MA 544 Spring 2021: Programming Assignment - 4

In [1]:

```
import os
import numpy as np
import pandas as pd
from glob import glob
import matplotlib.pyplot as pt
from typing import Iterable, List
```

Question 1

Find the nonnegative basis representation of images from one of the following databases. Show a comparison of some sample images with their reconstruction from the basis.

- The ORL database of faces at ORL link.
- The CBCL database of faces at MIT link.
- Yale faces B facial images at UCSD.

In [2]:

```
def list_files(directory: str, search: Iterable) -> List[str]:
    """
    list files
    """
    if isinstance(search, str):
        search = [search]

    output: List[str] = []
    for term in search:
        for filepath in glob(os.path.join(directory, term)):
            output.append(filepath)

    return output
```

In [3]:

```
# to avoid having to write code to fully parse the data by subject I
# will write it to handle a single subject, yaleB01
data_folder: str = os.path.join('data', 'CroppedYale', 'yaleB01')
```

In [4]:

```
class PGMReader():
    def __init__(self, filepath, mode):
        assert filepath.split('.')[-1] == 'pgm'
        self.filepath = filepath
        self.mode = mode

    def __enter__(self):
        # return the file object after opening and setting it up
        self.pgm_image = open(self.filepath, self.mode)
        return self.read_pgm(self.pgm_image)

    def __exit__(self, type, value, traceback):
        self.pgm_image.close()

    def read_pgm(self, pgmf):
        """Return a raster of integers from a PGM as a list of lists."""
        assert pgmf.readline() == b'P5\n'
        (width, height) = [int(i) for i in pgmf.readline().split()]
        depth = int(pgmf.readline())
        assert depth <= 255

        raster = []
        for y in range(height):
            row = []
            for y in range(width):
                row.append(ord(pgmf.read(1)))
            raster.append(row)
        return np.array(raster)
```

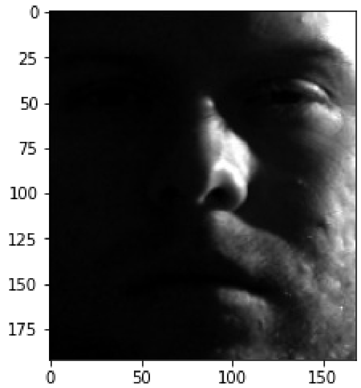
In [5]:

```
m, n = 192, 168
filepaths = list_files(data_folder, '*.pgm')
images = np.zeros((m*n, len(filepaths)))
for i, filepath in enumerate(filepaths):
    with PGMReader(filepath, 'rb') as image:
        images[:, i] = image.reshape((m*n,))

print(f"Shape of images: ({m}, {n})")
pt.imshow(images[:, 2].reshape((m, n)), cmap='gray')
```

```
Shape of images: (192, 168)
```

Out[5]:

```
<matplotlib.image.AxesImage at 0x7efc2c0eea60>
```

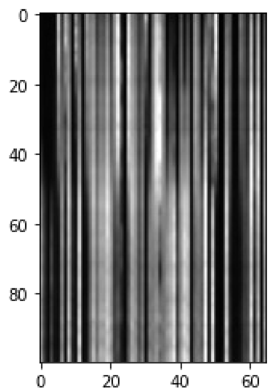


In [6]:

```
pt.imshow(images[:100, :], cmap='gray')
```

Out[6]:

```
<matplotlib.image.AxesImage at 0x7efc24057be0>
```



In [7]:

```
class LSNMF():
    def __init__(self, M):
        self.m, self.n = M.shape
        self.M = M

    def fit(self, threshold = 5e3, max_iter = 200):
        # initialize a random start state for W and H
        W = np.random.rand(self.m, self.n)
        H = np.random.rand(self.n, self.n)

        # @ delineates matrix multiplication
        # np.multiply delineates elementwise mutliplication
        # np.divide delineates elementwise division
        for i in range(max_iter):
            norm = np.linalg.norm(self.M - W @ H)
            if i % 50 == 0 or i == max_iter:
                print(f'Norm for iteration {i}: {norm}')
            if norm < threshold:
                print("Reached convergence through threshold")
                break

            wktv = np.dot(W.T, self.M)
            wktwk = np.dot(W.T, W)
```

```
            wktwkhk = np.dot(wktwk, H)

            H_kp1 = np.multiply(H, np.divide(wktv, wktwkhk))

            vhkp1t = np.dot(self.M, H_kp1.T)
            wkhkp1 = np.dot(W, H_kp1)
            wkhkp1hkp1t = np.dot(wkhkp1, H_kp1.T)

            W_kp1 = np.multiply(W, np.divide(vhkp1t, wkhkp1hkp1t))

            H = H_kp1
            W = W_kp1

            if i == max_iter-1:
                print("Reached convergence through max_iter")

        return W, H
```

