In [1]:
```
# *** PROBLEM 1 *** #
# a
success_probability = 4/52
print("a)", success_probability)

# b
def geometric_distribution(p, k):
    return ((1-p)**(k-1)) * (p)

print("b)", geometric_distribution(success_probability, 4))

# c
import numpy as np

results = np.random.geometric(success_probability, 100000)

print("c)", results)

# d
counter = 0
for trial in results:
    if (trial == 4):
        counter += 1

print("d)", counter/100000)

# e
experimental_results = [15, 6, 13, 14, 1, 10, 5, 2, 11, 3,
                        32, 8, 4, 4, 7, 20, 13, 12, 8, 4,
                        14, 15, 4, 37, 3, 2, 6, 12, 11, 5]

print("e)", experimental_results)

# f
counter = 0
for trial in experimental_results:
    if (trial == 4):
        counter += 1

print("f)", counter/30)

#a) 0.07692307692307693
#b) 0.060502083260390055
#c) [5 7 3 ... 4 1 5]
#d) 0.06103
#e) [15, 6, 13, 14, 1, 10, 5, 2, 11, 3, 32, 8, 4, 4, 7, 20, 13, 12, 8, 4, 14, 15, 4
#f) 0.13333333333333333
```

```
a) 0.07692307692307693
b) 0.060502083260390055
c) [15 16  6 ... 23  6 28]
d) 0.06122
e) [15, 6, 13, 14, 1, 10, 5, 2, 11, 3, 32, 8, 4, 4, 7, 20, 13, 12, 8, 4, 14, 15, 4,
37, 3, 2, 6, 12, 11, 5]
f) 0.13333333333333333
```

g:

Theoretical Probability: 0.0605 = 6.05% Python Sim: 0.0610 = 6.1% Physical Experiment: 0.13 = 13.3%

```
These results show that the Python simulation and the theoretical
probability are very close,
```

but the physical experiment resulted in a much higher rate of 4's than expected. This is in part due to the small sample size, (30 trials vs 100000) and due to the law of large numbers we would expect the frequency of 4's to decrease if we increased the number of trials. The physical experiment also includes a degree of human error when factoring in the shuffling procedure, two different shuffles could affect the order of the deck in very different ways, so a slight deviation from the expectation is not unusual.

In [2]:
```python
# *** PROBLEM 2 *** #
import pandas as pd
import numpy as np
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, log_loss, confusion_matrix
import seaborn as sns
```

In [3]:
```python
# Reading in data
train_df_ori = pd.read_csv('train.csv')
test_df_ori = pd.read_csv('test.csv')

# Saving passenger id's for kaggle submission
passenger_ids = test_df_ori["PassengerId"]

train_df = train_df_ori.copy()
test_df = test_df_ori.copy()
```

In [4]:
```python
# BEGINNING PREPROCESSING - This preprocessing pipeline is heavily inspired by
# the example code from the lecture 5 jupyter notebook.

# Dropping unimportant and poor features. These features are either
```

```python
# irrelevant to survival or in difficult to manage formats
irrelevant_feats = ['PassengerId', 'Name', 'Cabin', 'Ticket']
train_df.drop(irrelevant_feats, axis=1, inplace=True)
test_df.drop(irrelevant_feats, axis=1, inplace=True)
```

In [5]:
```python
# Imputing - This step will fill in blank or missing values in the dataset

numerical_feats = ["Pclass", "Age", "SibSp", "Parch", "Fare"]
categorical_feats = ["Sex", "Embarked"]

# We will replace missing numerical values with the median for that feature
num_imputer = SimpleImputer(missing_values=np.nan, strategy='median')
# We will replace missing categorical values with the mode for that feature
cat_imputer = SimpleImputer(missing_values=np.nan, strategy='most_frequent')

# For every column other than "Survived", search for missing values
# and replace them using the corresponding imputer
for column in train_df.columns[1:]:
    if (column in numerical_feats):
        fill = num_imputer.fit_transform(train_df[column].values.reshape(-1,1))
        train_df[column] = fill.ravel()
        fill = num_imputer.transform(test_df[column].values.reshape(-1,1))
        test_df[column] = fill.ravel()
    else:
        fill = cat_imputer.fit_transform(train_df[column].values.reshape(-1,1))
        train_df[column] = fill.ravel()
        fill = cat_imputer.transform(test_df[column].values.reshape(-1,1))
        test_df[column] = fill.ravel()
```

