In [1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

In [2]:
```
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.datasets import fetch_openml
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics.pairwise import euclidean_distances
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.datasets import fetch_openml
import nltk
from gensim.parsing import strip_tags, strip_numeric, strip_multiple_whitespac
from gensim.parsing import preprocess_string
from gensim import parsing
from sklearn.datasets import fetch_20newsgroups
import re
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import normalize
from sklearn.decomposition import PCA
```

Problem 1

Logistic Regression - MNIST

In [3]:
```
# Load MNIST dataset from OpenML
mnist = fetch_openml('mnist_784', version = 1)

# Split data and labels
X = mnist.data
y = mnist.target.astype(np.int)

# Select 10000 samples
X = X[:10000]
y = y[:10000]

# Split into train and test sets with 10,000 samples each
X_mnist_train, X_mnist_test, y_mnist_train, y_mnist_test = train_test_split(X,
```

In [4]:
```
# Train logistic regression model
clf = LogisticRegression(penalty = 'l2', solver = 'saga' ,max_iter = 100).fit(

# Predict on test set
y_mnist_pred = clf.predict(X_mnist_test)

# Calculate accuracy
accuracy = accuracy_score(y_mnist_test, y_mnist_pred)
print(f"Accuracy: {accuracy}")

# Get the coefficients and sort them in descending order
coef = clf.coef_[0]
sorted_coef = sorted(range(len(coef)), key = lambda k: abs(coef[k]), reverse =

# Print the top 30 features
print("Top 30 features:")
for i in range(30):
    print(f"{i+1}. Feature {sorted_coef[i]} with coefficient {coef[sorted_coef
```

```
Accuracy: 0.9165
Top 30 features:
1. Feature 379 with coefficient -0.0058
2. Feature 407 with coefficient -0.0058
3. Feature 434 with coefficient -0.0056
4. Feature 435 with coefficient -0.0051
5. Feature 408 with coefficient -0.0049
6. Feature 485 with coefficient 0.0048
7. Feature 380 with coefficient -0.0048
8. Feature 462 with coefficient -0.0047
9. Feature 242 with coefficient 0.0046
10. Feature 629 with coefficient 0.0045
11. Feature 324 with coefficient -0.0042
12. Feature 490 with coefficient -0.0039
13. Feature 378 with coefficient -0.0038
14. Feature 351 with coefficient -0.0037
15. Feature 517 with coefficient -0.0037
16. Feature 270 with coefficient 0.0036
17. Feature 571 with coefficient 0.0036
18. Feature 406 with coefficient -0.0035
19. Feature 512 with coefficient 0.0035
20. Feature 323 with coefficient -0.0035
21. Feature 489 with coefficient -0.0034
22. Feature 461 with coefficient -0.0033
23. Feature 383 with coefficient -0.0033
24. Feature 125 with coefficient 0.0033
25. Feature 437 with coefficient -0.0032
26. Feature 518 with coefficient -0.0032
27. Feature 454 with coefficient 0.0032
28. Feature 605 with coefficient -0.0032
29. Feature 655 with coefficient 0.0032
30. Feature 513 with coefficient 0.0031
```

Logistic Regression - 20NG

In [5]:
```
transform_to_lower = lambda s: s.lower()
remove_emails = lambda s: re.sub(r'^[a-zA-Z0-9+_.-]+@[a-zA-Z0-9.-]+$', '', s)
remove_single_char = lambda s: re.sub(r'\s+\w{1}\s+', '', s)

CLEAN_FILTERS = [remove_emails,
                 strip_tags,
                 strip_numeric,
                 remove_emails,
                 strip_punctuation,
                 strip_multiple_whitespaces,
                 transform_to_lower,
                 remove_stopwords]

def cleaningPipe(document):
    processed_words = preprocess_string(document, CLEAN_FILTERS)

    return processed_words

def joinList(processed_words):
    return ' '.join(processed_words)

def basicStemming(text):
    return parsing.stem_text(text)


newsgroups_train = fetch_20newsgroups(subset='train')
newsgroups_test = fetch_20newsgroups(subset='test')

ng_df_train = pd.DataFrame({"news" : newsgroups_train["data"] ,"class" : newsg
ng_df_train["cleanedText"] = ng_df_train["news"].apply(cleaningPipe).apply(joi
ng_df_train.head()
```

Out[5]:

	news	class	cleanedText
0	From: lerxst@wam.umd.edu (where's my thing)\nS...	7	lerxst wam umd edu s thing subject car nntp po...
1	From: guykuo@carson.u.washington.edu (Guy Kuo)...	4	guykuo carson u washington edu gui kuo subject...
2	From: twillis@ec.ecn.purdue.edu (Thomas E Will...	4	twilli ec ecn purdu edu thoma e willi subject ...
3	From: jgreen@amber (Joe Green)\nSubject: Re: W...	1	jgreen amber joe green subject weitek p organ ...
4	From: jcm@head-cfa.harvard.edu (Jonathan McDow...	14	jcm head cfa harvard edu jonathan mcdowel subj...

In [6]:
```
ng_df_test = pd.DataFrame({"news" : newsgroups_test["data"] ,"class" : newsgrc
ng_df_test["cleanedText"] = ng_df_test["news"].apply(cleaningPipe).apply(joinL
ng_df_test.head()
```

Out[6]:

	news	class	cleanedText
0	From: v064mb9k@ubvmsd.cc.buffalo.edu (NEIL B. ...	7	vmbk ubvmsd cc buffalo edu neil b gandler subj...
1	From: Rick Miller <rick@ee.uwm.edu>\nSubject: ...	5	rick miller subject x face organ line distribu...
2	From: mathew <mathew@mantis.co.uk>\nSubject: R...	0	mathew subject strong weak atheism organ manti...
3	From: bakken@cs.arizona.edu (Dave Bakken)\nSub...	17	bakken cs arizona edu dave bakken subject saud...
4	From: livesey@solntze.wpd.sgi.com (Jon Livesey...	19	livesei solntz wpd sgi com jon livesei subject...

In [7]:
```
num_points = 10000

ng_df_train = ng_df_train.iloc[:num_points,:]

vectorizer = TfidfVectorizer(stop_words="english")
X_train_ng = vectorizer.fit_transform(np.array(ng_df_train["cleanedText"]))

X_train = pd.DataFrame(X_train_ng.toarray())
y_train = np.array(ng_df_train["class"])
```

In [8]:
```
num_points = 10000

ng_df_test = ng_df_test.iloc[:num_points,:]

X_test_ng = vectorizer.transform(np.array(ng_df_test["cleanedText"]))

X_test = pd.DataFrame(X_test_ng.toarray())
y_test = np.array(ng_df_test["class"])
```