In [8]:

```
lsnmf = LSNMF(images)
```

In [9]:

```
W, H = lsnmf.fit()
```

```
Norm for iteration 0: 123871.53692533601
Norm for iteration 50: 14007.521071852227
Norm for iteration 100: 10615.854694153719
Norm for iteration 150: 8693.851355028339
Reached convergence through max_iter
```

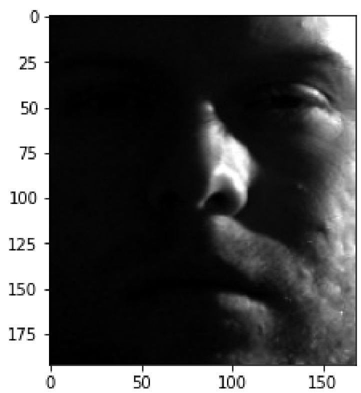
Original Image

In [10]:

```
# original image 2
pt.imshow(images[:, 2].reshape(m, n), cmap='gray')
```

Out[10]:

```
<matplotlib.image.AxesImage at 0x7efc23fc92b0>
```



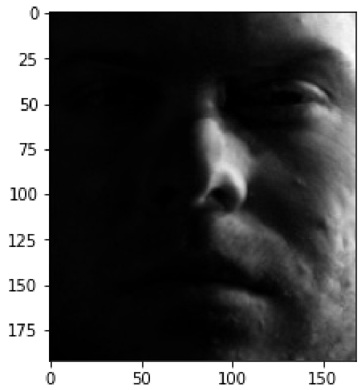
NMF Reconstruction using the Lee-Seung Algorithm

In [11]:

```
combinations = H[:, 2]
reconstruction = W @ combinations
pt.imshow(reconstruction.reshape(m, n), cmap='gray')
```

Out[11]:

```
<matplotlib.image.AxesImage at 0x7efc23f270a0>
```



Question 2

Set up a linear regression model for the miles per gallon on the data at automobile UCI. Discard the categorical data.

1. Analyze the data to get relevant insight.
2. Get feature matrix X, and target variable y.
3. Split data into training and testing.
4. Normalize data using MinMaxScaler.
5. Creat a LinearRegression object for modeling.
6. Train the model with training data.
7. Look at R^2 score for the goodness of fit for the train and test data.
8. Present a graphical comparison of true and observed responses for the test data.
9. Improve the performance of your model on the test data.

In [12]:

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
```

In [13]:

```
data_folder: str = os.path.join('data')
```

In [14]:

```
data = pd.read_csv(os.path.join(data_folder,'auto-mpg.data'),
                                 delim_whitespace=True,
                                 header=None)
column_names = ["mpg", "cylinders", "displacement", "horsepower", "weight", "acceleration", "model_year",
data.columns = column_names
data
```

Out[14]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year	origin	car_name
0	18.0	8	307.0	130.0	3504.0	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165.0	3693.0	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150.0	3436.0	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150.0	3433.0	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140.0	3449.0	10.5	70	1	ford torino
...	...	...	...	...	...	...	...	...	...
393	27.0	4	140.0	86.00	2790.0	15.6	82	1	ford mustang gl
394	44.0	4	97.0	52.00	2130.0	24.6	82	2	vw pickup
395	32.0	4	135.0	84.00	2295.0	11.6	82	1	dodge rampage
396	28.0	4	120.0	79.00	2625.0	18.6	82	1	ford ranger
397	31.0	4	119.0	82.00	2720.0	19.4	82	1	chevy s-10

398 rows × 9 columns

In [15]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64
 2   displacement  398 non-null    float64
 3   horsepower    398 non-null    object
 4   weight        398 non-null    float64
 5   acceleration  398 non-null    float64
 6   model_year    398 non-null    int64
 7   origin        398 non-null    int64
 8   car_name      398 non-null    object
dtypes: float64(4), int64(3), object(2)
memory usage: 28.1+ KB
```