In [6]:
```python
# One hot encoding
def dataframe_onehotencoder(encoder, df, columns_names, fit_transform=True):
    '''
    This is a helper function to apply sklearn onehotencoder function
    on multiple columns of a data frame.

    Args:
        encoder: initialized OneHotEncoder
        df: Pandas dataframe with data
        columns_names: names of the columns in dataframe to encode
        fit_transform: True when the encoder is seeing the categorical data for the

    Returns:
        dataframe: with one-hot-encoded columns
    '''

    # One-hot-encode the columns in column names
    if(fit_transform):
        data = encoder.fit_transform(df[columns_names])
    else:
        data = encoder.transform(df[columns_names])

    # Convert data to a dataframe
    df2 = pd.DataFrame(data, columns=encoder.get_feature_names_out(columns_names),

    # Recreate original dataframe
```

```
    df3 = pd.concat([df.drop(columns_names, axis=1), df2], axis=1)

    # Return
    return df3
```

In [7]:
```
encoder = OneHotEncoder(drop='first', sparse_output=False) # drops first feature to
df_OHE = dataframe_onehotencoder(encoder=encoder, df=train_df, columns_names=catego

train_df = dataframe_onehotencoder(encoder=encoder, df=train_df,
                                   columns_names=categorical_feats, fit_transform=T
test_df = dataframe_onehotencoder(encoder=encoder, df=test_df,
                                  columns_names=categorical_feats, fit_transform=Fa
```

In [8]:
```
def dataframe_normalization(transformer, df, fit_transform=True):
    '''
    This is a helper function to normalize the dataset features using the ColumnTra

    Args:
        transformer: initialized ColumnTransformer
        df: Pandas dataframe with the data
        fit_transform: True when the transformer is seeing the data for the first t

    Returns:
        dataframe: with specific normalized columns
    '''

    # Copy data
    df2 = df.copy()

    if(fit_transform):
        data = transformer.fit_transform(df2)
    else:
        data = transformer.transform(df2)

    # Add normalized data to dataframe
    for index, column in enumerate(transformer.get_feature_names_out()):
        df2[column] = data[:,index]

    # Return
    return df2
```

In [9]:
```
# Using ColumnTransformer to apply specific normalization to each column in our dat
norm_scaler = ColumnTransformer(
    transformers=[
        ('minmax', MinMaxScaler(), ['Pclass', 'Parch']),
        ('standard', StandardScaler(), ['Age', 'SibSp', 'Fare'])
    ], verbose_feature_names_out=False
)

# Normalize data (Treat all features the same)
train_df2 = dataframe_normalization(transformer=norm_scaler, df=train_df, fit_trans
test_df2 = dataframe_normalization(transformer=norm_scaler, df=test_df, fit_transfo
```

In [10]:
```
rng1 = np.random.RandomState(seed=45) # seeding our rng
```

```python
y = train_df2['Survived'].values # extracting targets
X = train_df2.iloc[:,1:].values # extracting parameters

# splitting data to create a validation set
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.15, random_stat

# ENDING PREPROCESSING - Data is now ready for model training
```

In [11]:
```python
# SKLEARN MODEL

log_classifier = LogisticRegression(max_iter=1000, random_state=rng1)
log_classifier.fit(X_train, y_train)
```

Out[11]:

LogisticRegression

▼ Parameters

penalty	'l2'
dual	False
tol	0.0001
C	1.0
fit_intercept	True
intercept_scaling	1
class_weight	None
random_state	RandomState(M... 0x1B36275AC40
solver	'lbfgs'
max_iter	1000
multi_class	'deprecated'
verbose	0
warm_start	False
n_jobs	None
l1_ratio	None

In [12]:
```python
# Predictions from SKlearn model
y_val_pred = log_classifier.predict(X_val)
y_val_probs = log_classifier.predict_proba(X_val)[:, 1]  # probability of "Survived

# Metrics
acc = accuracy_score(y_val, y_val_pred)
loss = log_loss(y_val, y_val_probs)
cm = confusion_matrix(y_val, y_val_pred)
```

```
print("Validation Accuracy:", acc)
print("Validation Log Loss (Binary Cross Entropy):", loss)
print("Confusion Matrix:\n", cm)
```

```
Validation Accuracy: 0.7985074626865671
Validation Log Loss (Binary Cross Entropy): 0.44009547402646
Confusion Matrix:
 [[75  8]
 [19 32]]
```

