items in validation set: 4608
number of items in test set: 4608
```

Part 2. Model Setup [5 pt]

Part (a) [4 pt]

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

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

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

In [ ]:
```
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, 40),
            nn.Linear(40, 20)
        )
        self.decoder = nn.Sequential(
            nn.Linear(20, 40),
            nn.Linear(40, 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.)

Answer: Because the input data is normalized in range of 0 to 1 and the output should be the same in this range. The sigmoid activation is used to convert the value of ouput to between the range 0 and 1.

Part 3. Training [18]

Part (a) [6 pt]

We will train our autoencoder in the following way:

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

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

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

In [ ]:
```
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, batch_size=64):
    """ Training loop. You should update this."""
    torch.manual_seed(42)
    criterion = nn.MSELoss()
    optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
```

```
    train_loss=[]
    val_loss=[]
    train_acc=[]
    val_acc=[]
    iters=[]
    for epoch in range(num_epochs):

        for data in train_loader:
            datam = zero_out_random_feature(data.clone()) # zero out o
ne categorical feature
            recon = model(datam)
            loss = criterion(recon, data)
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()

        iters.append(epoch)
        train_loss.append( float(loss/batch_size) )
        train_acc.append( get_accuracy(model, train_loader) )


        for data in valid_loader:
            datam = zero_out_random_feature(data.clone())
            recon = model(datam)
            valid_loss = criterion(recon, data)


        val_loss.append( float(valid_loss/batch_size))
        val_acc.append(get_accuracy(model, valid_loader))
        print("Epoch {} - Training Accuracy: {}, Validation Accuracy:
{}".format(
            epoch, train_acc[epoch], val_acc[epoch]))
    print("Final Training Accuracy:", train_acc[-1])
    print("Final Validation Accuracy:", val_acc[-1])
    return train_loss, val_loss, train_acc, val_acc, iters
```

Part (b) [3 pt]

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

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

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

In [ ]:
```
def get_accuracy(model, data_loader):
    """Return the "accuracy" of the autoencoder model across a data se
t.
    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=2
56, shuffle=True)
        >>> get_accuracy(model, vdl)
    """
    total = 0
    acc = 0
    for col in catcols:
        for item in data_loader: # minibatches
            inp = item.detach().numpy()
            out = model(zero_out_feature(item.clone(), col)).detach().
numpy()
            for i in range(out.shape[0]): # record in minibatch
                acc += int(get_feature(out[i], col) == get_feature(inp
[i], col))
                total += 1
    return acc / total
```

Part (c) [4 pt]

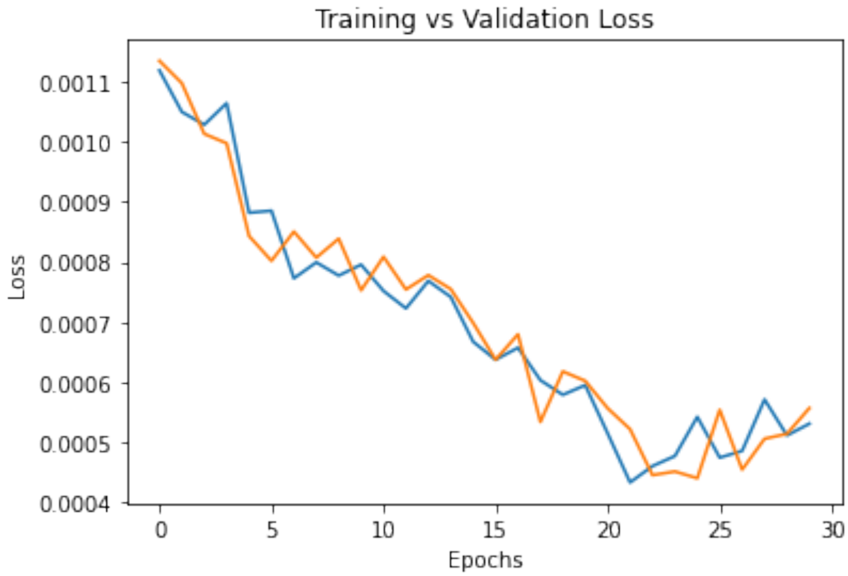
Run your updated training code, using reasonable initial hyperparameters.