In [16]:

```
data.describe()
```

Out[16]:

	mpg	cylinders	displacement	weight	acceleration	model_year	origin
count	398.000000	398.000000	398.000000	398.000000	398.000000	398.000000	398.000000
mean	23.514573	5.454774	193.425879	2970.424623	15.568090	76.010050	1.572864
std	7.815984	1.701004	104.269838	846.841774	2.757689	3.697627	0.802055
min	9.000000	3.000000	68.000000	1613.000000	8.000000	70.000000	1.000000
25%	17.500000	4.000000	104.250000	2223.750000	13.825000	73.000000	1.000000
50%	23.000000	4.000000	148.500000	2803.500000	15.500000	76.000000	1.000000
75%	29.000000	8.000000	262.000000	3608.000000	17.175000	79.000000	2.000000
max	46.600000	8.000000	455.000000	5140.000000	24.800000	82.000000	3.000000

In [17]:

```
def is_float(x):
    try:
        float(x)
    except ValueError:
        return False
    return True
```

In [18]:

```
data = data[data['horsepower'].apply(lambda x: is_float(x))]
```

In [19]:

```
names = data.pop('car_name')
print(data.head())
data = data.astype(np.float)
scaler = MinMaxScaler()
scaler.fit(data)
data = scaler.transform(data)
y = data[:, 0]
X = data[:, 1:]
```

```
    mpg  cylinders  displacement horsepower  weight  acceleration  model_year  \
0  18.0          8         307.0      130.0  3504.0          12.0          70
1  15.0          8         350.0      165.0  3693.0          11.5          70
2  18.0          8         318.0      150.0  3436.0          11.0          70
3  16.0          8         304.0      150.0  3433.0          12.0          70
4  17.0          8         302.0      140.0  3449.0          10.5          70

   origin
0       1
1       1
2       1
3       1
4       1
```

In [20]:

```
class LinearRegression():
    def __init__(self, validation_split: float = 0.2, reg: str = 'l2', lam: float = 1e-2):
        assert 0. <= validation_split <= 1.
        assert reg in ['none', 'l2']
        if reg != 'none':
            assert lam is not None
        self.reg = reg
        self.lam = lam
        self.validation_split = validation_split

    def fit(self, x_in, y_in):
        x_in = np.asarray(x_in)
        y_in = np.asarray(y_in)
        X, x_test, y, y_test = train_test_split(x_in, y_in, test_size=self.validation_split)

        X = np.hstack([X, np.ones((X.shape[0], 1))])
        if self.reg == 'none':
            self.coef_ = np.linalg.inv(X.T @ X) @ np.dot(X.T, y)
        if self.reg == 'l2':
            self.coef_ = np.linalg.inv(X.T @ X + self.lam*np.eye(X.shape[1])) @ np.dot(X.T, y)

        self.score_(x_test, y_test)

    def predict(self, features):
        features = np.hstack([features, np.array([1])])
        return np.dot(self.coef_, features)

    def score_(self, x_test, y_test):
        y_pred = []
        for x in x_test:
            y_pred.append(self.predict(x))

        self.r2 = np.corrcoef(y_test, y_pred)[0, 1]**2
```

In [21]:

```
linreg = LinearRegression(validation_split=0.1, reg='none')
```

In [22]:

```
linreg.fit(X, y)
```

Results

In [23]:

```
print(f"Calculated Coefficients [C0, C1, ..., Cn] (C0 = intercept):\n {linreg.coef_}")
```

```
Calculated Coefficients [C0, C1, ..., Cn] (C0 = intercept):
 [-0.0442424   0.14197519 -0.02332282 -0.61780592  0.06323224  0.23843948
  0.06642967  0.43917258]
```

In [24]:

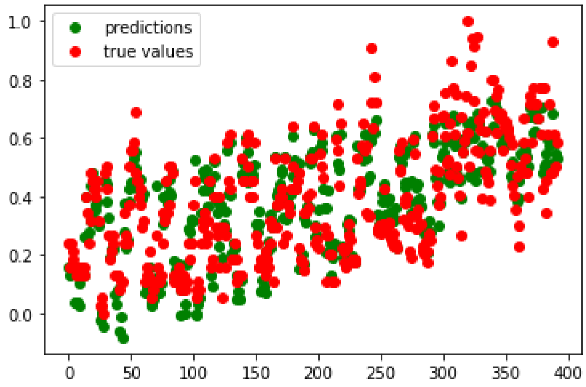
```
print(f"Calculated r2 on the test set: {linreg.r2}")
```

```
Calculated r2 on the test set: 0.8279471018412106
```