In [9]:
```
# Train logistic regression model
clf = LogisticRegression(penalty = 'l2', solver = 'lbfgs', max_iter = 100, rar
clf.fit(X_train, y_train)

# Test model
y_pred = clf.predict(X_test)

# Test model and print accuracy
accuracy = accuracy_score(y_test, y_pred)
print("\nAccuracy:", accuracy)

# Get top 30 features
coef_abs = abs(clf.coef_)
top_30_idx = coef_abs.argsort()[0][-30:]
top_30_values = clf.coef_[0][top_30_idx]
print("\nTop 30 features:\n")
for idx, value in zip(top_30_idx, top_30_values):
    print(f"Feature {vectorizer.get_feature_names()[idx]}: {value}")
```

```
Accuracy: 0.8231545406266596

Top 30 features:

Feature halat: 1.4952560749614519
Feature charlei: 1.498187620303281
Feature liar: 1.503001522249867
Feature gregg: 1.530709027405568
Feature write: 1.554191310867334
Feature osrh: 1.5726320652419132
Feature argument: 1.5751121561935715
Feature sandvik: 1.6131346654795269
Feature cco: 1.6376258676366071
Feature peopl: 1.6632263725661285
Feature punish: 1.7290137321852834
Feature schneider: 1.7354063682726226
Feature cobb: 1.8374590217572115
Feature wingat: 1.8388058922270343
Feature mango: 1.903250439963916
Feature rushdi: 1.9247682458952347
Feature caltech: 1.980170864717595
Feature jaeger: 2.030763767054162
Feature benedikt: 2.038256005320304
Feature livesei: 2.200817345898693
Feature okcforum: 2.247556256534399
Feature religion: 2.267245521092586
Feature bibl: 2.3246848657883
Feature mathew: 2.5497809991934623
Feature moral: 2.9938806391924726
Feature atheism: 3.2894051411807603
Feature atheist: 3.473578464229222
Feature islam: 3.6967976509903555
Feature god: 3.912815829931186
Feature keith: 4.691209911085273
```

Logistic Regression - Spambase

In [10]:
```
data_spam = pd.read_csv('/content/drive/MyDrive/spambase.data', header = None)
data_spam.rename(columns = {57 : 'spam'}, inplace = True)

X = data_spam.drop(['spam'], axis = 1)
y = data_spam['spam']

X = StandardScaler().fit_transform(X)

X_spam_train, X_spam_test, y_spam_train, y_spam_test=train_test_split(X, y, te
```

In [11]:
```
# Train logistic regression model
clf = LogisticRegression(penalty = 'l2', solver = 'liblinear', max_iter = 100)
clf.fit(X_spam_train, y_spam_train)

# Test model
y_spam_pred = clf.predict(X_spam_test)

# Test model and print accuracy
accuracy = accuracy_score(y_spam_test, y_spam_pred)
print("\nAccuracy:", accuracy)

# Get top 30 features
coef_abs = abs(clf.coef_)
top_30_idx = coef_abs.argsort()[0][-30:]
top_30_values = clf.coef_[0][top_30_idx]
print("\nTop 30 features:\n")
for idx, value in zip(top_30_idx, top_30_values):
    print(f"Feature {vectorizer.get_feature_names()[idx]}: {value}")
```

```
Accuracy: 0.9370249728555917

Top 30 features:

Feature aanerud: -0.3020368558356185
Feature aarskog: -0.3274998567327007
Feature aaaaaggggghhhh: 0.33841400348356093
Feature aaw: 0.3408397537722011
Feature aardvark: -0.35077874329181
Feature aaopwl: 0.37646916068842734
Feature aantal: -0.39737363860303293
Feature aario: -0.40394525972295603
Feature aalborg: 0.41258999177212263
Feature aafc: 0.5322641854280735
Feature aaaaaaaaaaa: 0.6269037455171719
Feature aangegeven: -0.7110945227345816
Feature aaron: -0.7227304025329542
Feature aarnet: -0.772462502155514
Feature aaltern: 0.7940853838684186
Feature aauwpiugyvnn: 0.8042297944763976
Feature aaah: 0.8165142496421441
Feature aamir: -0.8334169174492623
Feature aan: -0.9260149283382516
Feature aaf: 0.9512190385445416
Feature aarp: -1.069092061850569
Feature aau: 1.1625883801605654
Feature aaoepp: -1.2232526071749763
Feature aarhu: -1.2613630259593502
Feature aaronc: -1.3716497073791638
Feature aavso: 1.4952182157129057
Feature aav: 1.5518139906315318
Feature aarghhhh: -1.5657406465477584
Feature aamaz: -2.4301817188545822
Feature aammmaaaazzzzzziinnnngggggg: -4.1420385497411045
```

Decision Tree Classifier - MNIST

In [12]:
```
# Train decision tree model
clf = DecisionTreeClassifier()
clf.fit(X_mnist_train, y_mnist_train)

# Predict on test set
y_pred = clf.predict(X_mnist_test)

# Calculate accuracy
accuracy = accuracy_score(y_mnist_test, y_mnist_pred)
print(f"MNIST Accuracy: {accuracy}")
```

```
MNIST Accuracy: 0.9165
```

In [13]:
```
# Define a list of feature names based on the word index
feature_names = [f"word_{i}" for i in range(784)]

# Extract the feature indices and thresholds for the first 30 nodes of the dec
node_features = clf.tree_.feature[:30]
node_thresholds = clf.tree_.threshold[:30]

# Print out the feature names and threshold values for each node
for i in range(30):
    feature_idx = node_features[i]
    feature_name = feature_names[feature_idx]
    threshold = node_thresholds[i]
    print(f"Node {i}: feature = {feature_name}, threshold = {threshold:.2f}")
```

```
Node 0: feature=word_350, threshold=148.50
Node 1: feature=word_155, threshold=0.50
Node 2: feature=word_239, threshold=0.50
Node 3: feature=word_543, threshold=78.50
Node 4: feature=word_295, threshold=119.00
Node 5: feature=word_183, threshold=162.50
Node 6: feature=word_597, threshold=15.50
Node 7: feature=word_69, threshold=14.50
Node 8: feature=word_323, threshold=141.00
Node 9: feature=word_122, threshold=232.00
Node 10: feature=word_470, threshold=252.50
Node 11: feature=word_409, threshold=10.00
Node 12: feature=word_462, threshold=162.00
Node 13: feature=word_319, threshold=141.00
Node 14: feature=word_376, threshold=88.00
Node 15: feature=word_782, threshold=-2.00
Node 16: feature=word_580, threshold=46.50
Node 17: feature=word_782, threshold=-2.00
Node 18: feature=word_782, threshold=-2.00
Node 19: feature=word_782, threshold=-2.00
Node 20: feature=word_549, threshold=243.50
Node 21: feature=word_782, threshold=-2.00
Node 22: feature=word_782, threshold=-2.00
Node 23: feature=word_210, threshold=254.00
Node 24: feature=word_154, threshold=137.50
Node 25: feature=word_782, threshold=-2.00
Node 26: feature=word_177, threshold=21.50
Node 27: feature=word_782, threshold=-2.00
Node 28: feature=word_782, threshold=-2.00
Node 29: feature=word_782, threshold=-2.00
```

Decision Tree - 20NG

In [14]:
```
# Instantiate the classifier with max_depth
dtc_5 = DecisionTreeClassifier(max_depth = 50)

# Fit the classifier on the training data
dtc_5.fit(X_train, y_train)

# Predict on the test data
y_pred_5 = dtc_5.predict(X_test)

# Compute accuracy on the test data
accuracy_5 = accuracy_score(y_test, y_pred_5)

# Instantiate the classifier with max_depth
dtc_10 = DecisionTreeClassifier(max_depth = 100)

# Fit the classifier on the training data
dtc_10.fit(X_train, y_train)

# Predict on the test data
y_pred_10 = dtc_10.predict(X_test)

# Compute accuracy on the test data
accuracy_10 = accuracy_score(y_test, y_pred_10)

print("Accuracy for Decision Tree with max_depth = 50: {:.2f}".format(accuracy
print("Accuracy for Decision Tree with max_depth = 100: {:.2f}".format(accurac
```

```
Accuracy for Decision Tree with max_depth = 50: 0.51
Accuracy for Decision Tree with max_depth = 100: 0.56
```