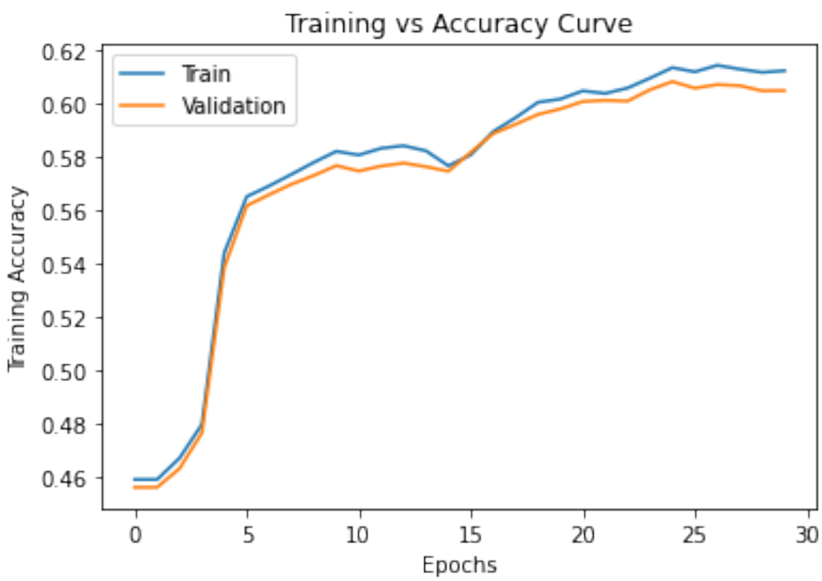
Include your training curve in your submission.

In [ ]:
```
train_loader = torch.utils.data.DataLoader(train_data, batch_size=64, shuffle=True)
valid_loader = torch.utils.data.DataLoader(val_data, batch_size=64, shuffle=True)
model = AutoEncoder()

train_loss, val_loss, train_acc, val_acc, iters=train(model, train_loader, valid_loader, num_epochs=30, learning_rate=1e-4,batch_size=64)

# Plotting
plt.title("Training vs Validation Loss")
plt.plot(iters, train_loss, label="Train")
plt.plot(iters, val_loss, label="Validation")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.show()

plt.title("Training vs Accuracy Curve")
plt.plot(iters, train_acc, label="Train")
plt.plot(iters, val_acc, label="Validation")
plt.xlabel("Epochs")
plt.ylabel("Training Accuracy")
plt.legend(loc='best')
plt.show()
```

```
Epoch 0 - Training Accuracy: 0.4588255356090906, Validation Accuracy
: 0.4558738425925926
Epoch 1 - Training Accuracy: 0.4588255356090906, Validation Accuracy
: 0.4558738425925926
Epoch 2 - Training Accuracy: 0.4668247914922643, Validation Accuracy
: 0.46292679398148145
Epoch 3 - Training Accuracy: 0.4795445384925433, Validation Accuracy
: 0.4763454861111111
Epoch 4 - Training Accuracy: 0.5440036585743961, Validation Accuracy
: 0.5385199652777778
Epoch 5 - Training Accuracy: 0.5650714662201965, Validation Accuracy
: 0.5616319444444444
Epoch 6 - Training Accuracy: 0.5690788453787244, Validation Accuracy
: 0.5657913773148148
Epoch 7 - Training Accuracy: 0.5734505317334821, Validation Accuracy
: 0.5697337962962963
Epoch 8 - Training Accuracy: 0.5779462375592969, Validation Accuracy
: 0.5730251736111112
Epoch 9 - Training Accuracy: 0.5820853874058227, Validation Accuracy
: 0.5767144097222222
Epoch 10 - Training Accuracy: 0.580697919573373, Validation Accuracy
: 0.5746889467592593
Epoch 11 - Training Accuracy: 0.5832170650792174, Validation Accurac
y: 0.5765335648148148
```

```
Epoch 12 - Training Accuracy: 0.5841782159799088, Validation Accurac
y: 0.5776548032407407
Epoch 13 - Training Accuracy: 0.5822791678293492, Validation Accurac
y: 0.5763165509259259
Epoch 14 - Training Accuracy: 0.5766207794623756, Validation Accurac
y: 0.5745804398148148
Epoch 15 - Training Accuracy: 0.5807444268750194, Validation Accurac
y: 0.5817057291666666
Epoch 16 - Training Accuracy: 0.5894722971506526, Validation Accurac
y: 0.5887225115740741
Epoch 17 - Training Accuracy: 0.5947198710197501, Validation Accurac
y: 0.5922309027777778
Epoch 18 - Training Accuracy: 0.6004945276408397, Validation Accurac
y: 0.5959563078703703
Epoch 19 - Training Accuracy: 0.6017192199175271, Validation Accurac
y: 0.5980179398148148
Epoch 20 - Training Accuracy: 0.6047887018261867, Validation Accurac
y: 0.6008029513888888
Epoch 21 - Training Accuracy: 0.6038275509254953, Validation Accurac
y: 0.6012369791666666
Epoch 22 - Training Accuracy: 0.6058583697640529, Validation Accurac
y: 0.6009476273148148
Epoch 23 - Training Accuracy: 0.6095712026788206, Validation Accurac
y: 0.6052155671296297
Epoch 24 - Training Accuracy: 0.61351657210182, Validation Accuracy:
0.6082899305555556
Epoch 25 - Training Accuracy: 0.6119430750627849, Validation Accurac
y: 0.6057942708333334
Epoch 26 - Training Accuracy: 0.6143769571822776, Validation Accurac
y: 0.6071325231481481
Epoch 27 - Training Accuracy: 0.6129507332651226, Validation Accurac
y: 0.6067346643518519
Epoch 28 - Training Accuracy: 0.6117492946392583, Validation Accurac
y: 0.6048177083333334
Epoch 29 - Training Accuracy: 0.6123306359098378, Validation Accurac
y: 0.6048900462962963
Final Training Accuracy: 0.6123306359098378
Final Validation Accuracy: 0.6048900462962963
```