Below, our predictions v true values are shown

In [25]:

```
predictions = []
for x in X:
    predictions.append(linreg.predict(np.hstack(x)))
pt.plot(range(len(X)), predictions, 'go')
pt.plot(range(len(X)), y, 'ro')

pt.legend(["predictions", "true values"])
pt.show()
```



Custom linear regression vs sklearn benchmark

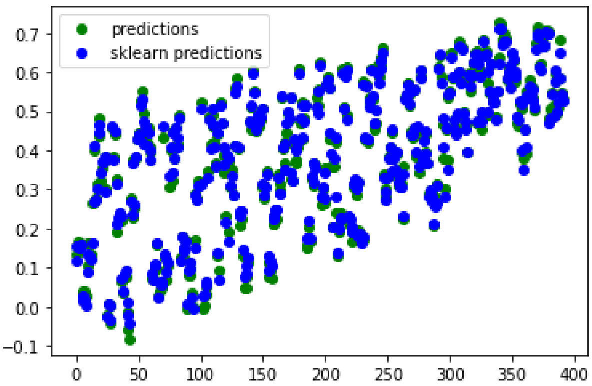
In [26]:

```
from sklearn.linear_model import Ridge
model = Ridge(alpha=1, fit_intercept=True)
model.fit(X, y)
print(f"Calculated Coefficients:\n {model.coef_}")
```

```
Calculated Coefficients:
 [-0.05512088  0.03582705 -0.1124368  -0.42336983 -0.00825621  0.2262201
  0.07311041]
```

In [27]:

```
bench = []
for row in X:
    bench.append(model.predict(row.reshape(1, -1)))
pt.plot(range(len(X)), predictions, 'go')
pt.plot(range(len(X)), bench, 'bo')
pt.legend(["predictions", "sklearn predictions"])
pt.show()
```



Improve through adding regularization

In [28]:

```
linreg2 = LinearRegression(validation_split=0.1, reg='l2', lam=1.)
```

In [29]:

```
linreg2.fit(X, y)
```

In [30]:

```
print(f"Calculated Coefficients [C0, C1, ..., Cn] (C0 = intercept):\n {linreg2.coef_}")
```

```
Calculated Coefficients [C0, C1, ..., Cn] (C0 = intercept):
 [-0.0488963   0.03359471 -0.05863788 -0.42248748  0.05375112  0.23727411
  0.08471192  0.41158973]
```

In [31]:

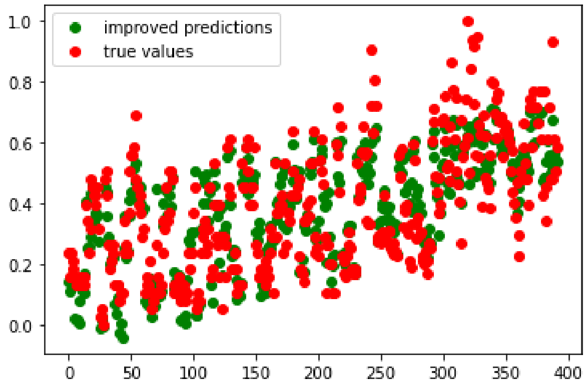
```
print(f"Calculated r2 on the test set: {linreg2.r2}")
```

```
Calculated r2 on the test set: 0.8300385504557488
```

Below, our predictions v true values are shown

In [32]:

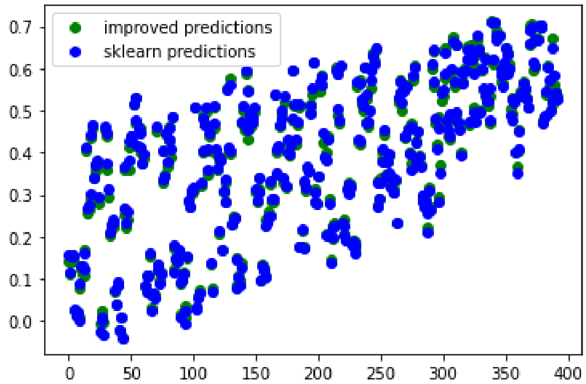
```
predictions2 = []
for x in X:
    predictions2.append(linreg2.predict(np.hstack(x)))
pt.plot(range(len(X)), predictions2, 'go')
pt.plot(range(len(X)), y, 'ro')

pt.legend(["improved predictions", "true values"])
pt.show()
```