In [15]:
```
# Define a list of feature names based on the pixel index in the flattened ima
feature_names = [f"pixel_{i}" for i in range(X_train.shape[1])]

# Extract the feature indices and thresholds for the first 30 nodes of the dec
node_features = dtc_5.tree_.feature[:30]
node_thresholds = dtc_5.tree_.threshold[:30]

# Print out the feature names and threshold values for each node
for i in range(30):
    feature_idx = node_features[i]
    feature_name = feature_names[feature_idx]
    threshold = node_thresholds[i]
    print(f"Node {i}: feature = {feature_name}, threshold = {threshold:.2f}")
```

```
Node 0: feature=pixel_15425, threshold=0.00
Node 1: feature=pixel_5015, threshold=0.01
Node 2: feature=pixel_7241, threshold=0.04
Node 3: feature=pixel_58347, threshold=0.03
Node 4: feature=pixel_22714, threshold=0.00
Node 5: feature=pixel_21002, threshold=0.03
Node 6: feature=pixel_25471, threshold=0.01
Node 7: feature=pixel_8476, threshold=0.01
Node 8: feature=pixel_45958, threshold=0.05
Node 9: feature=pixel_49094, threshold=0.04
Node 10: feature=pixel_4084, threshold=0.02
Node 11: feature=pixel_31010, threshold=0.02
Node 12: feature=pixel_2594, threshold=0.01
Node 13: feature=pixel_13526, threshold=0.03
Node 14: feature=pixel_51849, threshold=0.03
Node 15: feature=pixel_8971, threshold=0.01
Node 16: feature=pixel_19321, threshold=0.02
Node 17: feature=pixel_20492, threshold=0.04
Node 18: feature=pixel_20118, threshold=0.03
Node 19: feature=pixel_8671, threshold=0.03
Node 20: feature=pixel_13517, threshold=0.01
Node 21: feature=pixel_46497, threshold=0.01
Node 22: feature=pixel_57360, threshold=0.02
Node 23: feature=pixel_38184, threshold=0.01
Node 24: feature=pixel_8956, threshold=0.01
Node 25: feature=pixel_8869, threshold=0.02
Node 26: feature=pixel_34435, threshold=0.02
Node 27: feature=pixel_40532, threshold=0.01
Node 28: feature=pixel_2245, threshold=0.05
Node 29: feature=pixel_18046, threshold=0.04
```

In [16]:
```
# Define a list of feature names based on the pixel index in the flattened ima
feature_names = [f"pixel_{i}" for i in range(X_train.shape[1])]

# Extract the feature indices and thresholds for the first 30 nodes of the dec
node_features = dtc_10.tree_.feature[:30]
node_thresholds = dtc_10.tree_.threshold[:30]

# Print out the feature names and threshold values for each node
for i in range(30):
    feature_idx = node_features[i]
    feature_name = feature_names[feature_idx]
    threshold = node_thresholds[i]
    print(f"Node {i}: feature = {feature_name}, threshold = {threshold:.2f}")
```

```
Node 0: feature=pixel_15425, threshold=0.00
Node 1: feature=pixel_5015, threshold=0.01
Node 2: feature=pixel_7241, threshold=0.04
Node 3: feature=pixel_58347, threshold=0.03
Node 4: feature=pixel_22714, threshold=0.00
Node 5: feature=pixel_21002, threshold=0.03
Node 6: feature=pixel_25471, threshold=0.01
Node 7: feature=pixel_8476, threshold=0.01
Node 8: feature=pixel_45958, threshold=0.05
Node 9: feature=pixel_49094, threshold=0.04
Node 10: feature=pixel_4084, threshold=0.02
Node 11: feature=pixel_31010, threshold=0.02
Node 12: feature=pixel_2594, threshold=0.01
Node 13: feature=pixel_13526, threshold=0.03
Node 14: feature=pixel_51849, threshold=0.03
Node 15: feature=pixel_8971, threshold=0.01
Node 16: feature=pixel_19321, threshold=0.02
Node 17: feature=pixel_20492, threshold=0.04
Node 18: feature=pixel_20118, threshold=0.03
Node 19: feature=pixel_8671, threshold=0.03
Node 20: feature=pixel_13517, threshold=0.01
Node 21: feature=pixel_46497, threshold=0.01
Node 22: feature=pixel_57360, threshold=0.02
Node 23: feature=pixel_38184, threshold=0.01
Node 24: feature=pixel_8956, threshold=0.01
Node 25: feature=pixel_8869, threshold=0.02
Node 26: feature=pixel_34435, threshold=0.02
Node 27: feature=pixel_40532, threshold=0.01
Node 28: feature=pixel_2245, threshold=0.05
Node 29: feature=pixel_18046, threshold=0.04
```

Decision Tree - Spambase

In [17]:
```
# Create a decision tree classifier
dt = DecisionTreeClassifier()

# Train the classifier on the training data
dt.fit(X_spam_train, y_spam_train)

# Make predictions on the test data
spam_test_predictions = dt.predict(X_spam_test)

# Calculate the accuracy of the classifier
spam_test_accuracy = accuracy_score(y_spam_test, spam_test_predictions)
print(f"Spambase Accuracy: {spam_test_accuracy:.4f}")
```

```
Spambase Accuracy: 0.9186
```

In [18]:
```
# Define a list of feature names based on the pixel index in the flattened ima
feature_names = [f"{i}" for i in range(X_spam_train.shape[1])]

# Extract the feature indices and thresholds for the first 30 nodes of the dec
node_features = dt.tree_.feature[:30]
node_thresholds = dt.tree_.threshold[:30]

# Print out the feature names and threshold values for each node
for i in range(30):
    feature_idx = node_features[i]
    feature_name = feature_names[feature_idx]
    threshold = node_thresholds[i]
    print(f"Node {i}: feature = {feature_name}, threshold = {threshold:.2f}")
```

```
Node 0: feature=52, threshold=-0.08
Node 1: feature=6, threshold=-0.16
Node 2: feature=51, threshold=0.10
Node 3: feature=15, threshold=-0.27
Node 4: feature=23, threshold=-0.17
Node 5: feature=54, threshold=0.09
Node 6: feature=4, threshold=1.92
Node 7: feature=27, threshold=12.96
Node 8: feature=24, threshold=-0.32
Node 9: feature=16, threshold=0.75
Node 10: feature=35, threshold=1.06
Node 11: feature=55, threshold=-0.20
Node 12: feature=7, threshold=20.92
Node 13: feature=22, threshold=5.93
Node 14: feature=19, threshold=18.90
Node 15: feature=39, threshold=2.44
Node 16: feature=18, threshold=-0.30
Node 17: feature=56, threshold=-0.25
Node 18: feature=54, threshold=-0.12
Node 19: feature=54, threshold=-0.12
Node 20: feature=56, threshold=-0.41
Node 21: feature=56, threshold=-0.46
Node 22: feature=55, threshold=-2.00
Node 23: feature=56, threshold=-0.45
Node 24: feature=26, threshold=0.28
Node 25: feature=55, threshold=-0.26
Node 26: feature=45, threshold=1.51
Node 27: feature=9, threshold=2.99
Node 28: feature=44, threshold=2.79
Node 29: feature=55, threshold=-2.00
```

Problem 2

A)