Part (d) [5 pt]

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

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

In [ ]:
```
#hyperparameters: num_epochs=30, learning_rate=1e-4, batch_size=128
#The loss curve in Part c is a little noisy,
#so I increase the batch size to 128 and try to make the loss plot smo
other
train_loader = torch.utils.data.DataLoader(train_data, batch_size=128,
shuffle=True)
valid_loader = torch.utils.data.DataLoader(val_data, batch_size=128, s
huffle=True)
model2 = AutoEncoder()

train_loss, val_loss, train_acc, val_acc, iters=train(model2, train_lo
ader, valid_loader, num_epochs=30, learning_rate=1e-4,batch_size=128)
```

```
Epoch 0 - Training Accuracy: 0.33160481195547703, Validation Accurac
y: 0.3314163773148148
Epoch 1 - Training Accuracy: 0.4588255356090906, Validation Accuracy
: 0.4558738425925926
Epoch 2 - Training Accuracy: 0.4589650575140297, Validation Accuracy
: 0.4560546875
Epoch 3 - Training Accuracy: 0.45978668650978205, Validation Accurac
y: 0.45601851851851855
Epoch 4 - Training Accuracy: 0.4648947384739404, Validation Accuracy
: 0.46198640046296297
Epoch 5 - Training Accuracy: 0.4668170402753232, Validation Accuracy
: 0.46274594907407407
Epoch 6 - Training Accuracy: 0.48371469320683347, Validation Accurac
y: 0.4794921875
Epoch 7 - Training Accuracy: 0.5345936812079497, Validation Accuracy
: 0.5348668981481481
Epoch 8 - Training Accuracy: 0.5501658760425386, Validation Accuracy
: 0.5464048032407407
Epoch 9 - Training Accuracy: 0.5576768052584256, Validation Accuracy
: 0.5553747106481481
Epoch 10 - Training Accuracy: 0.5645831395529098, Validation Accurac
y: 0.5607277199074074
Epoch 11 - Training Accuracy: 0.5641413201872694, Validation Accurac
y: 0.5623191550925926
Epoch 12 - Training Accuracy: 0.5697376988187145, Validation Accurac
y: 0.5656467013888888
Epoch 13 - Training Accuracy: 0.5724583759650265, Validation Accurac
y: 0.5689380787037037
Epoch 14 - Training Accuracy: 0.5750782872911047, Validation Accurac
y: 0.5704933449074074
Epoch 15 - Training Accuracy: 0.5785740861315226, Validation Accurac
y: 0.5748697916666666
Epoch 16 - Training Accuracy: 0.5814420363997147, Validation Accurac
y: 0.5755570023148148
Epoch 17 - Training Accuracy: 0.5809382072985458, Validation Accurac
```

```
y: 0.5752314814814815
Epoch 18 - Training Accuracy: 0.5821318947074691, Validation Accurac
y: 0.5764250578703703
Epoch 19 - Training Accuracy: 0.5822326605277028, Validation Accurac
y: 0.5755570023148148
Epoch 20 - Training Accuracy: 0.5825349579884042, Validation Accurac
y: 0.5754484953703703
Epoch 21 - Training Accuracy: 0.581860602114531 9, Validation Accurac
y: 0.5747251157407407
Epoch 22 - Training Accuracy: 0.5821473971413512, Validation Accurac
y: 0.5757378472222222
Epoch 23 - Training Accuracy: 0.5813102657117167, Validation Accurac
y: 0.5753761574074074
Epoch 24 - Training Accuracy: 0.5761867113136763, Validation Accurac
y: 0.5712528935185185
Epoch 25 - Training Accuracy: 0.5758379065513286, Validation Accurac
y: 0.5732060185185185
Epoch 26 - Training Accuracy: 0.5711019130003411, Validation Accurac
y: 0.5669487847222222
Epoch 27 - Training Accuracy: 0.5719778005146808, Validation Accurac
y: 0.5683232060185185
Epoch 28 - Training Accuracy: 0.5751635506774564, Validation Accurac
y: 0.5713975694444444
Epoch 29 - Training Accuracy: 0.5761324527950888, Validation Accurac
y: 0.5714699074074074
Final Training Accuracy: 0.5761324527950888
Final Validation Accuracy: 0.5714699074074074
```