Custom linear regression vs sklearn benchmark

In [33]:

```
y_pred2 = []
pt.plot(range(len(X)), predictions2, 'go')
pt.plot(range(len(X)), bench, 'bo')
pt.legend(["improved predictions", "sklearn predictions"])
pt.show()
```



Question 3

Setup a logistic regression model on the data at adultUCI. Discuss the performance of your model using appropriate statistics. Use dummy variables to handle categorical variables.

1. Prepare the data. Create dummy variables for categorical variables. See this
2. Analyze the data to get relevant insight.
3. Get feature matrix X, and target variable y (>50k or <50k)
4. Split data into training and testing
5. Normalize data using MinMaxScaler
6. Creat a LogisticRegression object for modeling
7. Train the model with training data
8. Compare the precision, recall, and F1-score on the train and test data.
9. Improve the performance of your model on the test data.

As an interesting thought experiment, a logistic regression can be thought of as a dense network with num_features input nodes, num_classes output nodes, and a sigmoid activation. I will build this network using the Tensorflow API

In [34]:

```
data = pd.read_csv(os.path.join(data_folder, 'adult.data'), header=None)
orig_cols = ['age', 'workclass', 'fnlwgt', 'education', 'education_num', 'marital_status', 'occupation',
data.columns = orig_cols
data.head()
```

Out[34]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_pe
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	

In [35]:

```
import tensorflow as tf
from tensorflow.data import Dataset
from tensorflow.keras.layers import Dense, Input
from tensorflow.keras.models import Model
```

In [36]:

```
data = pd.concat([data, pd.get_dummies(data["workclass"], prefix="wc")], axis=1)
data = pd.concat([data, pd.get_dummies(data["education"], prefix="edu")], axis=1)
data = pd.concat([data, pd.get_dummies(data["marital_status"], prefix="ms")], axis=1)
data = pd.concat([data, pd.get_dummies(data["occupation"], prefix="occ")], axis=1)
data = pd.concat([data, pd.get_dummies(data["relationship"], prefix="rel")], axis=1)
data = pd.concat([data, pd.get_dummies(data["race"], prefix="rac")], axis=1)
data = pd.concat([data, pd.get_dummies(data["sex"], prefix="s")], axis=1)
data = pd.concat([data, pd.get_dummies(data["native_country"], prefix="s")], axis=1)

data.target = data.target.astype('category')
data.target = data.target.cat.codes

for colname in ["workclass", "education", "marital_status", "occupation", "relationship", "race", "sex", '
    data.drop([colname], axis=1, inplace=True)
```

In [37]:

```
data.head(1)
```

Out[37]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week	target	wc_ ?	wc_ Federal-gov	wc_ Local-gov	...	s_ Portugal	s_ Puerto-Rico	s_ Scotland	s_ South
0	39	77516	13	2174	0	40	0	0	0	0	...	0	0	0	0

1 rows × 109 columns

In [38]:

```
y = data.pop('target').values
X = data.values
```

In [39]:

```
scaler = MinMaxScaler()
scaler.fit(X)
```

```python
X = scaler.transform(X)
```

In [40]:

```python
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

In [41]:

```python
class LogisticRegression(tf.keras.Model):
    def __init__(self, num_features: int = None, reg = None):
        assert num_features is not None and num_features >= 1 and isinstance(num_features, int)
        assert len(reg) == 2 and 0. <= reg[0] and 0. <= reg[1]

        super(LogisticRegression, self).__init__()
        self.inp = Input((num_features,))
        self.outputs = Dense(1, activation='sigmoid', kernel_regularizer=tf.keras.regularizers.L1L2(l1=re

    def call(self, features):
        return self.outputs(features)
```

In [42]:

```python
logistic = LogisticRegression(num_features=X.shape[1], reg = [0.001, 0.001])
logistic.compile(optimizer='rmsprop',
                 loss='binary_crossentropy',
                 metrics=[tf.keras.metrics.Precision(),
                          tf.keras.metrics.Recall(),
                          tf.keras.metrics.TruePositives(),
                          tf.keras.metrics.TrueNegatives(),
                          tf.keras.metrics.FalsePositives(),
                          tf.keras.metrics.FalseNegatives(),
                          tf.keras.metrics.AUC()])

print(f'random output for initialization = {logistic(X[0, :].reshape(1, -1))}')
```