Logistic Regression with PCA - MNIST

In [19]:
```
# PCA fit
pca = PCA(n_components = 5)
mnist_train_reduced = pca.fit_transform(X_mnist_train)
mnist_test_reduced = pca.transform(X_mnist_test)

# Train logistic regression model
clf = LogisticRegression(penalty = 'l2', solver = 'saga' ,max_iter = 100).fit(

# Predict on test set
y_mnist_pred = clf.predict(mnist_test_reduced)

# Calculate accuracy
accuracy = accuracy_score(y_mnist_test, y_mnist_pred)
print(f"MNIST Accuracy: {accuracy}")
```

```
MNIST Accuracy: 0.668
```

In [20]:
```
# PCA fit
pca = PCA(n_components = 20)
mnist_train_reduced = pca.fit_transform(X_mnist_train)
mnist_test_reduced = pca.transform(X_mnist_test)

# Train logistic regression model
clf = LogisticRegression(penalty = 'l2', solver = 'saga' ,max_iter = 100).fit(

# Predict on test set
y_mnist_pred = clf.predict(mnist_test_reduced)

# Calculate accuracy
accuracy = accuracy_score(y_mnist_test, y_mnist_pred)
print(f"MNIST Accuracy: {accuracy}")
```

```
MNIST Accuracy: 0.872
```

Decision Tree with PCA - MNIST

In [21]:
```
# PCA fit
pca = PCA(n_components = 5)
mnist_train_reduced = pca.fit_transform(X_mnist_train)
mnist_test_reduced = pca.transform(X_mnist_test)

# Train decision tree model
clf = DecisionTreeClassifier()
clf.fit(mnist_train_reduced, y_mnist_train)

# Predict on test set
y_pred = clf.predict(mnist_test_reduced)

# Calculate accuracy
accuracy = accuracy_score(y_mnist_test, y_mnist_pred)
print(f"MNIST Accuracy: {accuracy}")
```

```
MNIST Accuracy: 0.872
```

In [22]:
```
# PCA fit
pca = PCA(n_components = 20)
mnist_train_reduced = pca.fit_transform(X_mnist_train)
mnist_test_reduced = pca.transform(X_mnist_test)

# Train decision tree model
clf = DecisionTreeClassifier()
clf.fit(mnist_train_reduced, y_mnist_train)

# Predict on test set
y_pred = clf.predict(mnist_test_reduced)

# Calculate accuracy
accuracy = accuracy_score(y_mnist_test, y_mnist_pred)
print(f"MNIST Accuracy: {accuracy}")
```

```
MNIST Accuracy: 0.872
```

B)

Logistic Regression with PCA - Spambase

In [23]:
```
pca = PCA(n_components = 31).fit(X_spam_train, y_spam_train)
spam_train_reduced = pca.transform(X_spam_train)
spam_test_reduced = pca.transform(X_spam_test)

# Train logistic regression model
clf = LogisticRegression(solver = 'liblinear', max_iter = 100)
clf.fit(spam_train_reduced, y_spam_train)

# Test model and print confusion matrix
y_spam_pred = clf.predict(spam_test_reduced)

# Test model and print accuracy
accuracy = accuracy_score(y_spam_test, y_spam_pred)
print("\nAccuracy:", accuracy)
```

```
Accuracy: 0.9272529858849077
```

Probelm 3

In [24]:
```
# Load the MNIST dataset and extract the first 10,000 samples
mnist = fetch_openml("mnist_784")
X = mnist.data[:10000]
y = mnist.target[:10000]

# Normalize the data by subtracting the mean and dividing by the standard devi
scaler = StandardScaler()
X_norm = scaler.fit_transform(X)

# Calculate the covariance matrix
covariance_matrix = np.cov(X_norm.T)

# Calculate the eigenvalues and eigenvectors of the covariance matrix
eigenvalues, eigenvectors = np.linalg.eig(covariance_matrix)

# Sort the eigenvalues in descending order
idx = np.argsort(eigenvalues)[::-1]
eigenvalues = eigenvalues[idx]
eigenvectors = eigenvectors[:, idx]

# Choose the number of principal components (K)
K = 5

# Project the dataset onto the K principal components
projection_matrix = eigenvectors[:, :K]
X_pca = np.dot(X_norm, projection_matrix)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size = 0.2,

# Train a logistic regression model on the training data
clf = LogisticRegression(max_iter = 100)
clf.fit(X_train, y_train)

# Evaluate the accuracy of the model on the testing data
accuracy = clf.score(X_test, y_test)
print("MNIST PCA Accuracy:", accuracy)
```

```
MNIST PCA Accuracy: 0.6995
```

In [25]:
```
import numpy as np
from sklearn.datasets import fetch_openml
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

# Load the MNIST dataset and extract the first 10,000 samples
mnist = fetch_openml("mnist_784")
X = mnist.data[:10000]
y = mnist.target[:10000]

# Normalize the data by subtracting the mean and dividing by the standard devi
scaler = StandardScaler()
X_norm = scaler.fit_transform(X)

# Calculate the covariance matrix
covariance_matrix = np.cov(X_norm.T)

# Calculate the eigenvalues and eigenvectors of the covariance matrix
eigenvalues, eigenvectors = np.linalg.eig(covariance_matrix)

# Sort the eigenvalues in descending order
idx = np.argsort(eigenvalues)[::-1]
eigenvalues = eigenvalues[idx]
eigenvectors = eigenvectors[:, idx]

# Choose the number of principal components (K)
K = 20

# Project the dataset onto the K principal components
projection_matrix = eigenvectors[:, :K]
X_pca = np.dot(X_norm, projection_matrix)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size = 0.2,

# Train a logistic regression model on the training data
clf = LogisticRegression(max_iter=1000)
clf.fit(X_train, y_train)

# Evaluate the accuracy of the model on the testing data
accuracy = clf.score(X_test, y_test)
print("MNIST PCA Accuracy:", accuracy)
```

```
MNIST PCA Accuracy: 0.8835
```