In [ ]:

```
#hyperparameters: num_epochs=30, learning_rate=2e-4, batch_size=128
#from model 2, we can see increase the batch size did make the loss pl
ot becomes smoother,
#but the final accuracy of both training and validation decreases a li
ttle.
#so I increase the learning rate to 2e-4 and try to increase the accur
acy.
train_loader = torch.utils.data.DataLoader(train_data, batch_size=128,
shuffle=True)
valid_loader = torch.utils.data.DataLoader(val_data, batch_size=128, s
huffle=True)
model3 = AutoEncoder()

train_loss, val_loss, train_acc, val_acc, iters=train(model3, train_lo
ader, valid_loader, num_epochs=30, learning_rate=2e-4,batch_size=128)
```

```
Epoch 0 - Training Accuracy: 0.43773447431246704, Validation Accurac
y: 0.4343894675925926
Epoch 1 - Training Accuracy: 0.4588255356090906, Validation Accuracy
: 0.4558738425925926
Epoch 2 - Training Accuracy: 0.4669100548786159, Validation Accuracy
: 0.46292679398148145
```

```
Epoch 3 - Training Accuracy: 0.5273617958019409, Validation Accuracy
: 0.5255714699074074
Epoch 4 - Training Accuracy: 0.5552041670542275, Validation Accuracy
: 0.5510344328703703
Epoch 5 - Training Accuracy: 0.5673813288686324, Validation Accuracy
: 0.5646701388888888
Epoch 6 - Training Accuracy: 0.5724428735311444, Validation Accuracy
: 0.5687210648148148
Epoch 7 - Training Accuracy: 0.5787988714228134, Validation Accuracy
: 0.5750144675925926
Epoch 8 - Training Accuracy: 0.5798762905776207, Validation Accuracy
: 0.5742910879629629
Epoch 9 - Training Accuracy: 0.5781400179828233, Validation Accuracy
: 0.5725911458333334
Epoch 10 - Training Accuracy: 0.5794499736458624, Validation Accurac
y: 0.5735677083333334
Epoch 11 - Training Accuracy: 0.5836511332279167, Validation Accurac
y: 0.5786313657407407
Epoch 12 - Training Accuracy: 0.5804886367159644, Validation Accurac
y: 0.5778356481481481
Epoch 13 - Training Accuracy: 0.5790934176665736, Validation Accurac
y: 0.5772569444444444
Epoch 14 - Training Accuracy: 0.5924642668899017, Validation Accurac
y: 0.5883969907407407
Epoch 15 - Training Accuracy: 0.5960685827674945, Validation Accurac
y: 0.5917607060185185
Epoch 16 - Training Accuracy: 0.5983086844634607, Validation Accurac
y: 0.5951605902777778
Epoch 17 - Training Accuracy: 0.5962701144079621, Validation Accurac
y: 0.5929181134259259
Epoch 18 - Training Accuracy: 0.6024090782252813, Validation Accurac
y: 0.5979094328703703
Epoch 19 - Training Accuracy: 0.60027749356649, Validation Accuracy:
0.5958478009259259
Epoch 20 - Training Accuracy: 0.6026648683843363, Validation Accurac
y: 0.5976924189814815
Epoch 21 - Training Accuracy: 0.6061296623569901, Validation Accurac
y: 0.6021773726851852
Epoch 22 - Training Accuracy: 0.599378352401327, Validation Accuracy
: 0.5957754629629629
Epoch 23 - Training Accuracy: 0.6014634297584721, Validation Accurac
y: 0.5974392361111112
Epoch 24 - Training Accuracy: 0.6055018137847642, Validation Accurac
y: 0.6008752893518519
Epoch 25 - Training Accuracy: 0.5989287818187455, Validation Accurac
y: 0.5902054398148148
Epoch 26 - Training Accuracy: 0.6055405698694695, Validation Accurac
y: 0.6000072337962963
Epoch 27 - Training Accuracy: 0.6008898397048337, Validation Accurac
y: 0.5949074074074074
```

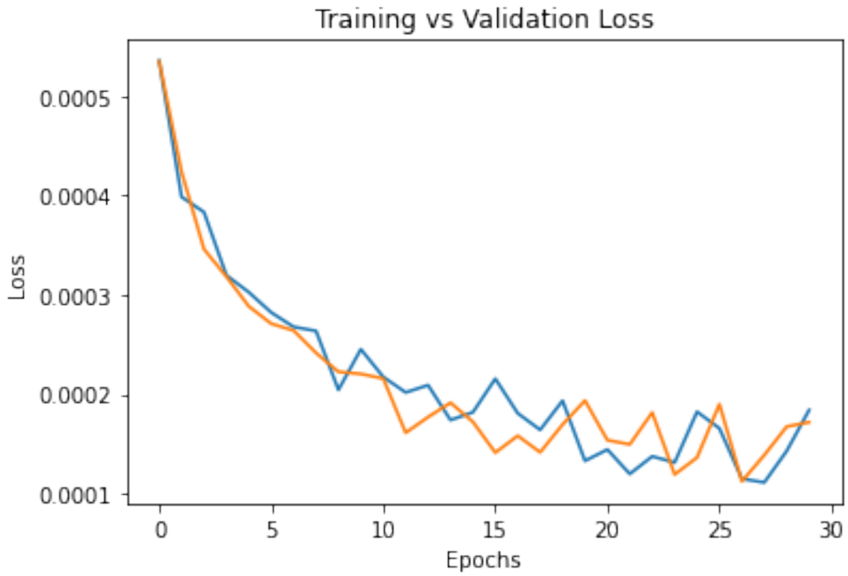
```
Epoch 28 - Training Accuracy: 0.6052382724087682, Validation Accurac
y: 0.5999348958333334
Epoch 29 - Training Accuracy: 0.602881902458686, Validation Accuracy
: 0.5991391782407407
Final Training Accuracy: 0.602881902458686
Final Validation Accuracy: 0.5991391782407407
```