In [13]:
```
# SCRATCH MODEL

# TRAINING AND INTERNAL FUNCTIONS

# Computes the sigmoid function
def sigmoid(z):
    return (1 / (1 + np.exp(-z)))

# Initializes the starting parameters w and b with an optional seed
def initialize_params(m_features, seed=None):
    if (seed is not None):
        np.random.seed(seed)

    w = np.random.rand(m_features, 1)
    b = 0

    # returns parameters
    return w, b

# Computes the linear combination of featurs and uses the sigmoid
# to calculate probabilities of survival
def forward(X, w, b):
    z = X.dot(w) + b
    y_hat = sigmoid(z)

    # returns raw score prediction and normalized [0,1] prediction
    return z, y_hat

# Uses binary cross entropy to calculate the log-loss of the training
def compute_cost(y, y_hat, w):
    #Force shapes
    y_hat = y_hat.reshape(-1, 1)
    y = y.reshape(-1, 1)

    # Assumes LogLoss
    eps = 1e-12
    cost = -(np.dot(y.T,np.log(y_hat+eps)) + np.dot(1-y.T,np.log(1-y_hat+eps))) / l

    # returns error as a scalar
    return np.squeeze(cost)

# Computes gradients for our gradient descent algorithm
def compute_gradients(X, y, y_hat, w, reg_lambda=0.0):
    #Force shapes
    y_hat = y_hat.reshape(-1,1)
    y = y.reshape(-1,1)
```