```
random output for initialization = [[0.5663379]]
```

In [43]:

```python
logistic.summary()
```

```
Model: "logistic_regression"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                multiple                  109
=================================================================
Total params: 109
Trainable params: 109
Non-trainable params: 0
_________________________________________________________________
```

In [44]:

```python
history = logistic.fit(x_train, y_train, batch_size=32, epochs=5)
```

```
Epoch 1/5
814/814 [==============================] - 3s 2ms/step - loss: 0.5309 - precision: 0.4037 - recall:
0.0424 - true_positives: 204.8000 - true_negatives: 9773.6687 - false_positives: 122.7840 -
false_negatives: 2954.7080 - auc: 0.7084
Epoch 2/5
814/814 [==============================] - 2s 2ms/step - loss: 0.4146 - precision: 0.7195 - recall:
0.4244 - true_positives: 1387.7436 - true_negatives: 9370.1387 - false_positives: 535.5080 -
false_negatives: 1762.5706 - auc: 0.8609
Epoch 3/5
814/814 [==============================] - 2s 3ms/step - loss: 0.4042 - precision: 0.7106 - recall:
0.4701 - true_positives: 1488.4724 - true_negatives: 9309.8626 - false_positives: 612.4025 -
false_negatives: 1645.2233 - auc: 0.8674
Epoch 4/5
814/814 [==============================] - 2s 3ms/step - loss: 0.3998 - precision: 0.7184 - recall:
0.4791 - true_positives: 1520.5325 - true_negatives: 9311.4687 - false_positives: 605.6209 -
false_negatives: 1618.3387 - auc: 0.8747
Epoch 5/5
814/814 [==============================] - 3s 3ms/step - loss: 0.3977 - precision: 0.7279 - recall:
0.5066 - true_positives: 1580.5706 - true_negatives: 9298.9436 - false_positives: 608.0736 -
false_negatives: 1568.3730 - auc: 0.8781
```

In [45]:

```python
history.history.keys()
```

Out[45]:

```
dict_keys(['loss', 'precision', 'recall', 'true_positives', 'true_negatives', 'false_positives',
'false_negatives', 'auc'])
```

In [46]:

```
precision = history.history['precision'][-1]
recall = history.history['recall'][-1]
tp = history.history['true_positives'][-1]
tn = history.history['true_negatives'][-1]
fp = history.history['false_positives'][-1]
fn = history.history['false_negatives'][-1]
auc = history.history['auc'][-1]
```

In [47]:

```
f1 = 2*precision*recall / (precision+recall)
```

Training stats

In [48]:

```
print(f'precision: {precision}')
print(f'recall: {recall}')
print(f'f1 score: {f1}')
print(f'true pos: {tp}')
print(f'true neg: {tn}')
print(f'false pos: {fp}')
print(f'false neg: {fn}')
print(f'auc: {auc}')
```

```
precision: 0.7135922312736511
recall: 0.4946322739124298
f1 score: 0.5842717913534946
true pos: 3087.0
true neg: 18568.0
false pos: 1239.0
false neg: 3154.0
auc: 0.8746693134307861
```

Test stats

In [49]:

```
results = logistic.evaluate(x_test, y_test, batch_size=32)
```

```
204/204 [==============================] - 1s 3ms/step - loss: 0.4024 - precision: 0.7297 - recall:
0.4706 - true_positives: 753.0000 - true_negatives: 4634.0000 - false_positives: 279.0000 -
false_negatives: 847.0000 - auc: 0.8768
```

In [50]:

```
testf1 = 2 * results[1] * results[2] / (results[1] + results[2])
print(f'test f1 score: {testf1}')
```

```
test f1 score: 0.572188456556238
```

Improve through tuning elasticnet regularization

In [51]:

```
logistic_reg = LogisticRegression(num_features=X.shape[1], reg = [0.0001, 0.0001])
logistic_reg.compile(optimizer='rmsprop',
                 loss='binary_crossentropy',
                 metrics=[tf.keras.metrics.Precision(),
                          tf.keras.metrics.Recall(),
                          tf.keras.metrics.TruePositives(),
                          tf.keras.metrics.TrueNegatives(),
                          tf.keras.metrics.FalsePositives(),
                          tf.keras.metrics.FalseNegatives(),
                          tf.keras.metrics.AUC()])

print(f'random output for initialization = {logistic_reg(X[0, :].reshape(1, -1))}')
```

```
random output for initialization = [[0.7327791]]
```

In [52]:

```
logistic_reg.summary()
```

```
Model: "logistic_regression_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_1 (Dense)              multiple                  109       
=================================================================
Total params: 109
Trainable params: 109
Non-trainable params: 0
_________________________________________________________________
```

In [53]:

```
history_reg = logistic_reg.fit(x_train, y_train, epochs=5, batch_size=32)
```

```
Epoch 1/5
814/814 [==============================] - 3s 3ms/step - loss: 0.5841 - precision_1: 0.2359 - recall_1: 0.1310 - true_positives_1: 317.2037 - true_negatives_1: 9010.2196 - false_positives_1: 888.7239 - false_negatives_1: 2839.8135 - auc_1: 0.5842
Epoch 2/5
814/814 [==============================] - 2s 3ms/step - loss: 0.3930 - precision_1: 0.7391 - recall_1: 0.3966 - true_positives_1: 1311.0466 - true_negatives_1: 9454.6675 - false_positives_1: 468.6270 - false_negatives_1: 1821.6196 - auc_1: 0.8623
Epoch 3/5
814/814 [==============================] - 2s 3ms/step - loss: 0.3678 - precision_1: 0.7226 - recall_1: 0.5007 - true_positives_1: 1572.9325 - true_negatives_1: 9294.2712 - false_positives_1: 624.6638 - false_negatives_1: 1564.0933 - auc_1: 0.8786
Epoch 4/5
814/814 [==============================] - 2s 3ms/step - loss: 0.3641 - precision_1: 0.7059 - recall_1: 0.5158 - true_positives_1: 1636.0969 - true_negatives_1: 9254.2957 - false_positives_1: 662.8209 - false_negatives_1: 1502.7472 - auc_1: 0.8803
Epoch 5/5
814/814 [==============================] - 2s 3ms/step - loss: 0.3621 - precision_1: 0.7074 - recall_1: 0.5226 - true_positives_1: 1657.9288 - true_negatives_1: 9238.9485 - false_positives_1: 676.0564 - false_negatives_1: 1483.0270 - auc_1: 0.8825
```

In [54]:

```
history_reg.history.keys()
```

Out[54]:

```
dict_keys(['loss', 'precision_1', 'recall_1', 'true_positives_1', 'true_negatives_1', 'false_positives_1', 'false_negatives_1', 'auc_1'])
```

In [55]:

```
precision = history_reg.history['precision_1'][-1]
recall = history_reg.history['recall_1'][-1]
tp = history_reg.history['true_positives_1'][-1]
tn = history_reg.history['true_negatives_1'][-1]
fp = history_reg.history['false_positives_1'][-1]
fn = history_reg.history['false_negatives_1'][-1]
auc = history_reg.history['auc_1'][-1]
```

Improved training stats

In [56]:

```
print(f'precision: {precision}')
print(f'recall: {recall}')
print(f'f1 score: {f1}')
print(f'true pos: {tp}')
print(f'true neg: {tn}')
print(f'false pos: {fp}')
print(f'false neg: {fn}')
print(f'auc: {auc}')
```

```
precision: 0.7128393054008484
recall: 0.5302035212516785
f1 score: 0.5842717913534946
true pos: 3309.0
true neg: 18474.0
false pos: 1333.0
false neg: 2932.0
auc: 0.8847647309303284
```

Improved test stats

In [57]:

```
results = logistic_reg.evaluate(x_test, y_test, batch_size=32)
```

```
204/204 [==============================] - 1s 2ms/step - loss: 0.3588 - precision_1: 0.7210 - recall_1:
0.5331 - true_positives_1: 853.0000 - true_negatives_1: 4583.0000 - false_positives_1: 330.0000 -
false_negatives_1: 747.0000 - auc_1: 0.8876
```

In [58]:

```
testf1 = 2 * results[1] * results[2] / (results[1] + results[2])
print(f'test f1 score: {testf1}')
```

```
test f1 score: 0.6130075325051406
```