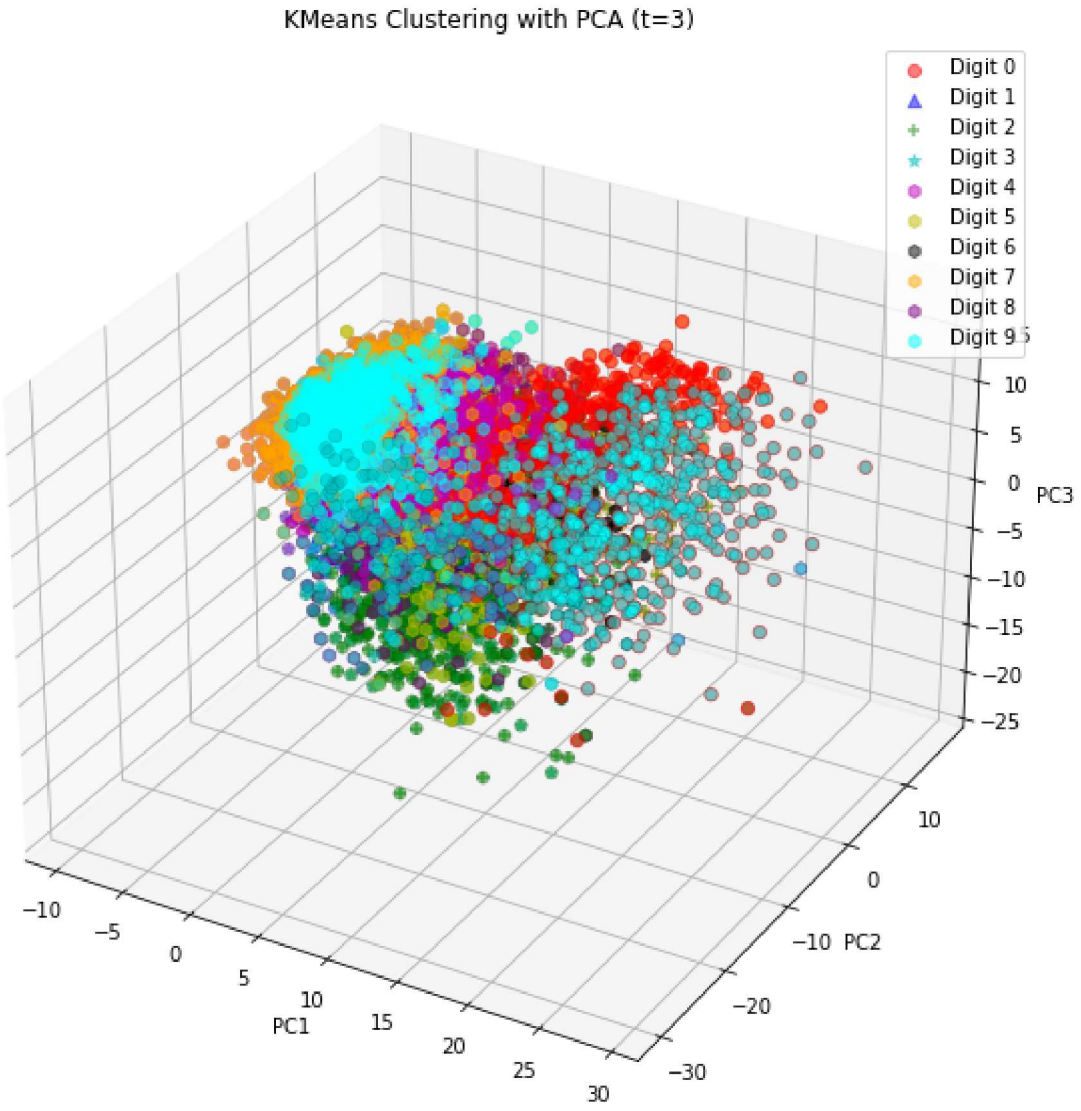
Problem 4

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from sklearn.cluster import KMeans
from sklearn.datasets import fetch_openml
from sklearn.utils import shuffle
from sklearn.preprocessing import StandardScaler
import warnings
warnings.filterwarnings('ignore')
```

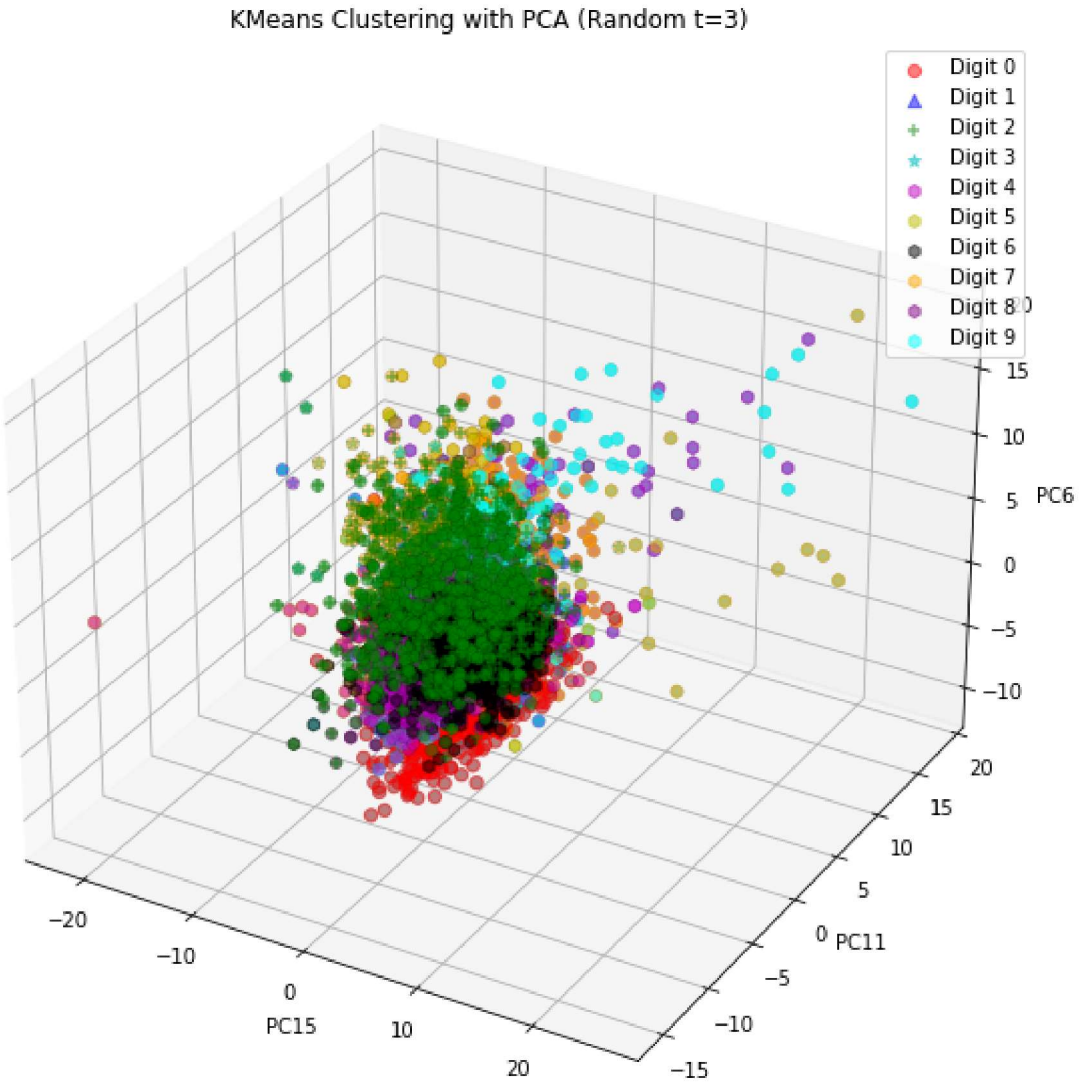
In [2]:
```
# Load MNIST dataset
mnist = fetch_openml('mnist_784')
X, y = mnist.data, mnist.target.astype(int)

# Shuffle and select a sample of 10000 data points
X, y = shuffle(X, y, random_state = 42)
X, y = X[:10000], y[:10000]

# Normalize the data by subtracting the mean and dividing by the standard devi
scaler = StandardScaler()
X = scaler.fit_transform(X)

# Perform KMeans clustering with 10 clusters
kmeans = KMeans(n_clusters = 10, random_state=42)
y_pred = kmeans.fit_predict(X)
```

In [3]:
```
# Calculate the covariance matrix
covariance_matrix = np.cov(X.T)

# Calculate the eigenvalues and eigenvectors of the covariance matrix
eigenvalues, eigenvectors = np.linalg.eig(covariance_matrix)

# Sort the eigenvalues in descending order
idx = np.argsort(eigenvalues)[::-1]
eigenvalues = eigenvalues[idx]
eigenvectors = eigenvectors[:, idx]