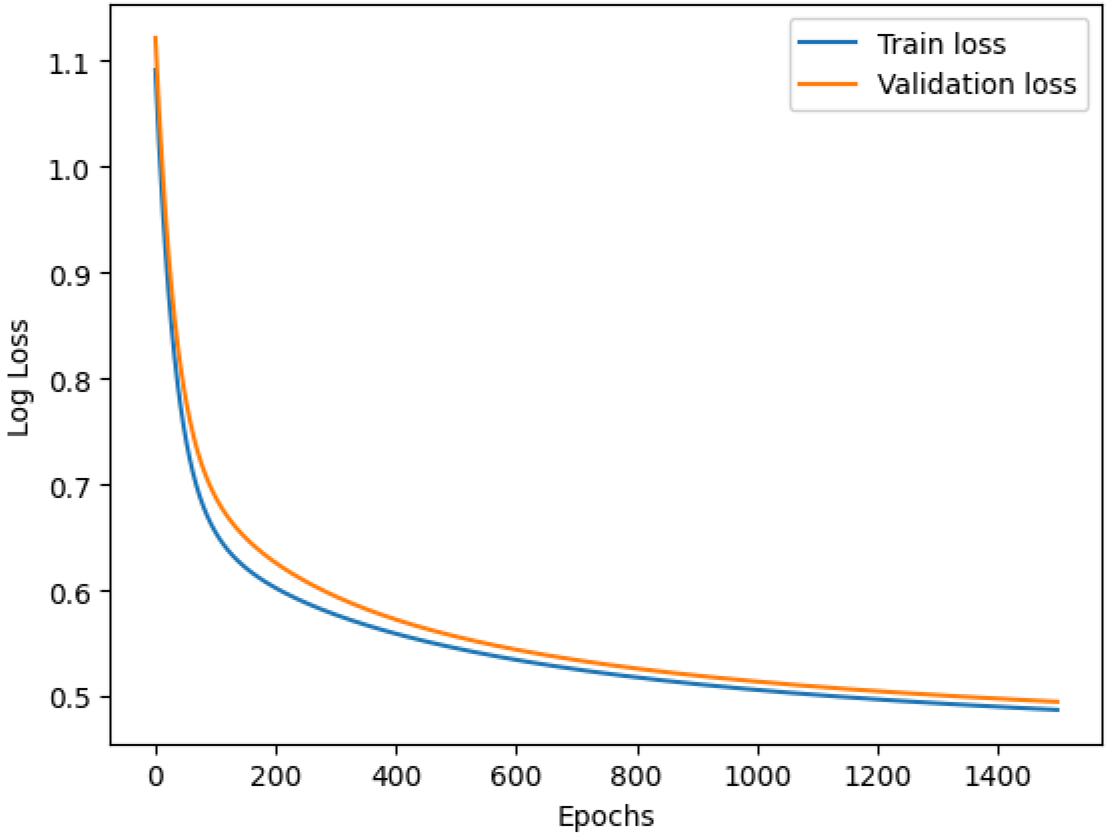
```
    # number of samples
    n = len(y)

    # finding gradients of b and w respectively
    db = (1/n)*np.sum(y_hat-y)
    dw = (1/n)*X.T.dot(y_hat-y)

    # returns our gradients for w and b
    return dw, db

# Updates parameters using calculated gradients and provided learning rate
def update_params(w, b, dw, db, lr):
    w = w - lr * dw
    b = b - lr * db

    # returns updated w and b params
    return w, b

# Core training loop
def train(X, y, lr, n_epochs, X_val=None, y_val=None, seed=None):
    # initialize our parameters
    samples, features = X.shape
    w, b = initialize_params(features, seed)

    # Initialize two lists to track loss across epochs
    train_losses = []
    val_losses = []

    # For each training iteration
    for i in range(n_epochs):
        z, y_hat = forward(X, w, b) # Make one forward pass
        cost = compute_cost(y, y_hat, w) # Calculate error
        train_losses.append(cost) # Track error
        dw, db = compute_gradients(X, y, y_hat, w) # Perform gradient descent
        w, b = update_params(w, b, dw, db, lr) # Update our parameters

        # If we have a provided validation set
        if (X_val is not None and y_val is not None):
            z_val, y_hat_val = forward(X_val, w, b) # Perform one forward pass
            # Calculate and track error on validation set
            val_cost = compute_cost(y_val, y_hat_val, w)
            val_losses.append(val_cost)

    # Return our trained parameters and our loss history
    return w, b, train_losses, val_losses


# PREDICTION FUNCTIONS - USE AFTER TRAINING

# Calculate probability of survival for a sample
# EXPECTS TRAINED PARAMETERS
def predict_prob(X, w, b):
    z, y_hat = forward(X, w, b)

    # returns probability of survival
```

```
    return y_hat

# Predict wether a sample survived, returns a binary int (1 for lived, 0 for died)
# EXPECTS TRAINED PARAMETERS
def predict(X, w, b):
    prob = predict_prob(X, w, b)

    # return boolean for survival as an integer
    return (prob >= 0.5).astype(int)
```

In [14]:
```
# Training and validating scratch model
w, b, training_loss, val_loss = train(X_train, y_train, .0275, 1500, X_val, y_val,

# Validating scratch model
y_val_prob = predict_prob(X_val, w, b)
y_val_prediction = predict(X_val, w, b)

print("Val accuracy:", accuracy_score(y_val, y_val_prediction))
print("Val log loss:", log_loss(y_val, y_val_prob))
print("Confusion matrix:\n", confusion_matrix(y_val, y_val_prediction))
```

```
Val accuracy: 0.8134328358208955
Val log loss: 0.4947885571796464
Confusion matrix:
 [[78  5]
 [20 31]]
```

In [15]:
```
# Plotting loss over epochs
import matplotlib.pyplot as plt

plt.plot(training_loss, label='Train loss')
plt.plot(val_loss, label='Validation loss')
plt.xlabel('Epochs')
plt.ylabel('Log Loss')
plt.legend()
plt.show()
```



In [16]:

```
# TESTING

# SCRATCH TESTING
X_test = test_df2.values
y_test_pred_scratch = predict(X_test, w, b).flatten()

# Build submission DataFrame
submission = pd.DataFrame({
    "PassengerId": passenger_ids,
    "Survived": y_test_pred_scratch.astype(int)
})

# Save file
submission.to_csv("scratch_submission.csv", index=False)

# SKLEARN TESTING
y_test_pred_sk = log_classifier.predict(X_test)

# Build submission DataFrame
submission = pd.DataFrame({
    "PassengerId": passenger_ids,
    "Survived": y_test_pred_sk.astype(int)
})

# Save file
submission.to_csv("sklearn_submission.csv", index=False)
```