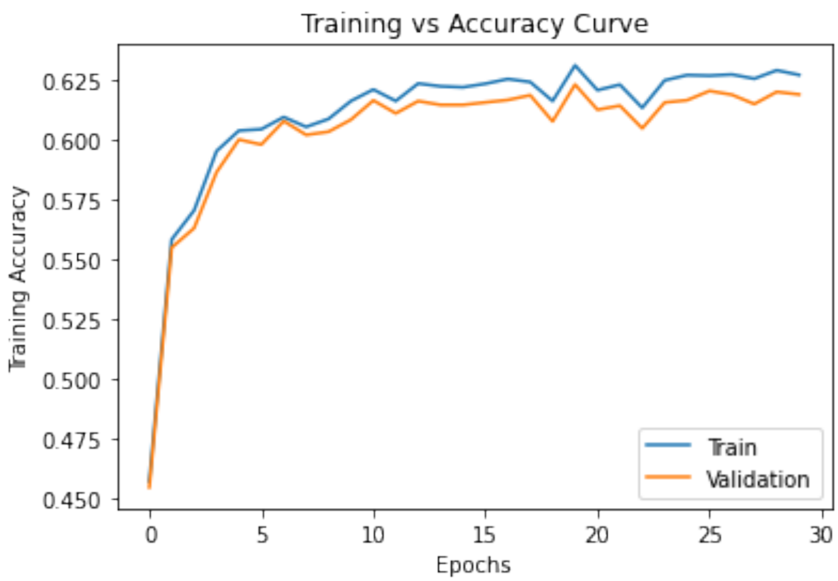
In [215]:

```
#hyperparameters: num_epochs=30, learning_rate=1e-3, batch_size=128
#from model3, we can see the accuracy still not good as the one in par
t c
#since large batch size allows for larger learning rates
#the learning rate might not large enough
#so I keep increasing the learning rate to 1e-3
train_loader = torch.utils.data.DataLoader(train_data, batch_size=128,
shuffle=True)
valid_loader = torch.utils.data.DataLoader(val_data, batch_size=128, s
huffle=True)
model4 = AutoEncoder()

train_loss, val_loss, train_acc, val_acc, iters=train(model4, train_lo
ader, valid_loader, num_epochs=30, learning_rate=1e-3,batch_size=128)

# Plotting
plt.title("Training vs Validation Loss")
plt.plot(iters, train_loss, label="Train")
plt.plot(iters, val_loss, label="Validation")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.show()

plt.title("Training vs Accuracy Curve")
plt.plot(iters, train_acc, label="Train")
plt.plot(iters, val_acc, label="Validation")
plt.xlabel("Epochs")
plt.ylabel("Training Accuracy")
plt.legend(loc='best')
plt.show()
```

```
Epoch 0 - Training Accuracy: 0.45680246798747404, Validation Accurac
y: 0.45424623842592593
Epoch 1 - Training Accuracy: 0.5581651319257124, Validation Accuracy
: 0.5547598379629629
Epoch 2 - Training Accuracy: 0.5703500449570582, Validation Accuracy
: 0.5629340277777778
Epoch 3 - Training Accuracy: 0.5952004464700958, Validation Accuracy
: 0.5863353587962963
Epoch 4 - Training Accuracy: 0.60378879484079, Validation Accuracy:
0.6000434027777778
Epoch 5 - Training Accuracy: 0.6043856385452516, Validation Accuracy
: 0.5979456018518519
```

```
Epoch 6 - Training Accuracy: 0.6094781880755279, Validation Accuracy
: 0.6077835648148148
Epoch 7 - Training Accuracy: 0.6053622918798252, Validation Accuracy
: 0.6019965277777778
Epoch 8 - Training Accuracy: 0.6086953151644808, Validation Accuracy
: 0.6033347800925926
Epoch 9 - Training Accuracy: 0.6162217468142498, Validation Accuracy
: 0.6083984375
Epoch 10 - Training Accuracy: 0.621035252534648, Validation Accuracy
: 0.6164641203703703
Epoch 11 - Training Accuracy: 0.6162139955973088, Validation Accurac
y: 0.6110387731481481
Epoch 12 - Training Accuracy: 0.6235466468235513, Validation Accurac
y: 0.6161747685185185
Epoch 13 - Training Accuracy: 0.6223684618485102, Validation Accurac
y: 0.6145833333333334
Epoch 14 - Training Accuracy: 0.6219886522183983, Validation Accurac
y: 0.6145833333333334
Epoch 15 - Training Accuracy: 0.6234613834371996, Validation Accurac
y: 0.615632237962963
Epoch 16 - Training Accuracy: 0.6254379437571699, Validation Accurac
y: 0.6166449652777778
Epoch 17 - Training Accuracy: 0.6241899978296592, Validation Accurac
y: 0.6186342592592593
Epoch 18 - Training Accuracy: 0.6162139955973088, Validation Accurac
y: 0.6076750578703703
Epoch 19 - Training Accuracy: 0.631166093076613, Validation Accuracy
: 0.6231192129629629
Epoch 20 - Training Accuracy: 0.6207562087247698, Validation Accurac
y: 0.6125578703703703
Epoch 21 - Training Accuracy: 0.6230738225901467, Validation Accurac
y: 0.6142578125
Epoch 22 - Training Accuracy: 0.6133537965460577, Validation Accurac
y: 0.6047453703703703
Epoch 23 - Training Accuracy: 0.6248721049204725, Validation Accurac
y: 0.6155960648148148
Epoch 24 - Training Accuracy: 0.6270734505317335, Validation Accurac
y: 0.6165364583333334
Epoch 25 - Training Accuracy: 0.6268409140235017, Validation Accurac
y: 0.6204427083333334
Epoch 26 - Training Accuracy: 0.6273292406907884, Validation Accurac
y: 0.6188512731481481
Epoch 27 - Training Accuracy: 0.6255619632282269, Validation Accurac
y: 0.6149450231481481
Epoch 28 - Training Accuracy: 0.629088766936409, Validation Accuracy
: 0.6200448495370371
Epoch 29 - Training Accuracy: 0.627143211484203, Validation Accuracy
: 0.6189597800925926
Final Training Accuracy: 0.627143211484203
Final Validation Accuracy: 0.6189597800925926
```

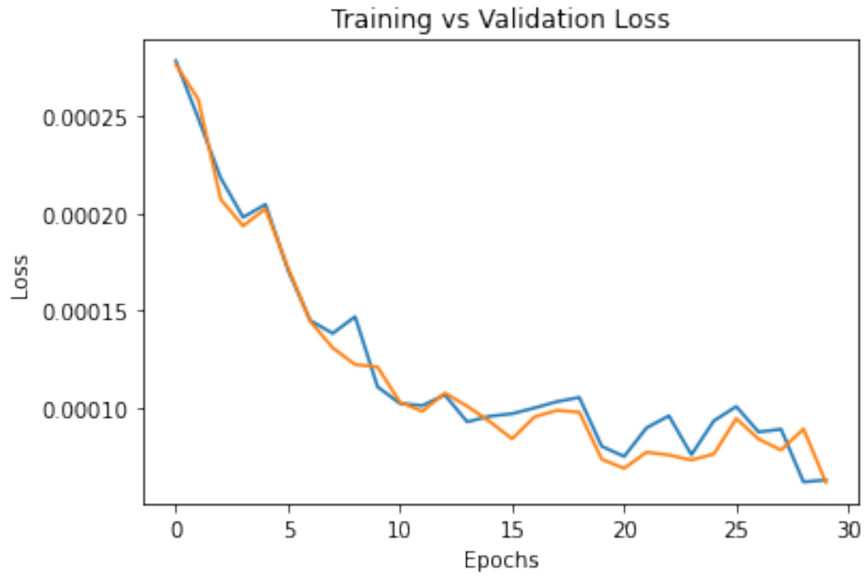

Training vs Validation Loss
Loss
0.0005
0.0004
0.0003
0.0002
0.0001
0
5
10
15
20
25
30
Epochs

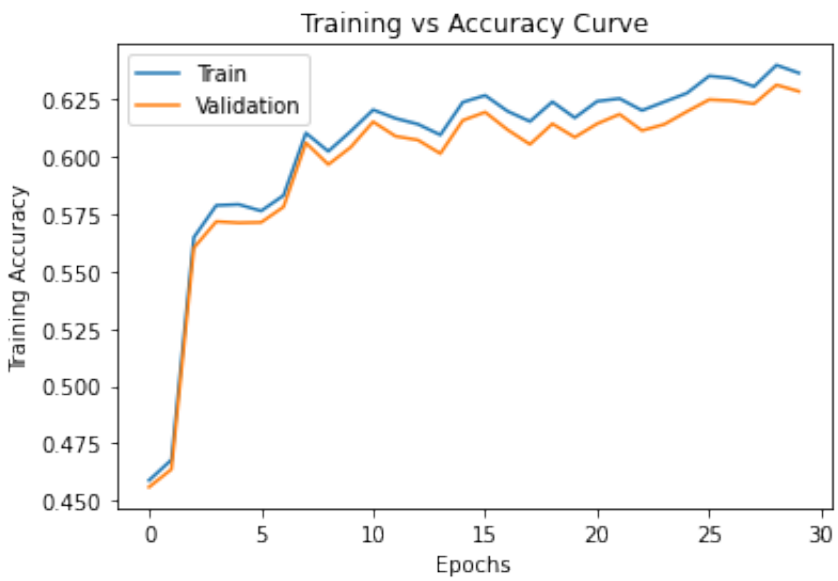

Training vs Accuracy Curve
Training Accuracy
0.625
0.600
0.575
0.550
0.525
0.500
0.475
0.450
0
5
10
15
20
25
30
Epochs
Train
Validation

In [220]:
```
#hyperparameters: num_epochs=30, learning_rate=1e-3, batch_size=256
#from model4, we can see the accuracy becomes higher than it in part c
#but I want to see if the loss curve can be more smooth and if can rea
ch higher accuracy
#so I increase the batch_size to 256
train_loader = torch.utils.data.DataLoader(train_data, batch_size=256,
shuffle=True)
valid_loader = torch.utils.data.DataLoader(val_data, batch_size=256, s
huffle=True)
model5 = AutoEncoder()

train_loss, val_loss, train_acc, val_acc, iters=train(model5, train_lo
ader, valid_loader, num_epochs=30, learning_rate=1e-3,batch_size=256)

# Plotting
plt.title("Training vs Validation Loss")
plt.plot(iters, train_loss, label="Train")
plt.plot(iters, val_loss, label="Validation")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.show()

plt.title("Training vs Accuracy Curve")
plt.plot(iters, train_acc, label="Train")
plt.plot(iters, val_acc, label="Validation")
plt.xlabel("Epochs")
plt.ylabel("Training Accuracy")
plt.legend(loc='best')
plt.show()
```

```
Epoch 0 - Training Accuracy: 0.4588255356090906, Validation Accuracy
: 0.4558738425925926
Epoch 1 - Training Accuracy: 0.46777819117601466, Validation Accurac
y: 0.4636501736111111
Epoch 2 - Training Accuracy: 0.5647924224103185, Validation Accuracy
: 0.5602575231481481
Epoch 3 - Training Accuracy: 0.5787368616872849, Validation Accuracy
: 0.5716869212962963
Epoch 4 - Training Accuracy: 0.5791554274021021, Validation Accuracy
: 0.5711443865740741
Epoch 5 - Training Accuracy: 0.5763107307847332, Validation Accuracy
: 0.5713252314814815
Epoch 6 - Training Accuracy: 0.5830465383065141, Validation Accuracy
: 0.5780526620370371
Epoch 7 - Training Accuracy: 0.6103075682882213, Validation Accuracy
: 0.6060112847222222
Epoch 8 - Training Accuracy: 0.6023083124050476, Validation Accuracy
: 0.5965711805555556
Epoch 9 - Training Accuracy: 0.6110439338976219, Validation Accuracy
```

```
: 0.6040943287037037
Epoch 10 - Training Accuracy: 0.6204229063963043, Validation Accurac
y: 0.6151982060185185
Epoch 11 - Training Accuracy: 0.6166868198307134, Validation Accurac
y: 0.6089048032407407
Epoch 12 - Training Accuracy: 0.614159923107928, Validation Accuracy
: 0.6072410300925926
Epoch 13 - Training Accuracy: 0.6094704368585868, Validation Accurac
y: 0.6013454861111112
Epoch 14 - Training Accuracy: 0.6237249248131956, Validation Accurac
y: 0.6158130787037037
Epoch 15 - Training Accuracy: 0.6267168945524447, Validation Accurac
y: 0.6193938078703703
Epoch 16 - Training Accuracy: 0.6198105602579606, Validation Accurac
y: 0.6117259837962963
Epoch 17 - Training Accuracy: 0.61534585929991, Validation Accuracy:
0.6053602430555556
Epoch 18 - Training Accuracy: 0.6239264564536632, Validation Accurac
y: 0.6143301504629629
Epoch 19 - Training Accuracy: 0.6169426099897684, Validation Accurac
y: 0.6084346064814815
Epoch 20 - Training Accuracy: 0.624151241744954, Validation Accuracy
: 0.6143663194444444
Epoch 21 - Training Accuracy: 0.625321675503054, Validation Accuracy
: 0.6184895833333334
Epoch 22 - Training Accuracy: 0.6201438625864261, Validation Accurac
y: 0.6113642939814815
Epoch 23 - Training Accuracy: 0.6239342076706043, Validation Accurac
y: 0.6141131365740741
Epoch 24 - Training Accuracy: 0.6276625430192541, Validation Accurac
y: 0.6196469907407407
Epoch 25 - Training Accuracy: 0.6351967258859641, Validation Accurac
y: 0.6248553240740741
Epoch 26 - Training Accuracy: 0.634150311598921, Validation Accuracy
: 0.6243851273148148
Epoch 27 - Training Accuracy: 0.6305614981552103, Validation Accurac
y: 0.623046875
Epoch 28 - Training Accuracy: 0.6399249682200105, Validation Accurac
y: 0.6312934027777778
Epoch 29 - Training Accuracy: 0.6364756766812389, Validation Accurac
y: 0.6284722222222222
Final Training Accuracy: 0.6364756766812389
Final Validation Accuracy: 0.6284722222222222
```


Training vs Validation Loss
0.00025
0.00020
0.00015
0.00010
Loss
0
5
10
15
20
25
30
Epochs


Training vs Accuracy Curve
Train
Validation
0.625
0.600
0.575
0.550
0.525
0.500
0.475
0.450
Training Accuracy
0
5
10
15
20
25
30
Epochs

Answer:

model2:

Hyperparameters: num_epochs=30, learning_rate=1e-4, batch_size=128

The loss curve in Part c is a little noisy, so I increase the batch size to 128 and try to make the loss plot smoother

model3:

Hyperparameters: num_epochs=30, learning_rate=2e-4, batch_size=128

From model 2, we can see increase the batch size did make the loss plot becomes smoother and less noisy, but the final accuracy of both training and validation decreases a little. So I increase the learning rate to 2e-4 and try to increase the accuracy.

model4:

Hhyperparameters: num_epochs=30, learning_rate=1e-3, batch_size=128

From model3, we can see the accuracy still not good as the one in part c. Since large batch size allows for larger learning rates, the learning rate might not large enough. So I keep increasing the learning rate to 1e-3

model5:

Hyperparameters: num_epochs=30, learning_rate=1e-3, batch_size=256

From model4, we can see the accuracy becomes higher than it in part c, but I want to see if the loss curve can be more smooth and if can reach higher accuracy. so I increase the batch_size to 256.

From the above analysis, I found model 5 perform the best fit so far, with highest accuracy and least noisy loss curve. The hyperparameters are num_epochs=30, learning_rate=1e-3, batch_size=256

Part 4. Testing [12 pt]

Part (a) [2 pt]

Compute and report the test accuracy.

In [221]:
```
test_loader = torch.utils.data.DataLoader(test_data, batch_size=256, s
huffle=True)
print("Test accuracy", get_accuracy(model5, test_loader))
```

```
Test accuracy 0.6366102430555556
```

Part (b) [4 pt]

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

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

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

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

What would be the test accuracy of this baseline model?

In [ ]:
```
most_common = []
sum=0
for col in catcols:
  # get the most common value for each column
  most_common.append(df_not_missing[col].value_counts().idxmax())
  sum+= df_not_missing[col].value_counts().max()

accuracy = sum/(df_not_missing.shape[0] *len(catcols))
print("The test accuracy for baseline model is:", accuracy)
```

```
The test accuracy for baseline model is: 0.459204158256831
```

In [ ]:
```
most_common
```

Out[ ]:
```
[' Private',
 ' Married-civ-spouse',
 ' Prof-specialty',
 ' HS-grad',
 ' Husband',
 ' Male']
```

Part (c) [1 pt]

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

Answer: My test accuracy is 0.6366102430555556 and baseline test accuracy is 0.459204158256831. So My test accuracy from part(a) is higher than the baseline test accuracy in part (b)

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.

Answer: Yes, I think it is reasonable for a human to be able to guess this person's education level based on their other features. For example, given the below info, a human might guess this person's education level based on occupation. A sales might require Bachelors education.

In [ ]:
```
get_features(test_data[0])
```

Out[ ]:
```
{'edu': 'Bachelors',
 'marriage': 'Married-civ-spouse',
 'occupation': 'Sales',
 'relationship': 'Husband',
 'sex': 'Male',
 'work': 'Private'}
```

Part (e) [2 pt]

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

Answer:

My model's prediction of this person's education level is Bachelors.

In [222]:
```
data_input = torch.from_numpy(test_data[0])
data_input = torch.reshape(data_input, (1, 57))
prediction = model5(zero_out_feature(data_input, 'edu')).detach().nump
y()
print(get_feature(prediction[0],'edu'))
```

```
Bachelors
```

Part (f) [2 pt]

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

Answer:

The baseline model prediction of this person is HS-grad.

In [ ]:
```
feature="edu"
prediction=df_not_missing[feature].value_counts().idxmax()
print("The baseline model's prediction of this person's education leve
l:",prediction)
```

```
The baseline model's prediction of this person's education level:  H
S-grad
```