# Choose the number of principal components (K)
K = 3

# Project the dataset onto the K principal components
projection_matrix = eigenvectors[:, :K]
X_pca = np.dot(X, projection_matrix)
```

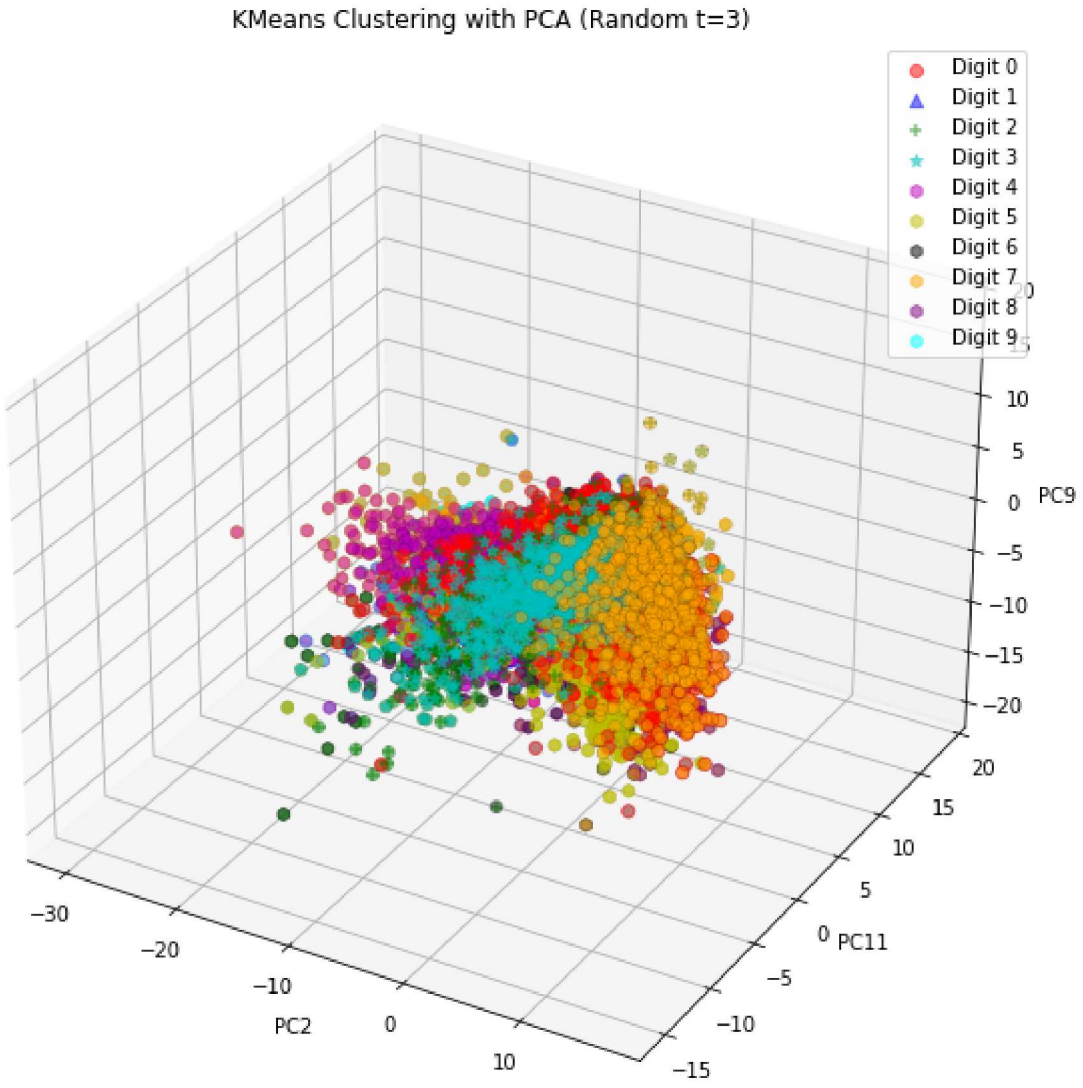
In [4]:
```
# Define shape and color mappings
markers = ['o', '^', '+', '*', 's', 'x', 'D', 'v', '>', '<']
colors = ['r', 'b', 'g', 'c', 'm', 'y', 'k', '#FFA500', '#800080', '#00FFFF']

# Plot the data in 3D with shape and color markers
fig = plt.figure(figsize=(10, 10))
ax = fig.add_subplot(111, projection='3d')

for i in range(10):
    marker = markers[i] if i < 4 else 'h'
    ax.scatter(
        X_pca[y == i, 0], X_pca[y == i, 1], X_pca[y == i, 2],
        marker=marker, s=40, c=colors[i], alpha=0.5, label=f"Digit {i}"
    )

for i in range(10):
    ax.scatter(
        X_pca[y_pred == i, 0], X_pca[y_pred == i, 1], X_pca[y_pred == i, 2],
        marker='o', s=40, c=colors[i], alpha=0.5, edgecolors='k', linewidths=0
    )

ax.set_xlabel('PC1')
ax.set_ylabel('PC2')
ax.set_zlabel('PC3')
ax.set_title('KMeans Clustering with PCA (t=3)')
ax.legend()
plt.show()
```


KMeans Clustering with PCA (t=3)
Digit 0
Digit 1
Digit 2
Digit 3
Digit 4
Digit 5
Digit 6
Digit 7
Digit 8
Digit 9
PC1
PC2
PC3

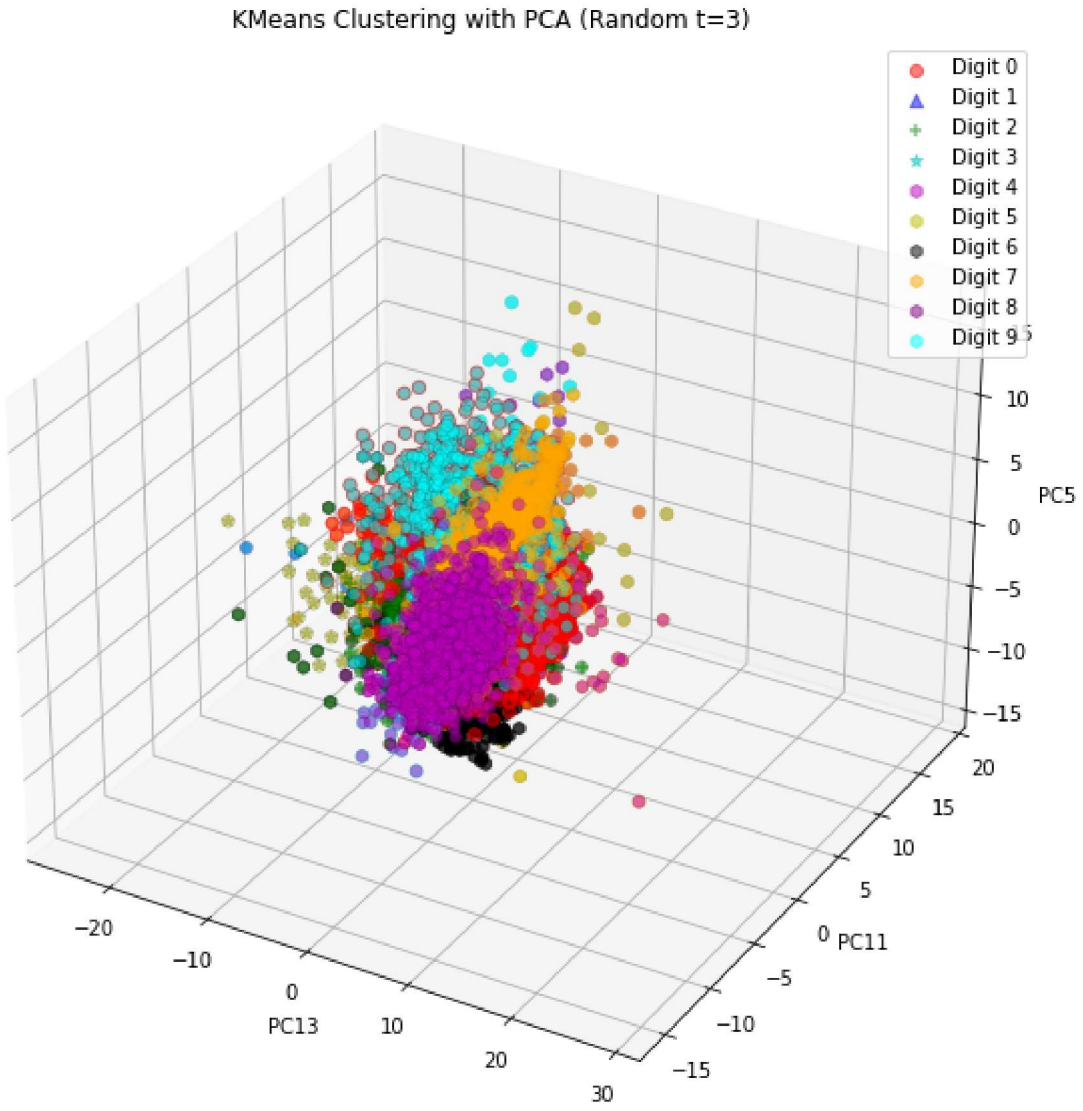
In [5]:
```
# Select 3 random eigenvalues from the top 20
random_eig_idx = np.random.choice(range(20), size=3, replace=False)
random_eig_vecs = eigenvectors[:, random_eig_idx]

# Project the dataset onto the 3 random principal components
X_pca_random = np.dot(X, random_eig_vecs)

# Plot the data in 3D with shape and color markers
fig = plt.figure(figsize=(10, 10))
ax = fig.add_subplot(111, projection='3d')

for i in range(10):
    marker = markers[i] if i < 4 else 'h'
    ax.scatter(
        X_pca_random[y == i, 0], X_pca_random[y == i, 1], X_pca_random[y == i,
        marker=marker, s=40, c=colors[i], alpha=0.5, label=f"Digit {i}"
    )

for i in range(10):
    ax.scatter(
        X_pca_random[y_pred == i, 0], X_pca_random[y_pred == i, 1], X_pca_rand
        marker='o', s=40, c=colors[i], alpha=0.5, edgecolors='k', linewidths=0
    )

ax.set_xlabel(f"PC{random_eig_idx[0]+1}")
ax.set_ylabel(f"PC{random_eig_idx[1]+1}")
ax.set_zlabel(f"PC{random_eig_idx[2]+1}")
ax.set_title('KMeans Clustering with PCA (Random t=3)')
ax.legend()
plt.show()
```


KMeans Clustering with PCA (Random t=3)
Digit 0
Digit 1
Digit 2
Digit 3
Digit 4
Digit 5
Digit 6
Digit 7
Digit 8
Digit 9
PC6
PC11
PC15
−20
−10
0
10
20
−15
−10
−5
0
5
10
15

In [6]:
```
# Select 3 random eigenvalues from the top 20
random_eig_idx = np.random.choice(range(20), size=3, replace=False)
random_eig_vecs = eigenvectors[:, random_eig_idx]

# Project the dataset onto the 3 random principal components
X_pca_random = np.dot(X, random_eig_vecs)

# Plot the data in 3D with shape and color markers
fig = plt.figure(figsize=(10, 10))
ax = fig.add_subplot(111, projection='3d')

for i in range(10):
    marker = markers[i] if i < 4 else 'h'
    ax.scatter(
        X_pca_random[y == i, 0], X_pca_random[y == i, 1], X_pca_random[y == i,
        marker=marker, s=40, c=colors[i], alpha=0.5, label=f"Digit {i}"
    )

for i in range(10):
    ax.scatter(
        X_pca_random[y_pred == i, 0], X_pca_random[y_pred == i, 1], X_pca_rand
        marker='o', s=40, c=colors[i], alpha=0.5, edgecolors='k', linewidths=0
    )

ax.set_xlabel(f"PC{random_eig_idx[0]+1}")
ax.set_ylabel(f"PC{random_eig_idx[1]+1}")
ax.set_zlabel(f"PC{random_eig_idx[2]+1}")
ax.set_title('KMeans Clustering with PCA (Random t=3)')
ax.legend()
plt.show()
```


KMeans Clustering with PCA (Random t=3)
Digit 0
Digit 1
Digit 2
Digit 3
Digit 4
Digit 5
Digit 6
Digit 7
Digit 8
Digit 9
PC9
PC11
PC2

In [7]:
```
# Select 3 random eigenvalues from the top 20
random_eig_idx = np.random.choice(range(20), size=3, replace=False)
random_eig_vecs = eigenvectors[:, random_eig_idx]

# Project the dataset onto the 3 random principal components
X_pca_random = np.dot(X, random_eig_vecs)

# Plot the data in 3D with shape and color markers
fig = plt.figure(figsize=(10, 10))
ax = fig.add_subplot(111, projection='3d')

for i in range(10):
    marker = markers[i] if i < 4 else 'h'
    ax.scatter(
        X_pca_random[y == i, 0], X_pca_random[y == i, 1], X_pca_random[y == i,
        marker=marker, s=40, c=colors[i], alpha=0.5, label=f"Digit {i}"
    )

for i in range(10):
    ax.scatter(
        X_pca_random[y_pred == i, 0], X_pca_random[y_pred == i, 1], X_pca_rand
        marker='o', s=40, c=colors[i], alpha=0.5, edgecolors='k', linewidths=0
    )

ax.set_xlabel(f"PC{random_eig_idx[0]+1}")
ax.set_ylabel(f"PC{random_eig_idx[1]+1}")
ax.set_zlabel(f"PC{random_eig_idx[2]+1}")
ax.set_title('KMeans Clustering with PCA (Random t=3)')
ax.legend()
plt.show()
```


KMeans Clustering with PCA (Random t=3)
Digit 0
Digit 1
Digit 2
Digit 3
Digit 4
Digit 5
Digit 6
Digit 7
Digit 8
Digit 9
PC5
PC11
PC13

In [7]:

In [2]:
```
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
```

```
Mounted at /content/drive
```

In [3]:
```
import pandas as pd

data = {'1': [], '2': [], '3': []}

with open('/content/drive/MyDrive/twoSpirals.txt', 'r') as f:
    for line in f:
        row = line.strip().split('\t')
        data['1'].append(float(row[0]))
        data['2'].append(float(row[1]))
        data['3'].append(float(row[2]))

df_spiral = pd.DataFrame(data)
```

In [4]:
```
df_spiral.head()
```

Out[4]:

	1	2	3
0	10.5192	-0.7170	-1.0
1	0.9987	-9.9681	-1.0
2	3.5763	8.3756	-1.0
3	1.9236	-10.6448	-1.0
4	8.1583	-5.9066	-1.0

In [5]:
```
data = {'1': [], '2': [], '3': []}

with open('/content/drive/MyDrive/threecircles.txt', 'r') as f:
    for line in f:
        row = line.strip().split(',')
        data['1'].append(float(row[0]))
        data['2'].append(float(row[1]))
        data['3'].append(float(row[2]))

df_circle = pd.DataFrame(data)
```

In [6]:
```
df_circle.head()
```

Out[6]:

	1	2	3
0	-0.208626	-0.264189	-1.0
1	0.499955	-0.073624	-1.0
2	-0.241661	-0.221071	-1.0
3	-0.356841	0.204201	-1.0
4	0.529480	0.170605	-1.0

In [8]:
```
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error


# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(df_spiral.iloc[:, :-1], df

# Fit a linear regression model on the training set
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions on the testing set and calculate RMSE
y_pred = model.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print("RMSE:", rmse)
```

```
RMSE: 0.9127353943716923
```

In [9]:
```
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error


# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(df_circle.iloc[:, :-1], df

# Fit a linear regression model on the training set
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions on the testing set and calculate RMSE
y_pred = model.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print("RMSE:", rmse)
```

```
RMSE: 0.8398584529459426
```

Two Spirals

In [17]:
```
import numpy as np
import pandas as pd

# Define the parameters of the Gaussian kernel
sigma = 1.0
gamma = 1.0 / (2.0 * sigma ** 2)

# Step 1: Calculate the kernel matrix K
n_samples = len(df_spiral)
K = np.zeros((n_samples, n_samples))
for i in range(n_samples):
    for j in range(n_samples):
        x_i = df_spiral.iloc[i].values
        x_j = df_spiral.iloc[j].values
        K[i, j] = np.exp(-gamma * np.linalg.norm(x_i - x_j) ** 2)

# Step 2: Center the kernel matrix K
one_n = np.ones((n_samples, n_samples)) / n_samples
K_centered = K - one_n.dot(K) - K.dot(one_n) + one_n.dot(K).dot(one_n)

# Step 3: Compute the eigenvectors and eigenvalues of the centered kernel matr
eigenvalues, eigenvectors = np.linalg.eig(K_centered)

# Step 4: Select the top T eigenvectors and compute the new representation of
T = 3 # number of principal components
idx = eigenvalues.argsort()[::-1][:T]
eigenvectors = eigenvectors[:, idx]
new_data = np.dot(K_centered, eigenvectors) / np.sqrt(eigenvalues[idx])

# Print the shape of the new data representation
print("Shape of the new data representation:", new_data.shape)
```

```
Shape of the new data representation: (1000, 3)
```

In [18]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import mean_squared_error

# Define the parameters of the Gaussian kernel
sigma = 1.0
gamma = 1.0 / (2.0 * sigma ** 2)

# Step 1: Calculate the kernel matrix K
n_samples = len(df_spiral)
K = np.zeros((n_samples, n_samples))
for i in range(n_samples):
    for j in range(n_samples):
        x_i = df_spiral.iloc[i].values
        x_j = df_spiral.iloc[j].values
        K[i, j] = np.exp(-gamma * np.linalg.norm(x_i - x_j) ** 2)

# Step 2: Center the kernel matrix K
one_n = np.ones((n_samples, n_samples)) / n_samples
K_centered = K - one_n.dot(K) - K.dot(one_n) + one_n.dot(K).dot(one_n)

# Step 3: Compute the eigenvectors and eigenvalues of the centered kernel matr
eigenvalues, eigenvectors = np.linalg.eig(K_centered)

# Try different values of D and evaluate the performance of linear regression
for D in [3, 20, 100]:
    # Select the top D eigenvectors and compute the new representation of the
    idx = eigenvalues.argsort()[::-1][:D]
    eigenvectors_D = eigenvectors[:, idx]
    new_data = np.dot(K_centered, eigenvectors_D) / np.sqrt(eigenvalues[idx])

    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(new_data, df_spiral.il

    # Fit a linear regression model on the training set using 10-fold cross-va
    model = LinearRegression()
    scores = cross_val_score(model, X_train, y_train, cv = 10, scoring='neg_me
    rmse = np.sqrt(-scores.mean())

    print(f"D = {D}, RMSE = {rmse}")
```

```
D = 3, RMSE = 0.8751436955790198
D = 20, RMSE = 0.37583346410762714
D = 100, RMSE = 0.09169852784284811
```

Three Circles

In [19]:
```
import numpy as np
import pandas as pd

# Define the parameters of the Gaussian kernel
sigma = 1.0
gamma = 1.0 / (2.0 * sigma ** 2)

# Step 1: Calculate the kernel matrix K
n_samples = len(df_circle)
K = np.zeros((n_samples, n_samples))
for i in range(n_samples):
    for j in range(n_samples):
        x_i = df_circle.iloc[i].values
        x_j = df_circle.iloc[j].values
        K[i, j] = np.exp(-gamma * np.linalg.norm(x_i - x_j) ** 2)

# Step 2: Center the kernel matrix K
one_n = np.ones((n_samples, n_samples)) / n_samples
K_centered = K - one_n.dot(K) - K.dot(one_n) + one_n.dot(K).dot(one_n)

# Step 3: Compute the eigenvectors and eigenvalues of the centered kernel matr
eigenvalues, eigenvectors = np.linalg.eig(K_centered)

# Step 4: Select the top T eigenvectors and compute the new representation of
T = 3 # number of principal components
idx = eigenvalues.argsort()[::-1][:T]
eigenvectors = eigenvectors[:, idx]
new_data = np.dot(K_centered, eigenvectors) / np.sqrt(eigenvalues[idx])

# Print the shape of the new data representation
print("Shape of the new data representation:", new_data.shape)
```

```
Shape of the new data representation: (1000, 3)
```

In [23]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import mean_squared_error

# Define the parameters of the Gaussian kernel
sigma = 1.0
gamma = 1.0 / (2.0 * sigma ** 2)

# Step 1: Calculate the kernel matrix K
n_samples = len(df_spiral)
K = np.zeros((n_samples, n_samples))
for i in range(n_samples):
    for j in range(n_samples):
        x_i = df_spiral.iloc[i].values
        x_j = df_spiral.iloc[j].values
        K[i, j] = np.exp(-gamma * np.linalg.norm(x_i - x_j) ** 2)

# Step 2: Center the kernel matrix K
one_n = np.ones((n_samples, n_samples)) / n_samples
K_centered = K - one_n.dot(K) - K.dot(one_n) + one_n.dot(K).dot(one_n)

# Step 3: Compute the eigenvectors and eigenvalues of the centered kernel matr
eigenvalues, eigenvectors = np.linalg.eig(K_centered)

# Try different values of D and evaluate the performance of linear regression
for D in [3, 20, 100]:
    # Select the top D eigenvectors and compute the new representation of the
    idx = eigenvalues.argsort()[::-1][:D]
    eigenvectors_D = eigenvectors[:, idx]
    new_data = np.dot(K_centered, eigenvectors_D) / np.sqrt(eigenvalues[idx])

    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(new_data, df_spiral.il

    # Fit a linear regression model on the training set using 100-fold cross-v
    model = LinearRegression()
    scores = cross_val_score(model, X_train, y_train, cv = 100, scoring='neg_m
    rmse = np.sqrt(-scores.mean())

    print(f"D = {D}, RMSE = {rmse}")
```

```
D = 3, RMSE = 0.8734927600018749
D = 20, RMSE = 0.37610237552700265
D = 100, RMSE = 0.0919786451129687
```

In [ ]: