

# 2025Final

May 11, 2025

```
[16]: import numpy as np
np.set_printoptions(precision=4) # Print few decimal places
np.set_printoptions(suppress=True) # Suppress scientific notation
import cvxpy as cp
import pandas as pd
from numpy.linalg import cholesky as llt
import matplotlib.pyplot as plt

X_train = pd.read_csv('/home/jovyan/work/Desktop/ORF307/X_train.csv').values
y_train = pd.read_csv('/home/jovyan/work/Desktop/ORF307/y_train.csv').values.
    ravel()
X_test = pd.read_csv('/home/jovyan/work/Desktop/ORF307/X_test.csv').values
y_test = pd.read_csv('/home/jovyan/work/Desktop/ORF307/y_test.csv').values.
    ravel()

n_train, m = X_train.shape
n_test, m = X_test.shape

print("-" * 50)
print("Fashion MNIST dataset")
print("-" * 50)
print(f"Number of features: {m} ({int(np.sqrt(m))} x {int(np.sqrt(m))} pixels)")
print(f"Training set:")
print(f" • Samples: {n_train}")
print(f" • Value range: [{X_train.min():.2f}, {X_train.max():.2f}]")
print(f"Test set:")
print(f" • Samples: {n_test}")
print(f" • Value range: [{X_train.min():.2f}, {X_train.max():.2f}]")

print(X_train.shape)
print(y_train)
print(y_train.shape)
```

---

Fashion MNIST dataset

---

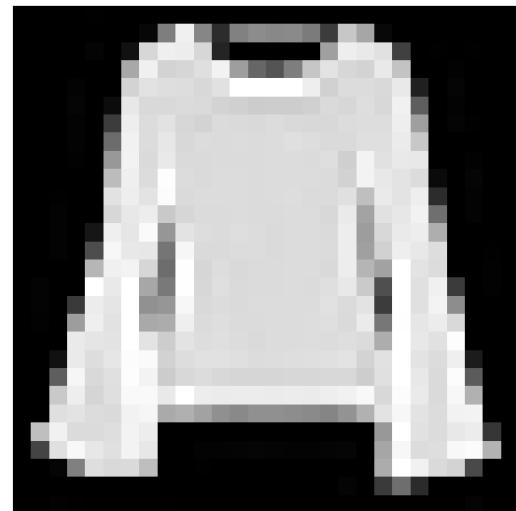
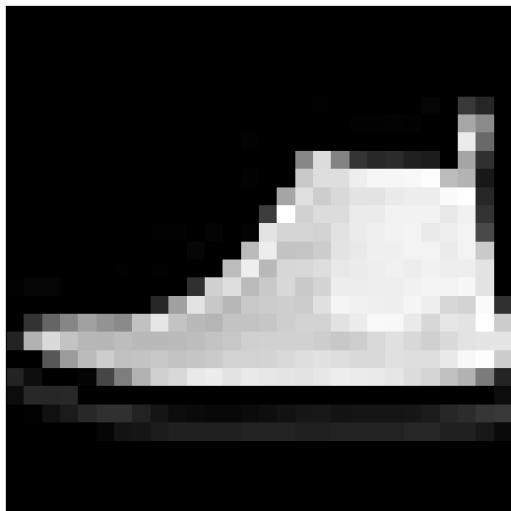
Number of features: 784 (28 x 28 pixels)

Training set:  
• Samples: 5000  
• Value range: [0.00, 255.00]

Test set:  
• Samples: 1000  
• Value range: [0.00, 255.00]  
(5000, 784)  
[ 1. -1. 1. ... 1. -1. 1.]  
(5000,)

```
[17]: def visualize_images(*images):
    n_images = len(images)
    fig, axes = plt.subplots(1, n_images, figsize=(14,6))
    if n_images == 1:
        axes = [axes]
    for i, (ax, img) in enumerate(zip(axes, images)):
        img_reshaped = img.reshape(28, 28)
        im = ax.imshow(img_reshaped, cmap='gray')
        ax.set_xticks([])
        ax.set_yticks([])
    plt.tight_layout()

example_boot = X_train[3]
example_shirt = X_train[0]
visualize_images(example_boot, example_shirt)
```



```
[18]: #Part 1 - b

def error(X, y, a, b):
    y_pred = np.sign(X @ a + b)
```

```

    return np.mean(y_pred != y)

a = cp.Variable(784)
b = cp.Variable(1)

lamda = np.array([0.0001,0.0005,0.001,0.005,0.01,0.05])
asol = [] # where to store solutions of a for different values of lamda
bsol = [] # where to store solutions of b for different values of lamda

for val in lamda:
    objective = cp.Minimize(cp.sum(cp.maximum(0, (1 - cp.multiply(y_train, ↴
        (X_train @ a + b)))))/5000
                            + val * cp.norm(a,1))
    problem = cp.Problem(objective)
    problem.solve(solver = cp.CLARABEL)
    asol.append(a.value)
    bsol.append(b.value)
    print("test error for lamda(val):", error(X_test, y_test, a.value, b.
        ↴value))

#since the lowest test error was with lamda = .05, we will use that a and b ↴
solution for other parts of this final

```

test error for lamda(val): 0.192  
 test error for lamda(val): 0.197  
 test error for lamda(val): 0.197  
 test error for lamda(val): 0.189  
 test error for lamda(val): 0.18  
 test error for lamda(val): 0.172

[3]: #Using linear programming  
 a2 = cp.Variable(784)  
 b2 = cp.Variable(1)  
 s = cp.Variable(5000)

```

z = cp.Variable(784)

lamda = np.array([0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05])
a2sol = []
b2sol = []

for val in lamda:
    objective = cp.Minimize((1/5000) * cp.sum(s) + val * cp.sum(z))
    constraints = [cp.multiply((-1 * y_train), (X_train @ a2 + b2)) <= s - ↵
    ↵1]
    constraints += [(-1 * s) <= 0]
    constraints += [a2 <= z]
    constraints += [(-1 * a2) <= z]
    problem = cp.Problem(objective, constraints)
    problem.solve(solver = cp.CLARABEL)
    a2sol.append(a2.value)
    b2sol.append(b2.value)
    #print(error(X_test, y_test, a2.value, b2.value))

```

[13]: #5 - checking dual-primal constraint relationship

```

print(z.value)
print(a2sol[5])
print(s.value)

```

```

[0.      0.      0.      0.      0.      0.0021  0.0074  0.0007  0.      0.0021
 0.0008  0.0021  0.003   0.003   0.0014  0.      0.0002  0.0031  0.0045  0.0018
 0.      0.      0.      0.      0.      0.      0.      0.      0.      0.
 0.      0.      0.      0.      0.0006  0.0009  0.0017  0.0042  0.0009  0.0023
 0.0002  0.0019  0.0001  0.0006  0.0014  0.0028  0.0002  0.0005  0.      0.0011
 0.0017  0.001  0.0016  0.      0.      0.      0.      0.      0.      0.
 0.0039  0.0026  0.0004  0.0026  0.      0.001  0.0004  0.0037  0.      0.0023
 0.0004  0.      0.0006  0.      0.0011  0.0005  0.0002  0.      0.      0.0025
 0.      0.      0.      0.      0.      0.001  0.      0.      0.0041  0.001
 0.001  0.0005  0.0054  0.      0.0001  0.0002  0.0009  0.0009  0.0004  0.0005
 0.0022  0.0009  0.0019  0.0014  0.0016  0.0017  0.0039  0.      0.0025  0.0003
 0.      0.      0.      0.      0.      0.      0.      0.      0.0003  0.0008
 0.0028  0.0002  0.0016  0.0009  0.0002  0.0019  0.0009  0.0003  0.0001  0.0007
 0.0004  0.001  0.0019  0.0013  0.0021  0.0015  0.0022  0.      0.      0.
 0.      0.      0.0024  0.0016  0.      0.      0.0013  0.0006  0.0017  0.
 0.      0.0002  0.0013  0.0022  0.0025  0.001  0.0002  0.0018  0.      0.0008
 0.0016  0.0022  0.      0.0004  0.      0.      0.002  0.      0.      0.
 0.      0.0019  0.0029  0.      0.0027  0.0026  0.0019  0.0009  0.0006  0.0002
 0.0009  0.0011  0.0001  0.0022  0.0038  0.0024  0.0008  0.0009  0.001  0.0016
 0.      0.      0.0005  0.      0.0028  0.      0.      0.0004  0.0009  0.
 0.0011  0.0013  0.      0.0021  0.      0.      0.001  0.0024  0.      0.
 0.0018  0.      0.      0.0004  0.      0.0004  0.0037  0.      0.0001  0.0006
 0.0008  0.0003  0.      0.      0.      0.0009  0.      0.      0.0029

```

0.0006	0.0008	0.0009	0.	0.	0.	0.0001	0.	0.	
0.0007	0.0001	0.0008	0.	0.0028	0.0004	0.	0.	0.	
0.0012	0.	0.	0.0039	0.	0.0012	0.	0.0011	0.0012	0.0005
0.0025	0.0023	0.0003	0.	0.0024	0.	0.	0.0006	0.001	0.
0.0001	0.0018	0.002	0.	0.	0.0007	0.0012	0.	0.0011	0.
0.	0.	0.0025	0.0022	0.	0.0015	0.0007	0.0001	0.	0.0008
0.	0.0006	0.	0.	0.0004	0.0017	0.	0.	0.	0.0002
0.0032	0.0007	0.0009	0.	0.0009	0.	0.	0.	0.	0.
0.0004	0.0005	0.0009	0.0002	0.0008	0.0021	0.0006	0.	0.0003	0.0009
0.0042	0.0015	0.	0.0005	0.0006	0.	0.0018	0.0005	0.0007	0.0014
0.0007	0.	0.0027	0.0019	0.0035	0.0021	0.	0.0011	0.0004	0.003
0.	0.0015	0.0023	0.0005	0.0001	0.0026	0.0008	0.0008	0.0018	0.
0.	0.	0.	0.0004	0.0011	0.	0.0001	0.0014	0.0005	0.0008
0.	0.	0.0002	0.	0.	0.	0.	0.	0.0003	0.0003
0.	0.	0.0004	0.	0.0028	0.0038	0.0007	0.0023	0.	0.0013
0.0011	0.	0.0011	0.0021	0.0007	0.0002	0.	0.0013	0.0006	0.
0.	0.	0.	0.0004	0.0007	0.	0.	0.	0.	0.
0.0005	0.0013	0.0004	0.0022	0.0025	0.0009	0.0006	0.0003	0.	0.0012
0.	0.0013	0.	0.	0.0003	0.0002	0.0002	0.0008	0.0003	0.
0.0072	0.0024	0.0001	0.0008	0.0012	0.	0.0001	0.001	0.	0.0001
0.0001	0.0008	0.001	0.	0.	0.0001	0.001	0.0034	0.	0.0026
0.	0.0001	0.0003	0.0008	0.	0.	0.0002	0.	0.011	0.
0.	0.0007	0.	0.0006	0.0001	0.	0.0012	0.	0.	0.0008
0.0007	0.	0.0007	0.0001	0.	0.	0.	0.0005	0.0015	0.0006
0.0009	0.	0.	0.0005	0.	0.	0.0001	0.0009	0.	0.
0.	0.0006	0.	0.	0.0021	0.	0.0007	0.	0.001	0.0008
0.	0.0012	0.	0.0021	0.0012	0.0002	0.	0.	0.	0.0013
0.	0.	0.0013	0.0053	0.	0.	0.0003	0.	0.	0.0008
0.002	0.0029	0.0016	0.	0.0024	0.0011	0.	0.	0.0015	0.0014
0.002	0.	0.0005	0.0006	0.0005	0.0016	0.0013	0.0007	0.0031	0.0017
0.	0.	0.0037	0.	0.	0.0007	0.	0.	0.0032	0.0046
0.0007	0.0032	0.0014	0.0013	0.0003	0.0004	0.003	0.001	0.0001	0.0003
0.	0.	0.0016	0.	0.0023	0.0001	0.	0.0015	0.0005	0.
0.0018	0.	0.0012	0.0007	0.004	0.	0.	0.0027	0.0018	0.
0.	0.	0.0003	0.	0.0006	0.	0.001	0.	0.	0.0013
0.0007	0.	0.0032	0.	0.	0.0007	0.	0.	0.	0.0013
0.	0.	0.0013	0.0002	0.	0.0019	0.	0.0022	0.	0.0025
0.0022	0.	0.0001	0.0021	0.	0.0002	0.	0.0019	0.0014	0.0004
0.0021	0.0005	0.0013	0.	0.	0.	0.001	0.001	0.	0.
0.0001	0.0008	0.	0.0039	0.	0.0002	0.001	0.	0.	0.
0.0021	0.0006	0.0003	0.0003	0.0009	0.0019	0.0004	0.0017	0.	0.
0.0005	0.0008	0.	0.0047	0.	0.	0.0007	0.	0.	0.
0.001	0.	0.0034	0.0016	0.0022	0.	0.	0.	0.0005	0.
0.0027	0.003	0.0003	0.	0.0018	0.	0.0005	0.0003	0.002	0.
0.	0.	0.	0.	0.	0.0036	0.	0.0004	0.	0.0011
0.0004	0.	0.005	0.0006	0.	0.0017	0.	0.0013	0.0022	0.
0.0006	0.0003	0.0005	0.0007	0.	0.0003	0.0021	0.	0.	0.
0.0018	0.	0.	0.0007	0.0025	0.0008	0.001	0.001	0.0004	0.0011

0.0002	0.0026	0.0024	0.0012	0.	0.	0.	0.0019	0.0006	0.0011
0.0012	0.0014	0.0016	0.0015	0.	0.0042	0.0017	0.	0.	0.
0.	0.0037	0.	0.0036	0.0015	0.	0.0013	0.0006	0.	0.0005
0.	0.	0.0024	0.0012	0.	0.0002	0.0014	0.0009	0.	0.0005
0.0011	0.0017	0.0014	0.0017	0.0006	0.0018	0.	0.	0.003	0.0025
0.0001	0.0014	0.0009	0.	0.	0.0043	0.0012	0.0002	0.0001	0.
0.0032	0.	0.0027	0.	0.0013	0.0009	0.0014	0.0034	0.0002	0.0004
0.	0.	0.	0.	0.	]				
[-0.	0.	0.	0.	0.	0.	0.0021	0.0074	-0.0007	-0.
0.0021	0.0008	-0.0021	0.003	-0.003	-0.0014	0.	-0.0002	-0.0031	
0.0045	-0.0018	0.	0.	0.	0.	0.	0.	0.	0.
0.	0.	-0.	0.	0.	0.	0.	0.0006	0.0009	
0.0017	-0.0042	-0.0009	-0.0023	-0.0002	-0.0019	0.0001	0.0006	-0.0014	
-0.0028	0.0002	-0.0005	0.	0.0011	0.0017	0.001	0.0016	-0.	
-0.	-0.	-0.	-0.	0.	0.	0.0039	0.0026	0.0004	
0.0026	-0.	0.001	-0.0004	0.0037	-0.	0.0023	-0.0004	-0.	
-0.	-0.0006	-0.	0.0011	-0.0005	-0.0002	-0.	0.0025	0.	
-0.	-0.	-0.	-0.	-0.	0.001	-0.	-0.0041	-0.001	
0.001	-0.0005	0.0054	-0.	0.0001	0.0002	0.0009	0.0009	0.0004	
-0.0005	-0.0022	0.0009	-0.0019	0.0014	0.0016	0.0017	-0.0039	-0.	
-0.0025	-0.0003	-0.	-0.	-0.	0.	0.	-0.	0.	
0.	-0.0003	0.0008	-0.0028	-0.0002	-0.0016	-0.0009	0.0002	0.0019	
-0.0009	0.0003	0.0001	0.0007	-0.0004	0.001	-0.0019	0.0013	-0.0021	
0.0015	-0.0022	0.	-0.	-0.	-0.	-0.	0.0024	0.0016	
-0.	0.	0.0013	-0.0006	0.0017	0.	-0.	-0.0002	-0.0013	
-0.0022	0.0025	-0.001	0.0002	-0.0018	0.	-0.0008	0.0016	0.0022	
-0.	0.0004	0.	-0.	-0.002	-0.	0.	0.	0.	
0.0019	-0.0029	0.	0.0027	-0.0026	0.0019	-0.0009	0.0006	-0.0002	
0.0009	0.0011	0.0001	-0.0022	-0.0038	0.0024	0.0008	0.0009	0.001	
-0.0016	-0.	-0.	-0.0005	0.	-0.0028	0.	0.	-0.0004	
0.0009	-0.	-0.0011	0.0013	-0.	0.0021	0.	-0.	-0.001	
0.0024	0.	0.	0.0018	-0.	0.	-0.0004	0.	0.0004	
-0.0037	-0.	-0.0001	0.0006	-0.0008	-0.0003	-0.	-0.	-0.	
-0.	-0.0009	-0.	-0.	-0.0029	-0.0006	0.0008	-0.0009	0.	
0.	-0.	0.	0.0001	-0.	0.	-0.0007	0.0001	-0.0008	
0.	0.0028	-0.0004	-0.	0.	0.	-0.	-0.0012	-0.	
0.	0.0039	-0.	-0.0012	0.	-0.0011	-0.0012	-0.0005	0.0025	
0.0023	0.0003	0.	0.0024	-0.	-0.	-0.0006	0.001	-0.	
0.0001	0.0018	-0.002	-0.	0.	-0.0007	0.0012	-0.	-0.0011	
0.	-0.	0.	0.0025	0.0022	-0.	0.0015	0.0007	-0.0001	
-0.	0.0008	0.	-0.0006	0.	0.	-0.0004	0.0017	0.	
0.	0.	0.0002	0.0032	-0.0007	-0.0009	0.	-0.0009	0.	
-0.	-0.	0.	0.	-0.0004	-0.0005	0.0009	0.0002	-0.0008	
0.0021	-0.0006	0.	-0.0003	-0.0009	0.0042	-0.0015	0.	0.0005	
0.0006	0.	0.0018	0.0005	-0.0007	-0.0014	0.0007	0.	-0.0027	
-0.0019	-0.0035	-0.0021	0.	0.0011	0.0004	0.003	0.	0.0015	
0.0023	-0.0005	0.0001	0.0026	-0.0008	-0.0008	-0.0018	-0.	-0.	
0.	0.	0.0004	-0.0011	0.	0.0001	0.0014	-0.0005	0.0008	

-0.	-0.	-0.0002	-0.	0.	-0.	0.	0.	-0.0003
-0.0003	0.	0.	0.0004	0.	0.0028	-0.0038	-0.0007	0.0023
-0.	-0.0013	-0.0011	-0.	0.0011	-0.0021	0.0007	-0.0002	-0.
0.0013	-0.0006	-0.	0.	0.	0.	-0.0004	0.0007	0.
-0.	0.	0.	0.	0.0005	0.0013	-0.0004	-0.0022	-0.0025
0.0009	-0.0006	0.0003	0.	-0.0012	0.	-0.0013	-0.	-0.
-0.0003	0.0002	0.0002	-0.0008	-0.0003	-0.	-0.0072	-0.0024	0.0001
0.0008	-0.0012	0.	0.0001	-0.001	-0.	0.0001	0.0001	-0.0008
-0.001	0.	-0.	-0.0001	0.001	-0.0034	-0.	0.0026	-0.
-0.0001	0.0003	0.0008	0.	0.	-0.0002	-0.	-0.011	0.
0.	0.0007	0.	-0.0006	-0.0001	-0.	0.0012	0.	0.
0.0008	-0.0007	0.	0.0007	0.0001	-0.	-0.	-0.	-0.0005
-0.0015	0.0006	0.0009	0.	-0.	0.0005	-0.	-0.	-0.0001
0.0009	0.	-0.	-0.	-0.0006	0.	0.	-0.0021	-0.
0.0007	0.	-0.001	0.0008	0.	0.0012	0.	-0.0021	0.0012
-0.0002	0.	-0.	-0.	-0.0013	0.	-0.	-0.0013	-0.0053
-0.	0.	0.0003	0.	0.	0.0008	-0.002	0.0029	-0.0016
-0.	-0.0024	-0.0011	0.	-0.	0.0015	0.0014	-0.002	-0.
-0.0005	-0.0006	0.0005	-0.0016	0.0013	-0.0007	0.0031	-0.0017	0.
0.	0.0037	0.	-0.	0.0007	0.	-0.	0.0032	-0.0046
0.0007	-0.0032	-0.0014	0.0013	-0.0003	0.0004	-0.003	0.001	-0.0001
0.0003	-0.	0.	0.0016	0.	-0.0023	-0.0001	0.	-0.0015
0.0005	0.	0.0018	-0.	-0.0012	0.0007	0.004	0.	-0.
-0.0027	-0.0018	-0.	0.	0.	0.0003	-0.	-0.0006	-0.
-0.001	0.	-0.	0.0013	-0.0007	0.	-0.0032	0.	0.
-0.0007	-0.	0.	0.	-0.0013	-0.	0.	-0.0013	0.0002
-0.	0.0019	0.	0.0022	-0.	-0.0025	-0.0022	0.	-0.0001
-0.0021	-0.	-0.0002	0.	-0.0019	0.0014	0.0004	0.0021	-0.0005
-0.0013	0.	0.	0.	0.	-0.001	-0.001	0.	-0.0001
-0.0008	-0.	0.0039	-0.	-0.0002	-0.001	0.	-0.	0.
0.0021	-0.0006	0.0003	0.0003	0.0009	0.0019	0.0004	0.0017	0.
-0.	-0.0005	-0.0008	0.	0.0047	-0.	0.	-0.0007	-0.
-0.	0.	0.001	0.	0.0034	-0.0016	-0.0022	-0.	-0.
0.	0.0005	0.	-0.0027	0.003	-0.0003	-0.	0.0018	0.
-0.0005	0.0003	0.002	-0.	-0.	0.	-0.	-0.	-0.
-0.0036	-0.	0.0004	0.	0.0011	0.0004	-0.	-0.005	-0.0006
0.	0.0017	-0.	0.0013	0.0022	-0.	-0.0006	0.0003	0.0005
0.0007	0.	-0.0003	-0.0021	-0.	-0.	0.	-0.0018	-0.
-0.	-0.0007	-0.0025	0.0008	-0.001	-0.001	-0.0004	0.0011	-0.0002
-0.0026	0.0024	0.0012	-0.	0.	-0.	-0.0019	0.0006	0.0011
-0.0012	0.0014	0.0016	-0.0015	0.	0.0042	0.0017	0.	-0.
-0.	0.	0.0037	-0.	-0.0036	0.0015	0.	-0.0013	0.0006
-0.	-0.0005	0.	0.	0.0024	0.0012	0.	-0.0002	-0.0014
0.0009	-0.	-0.0005	-0.0011	0.0017	0.0014	0.0017	0.0006	0.0018
-0.	-0.	-0.003	-0.0025	-0.0001	-0.0014	-0.0009	-0.	0.
-0.0043	-0.0012	-0.0002	0.0001	0.	0.0032	-0.	0.0027	0.
-0.0013	-0.0009	0.0014	-0.0034	0.0002	-0.0004	-0.	-0.	-0.
0.	]							

[0. 0. 0. ... 0. 0. 0.]

[19]: #Dual Problem- Part A question 4

```
w1 = cp.Variable(5000, nonneg = True)
w2 = cp.Variable(5000, nonneg = True)
w3 = cp.Variable(784, nonneg = True)
w4 = cp.Variable(784, nonneg = True)
lam = .025

objective = cp.Maximize(-cp.sum(w1))
constraints = [w3 + w4 == lam * np.ones(784)]
constraints += [(-1 *w1) @ y_train == 0]
constraints += [w3 - w4 == X_train.T @ (cp.multiply(w1, y_train))]
constraints += [w1 + w2 == (1/5000) * np.ones(5000)]
problem2 = cp.Problem(objective, constraints)
problem2.solve(solver = cp.CLARABEL)

print(w1.value)
print(w2.value)
print(w3.value)
print(w4.value)
```

## #Question 5





[161]: #Part B Question 3

```
u = cp.Variable(784)
x = cp.Variable(784)

objective = cp.Minimize(cp.sum(u))
```

```

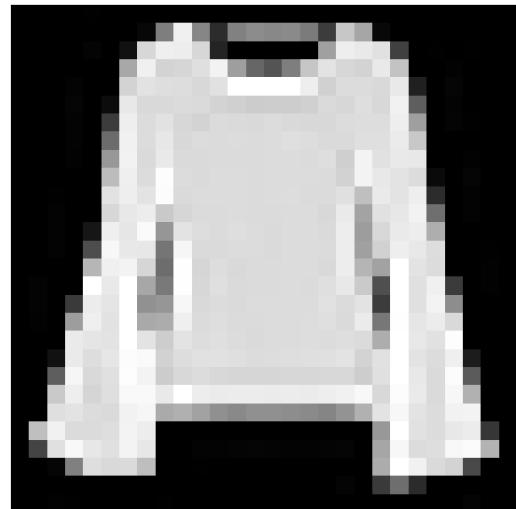
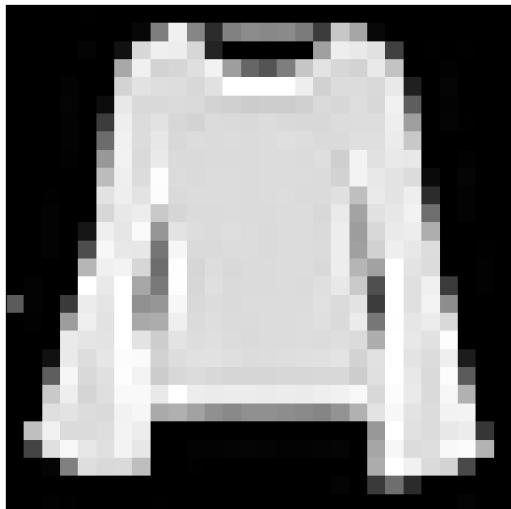
constraints = [x - example_shirt <= u]
constraints += [-(x - example_shirt) <= u]
constraints += [ x @ asol[5] + bsol[5] <= 0]
constraints += [x >= 0, x <= 255]
problem4 = cp.Problem(objective, constraints)
problem4.solve()
xsol = x.value
visualize_images(xsol, example_shirt)
#print(xsol)
#print(example_shirt)
t = np.sum(np.abs(xsol - example_shirt))
print("l1 norm distance:", t) # l1-norm distance
count = 0
for i in range(0, 784):
    if( xsol[i] == example_shirt[i]):
        count = count + 1

print("pixel difference:", count) #pixels that are different

```

l1 norm distance: 91.17502362538634

pixel difference: 1



[ ]:

[21]: #Part 3

```

# get shirt training and testing datasets
shirt_indices_train = np.where(y_train == 1)[0]

```

```

X_shirt_train = X_train[shirt_indices_train]
n_shirt_train = X_shirt_train.shape[0]
inspection_capacity_train = int(0.4 * n_shirt_train)

shirt_indices_test = np.where(y_test == 1)[0]
X_shirt_test = X_test[shirt_indices_test]
n_shirt_test = X_shirt_test.shape[0]
inspection_capacity_test = int(0.4 * n_shirt_test)
shirt_prob = []

#part a
for i in range(0, 2500):
    f = -(X_shirt_train[i] @ asol[5] + bsol[5])
    o = 1 / (1 + np.exp(-f))
    shirt_prob.append(o)
    #print(o)
print(X_shirt_train.shape)
print(X_shirt_test.shape)
print(len(shirt_prob))

#part b- "naive approach"

for j in range(0, 2500):
    if(shirt_prob[j] >= .8):
        print(shirt_prob[j], j)

print("cut-off")

for j in range(0, 2500):
    if(shirt_prob[j] >= .9):
        print(shirt_prob[j], j)

print("cut off")

for j in range(0, 2500):
    if(shirt_prob[j] >= .95):
        print(shirt_prob[j], j)

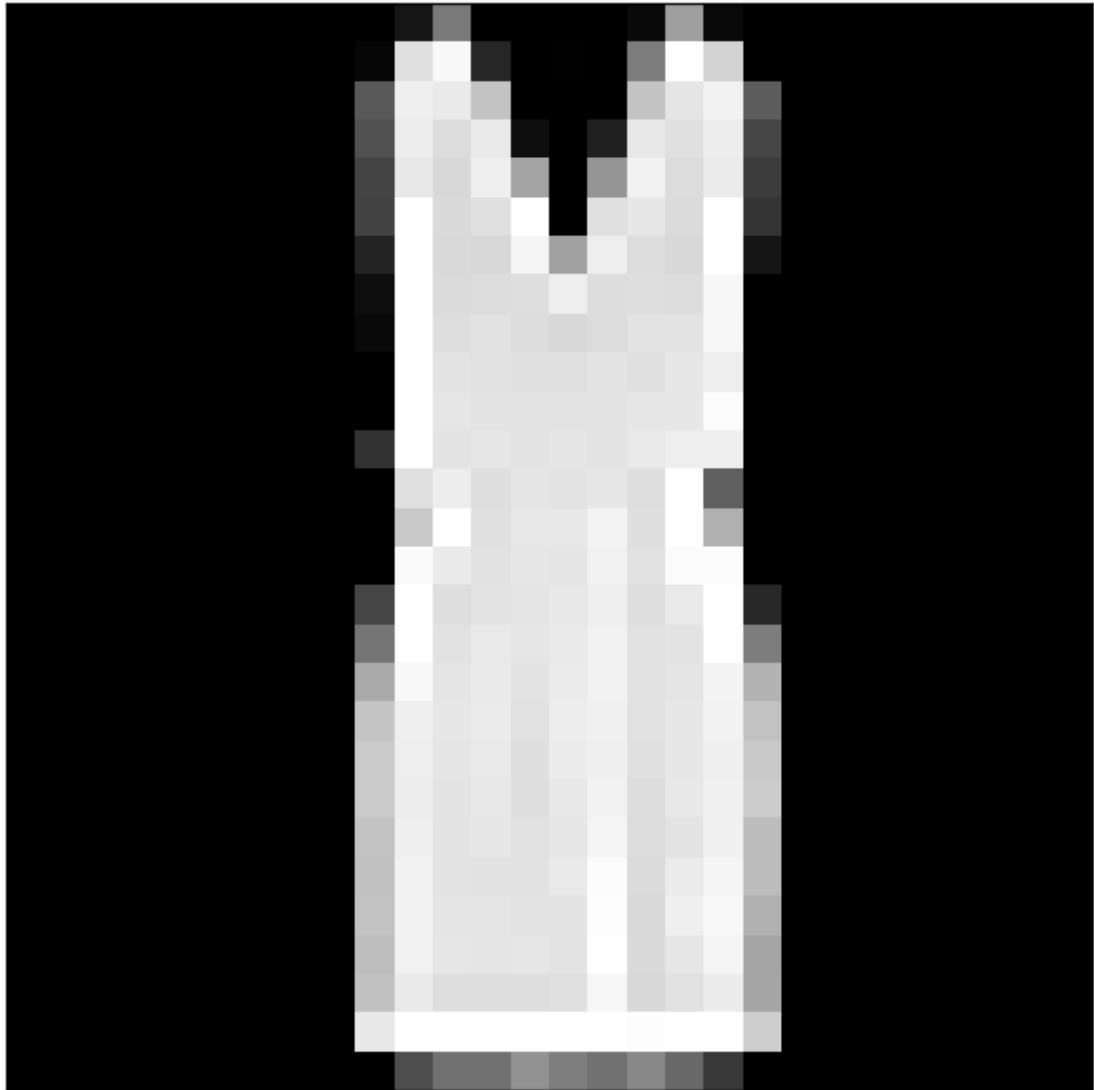
print("cut off")

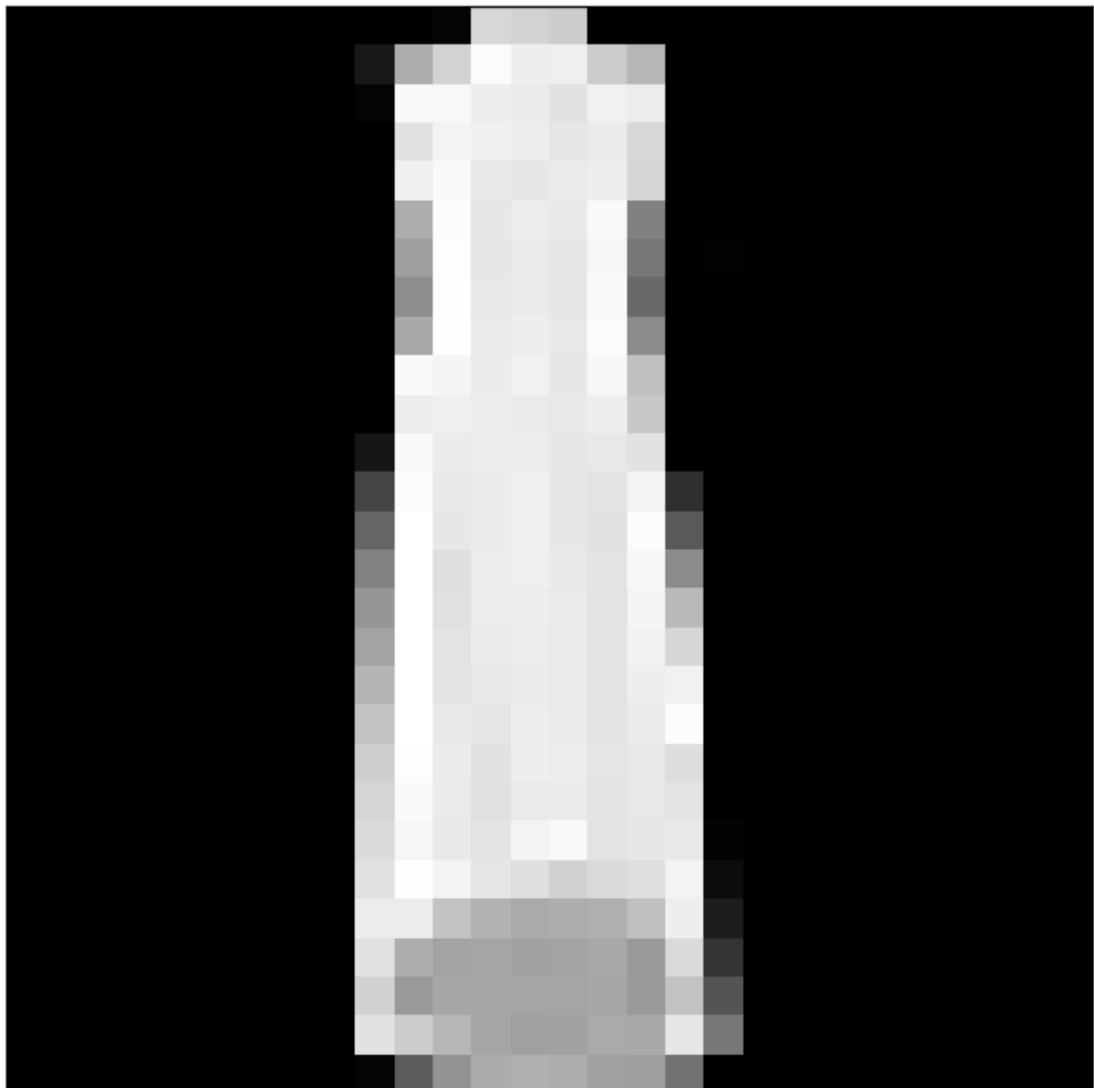
#shirt images
visualize_images(X_shirt_train[253])
visualize_images(X_shirt_train[914])
visualize_images(X_shirt_train[2366])

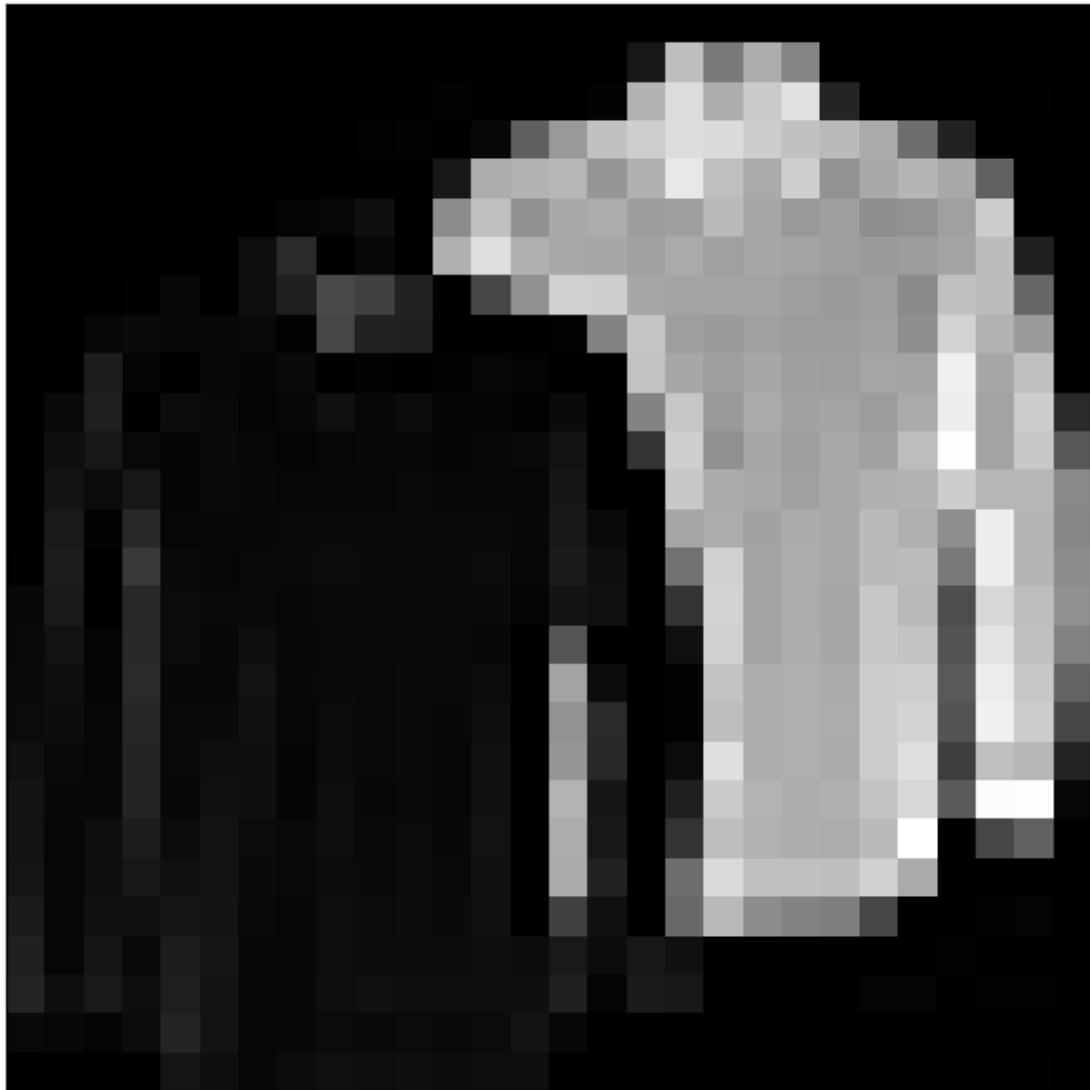
```

(2500, 784)  
(500, 784)  
2500  
[0.9148] 165  
[0.9972] 253  
[0.8637] 345  
[0.8014] 364  
[0.8119] 448  
[0.9092] 468  
[0.8537] 503  
[0.8988] 540  
[0.8284] 597  
[0.8768] 607  
[0.8472] 664  
[0.8357] 677  
[0.9411] 692  
[0.92] 863  
[0.9822] 914  
[0.8938] 954  
[0.8045] 1011  
[0.861] 1075  
[0.8351] 1158  
[0.8183] 1285  
[0.9326] 1306  
[0.8006] 1322  
[0.8535] 1363  
[0.8557] 1369  
[0.9302] 1422  
[0.9541] 1562  
[0.8264] 1583  
[0.804] 1609  
[0.8926] 1783  
[0.9443] 1815  
[0.8378] 1877  
[0.8324] 2271  
[0.9779] 2366  
[0.8394] 2393  
[0.932] 2477  
cut-off  
[0.9148] 165  
[0.9972] 253  
[0.9092] 468  
[0.9411] 692  
[0.92] 863  
[0.9822] 914  
[0.9326] 1306  
[0.9302] 1422  
[0.9541] 1562

```
[0.9443] 1815  
[0.9779] 2366  
[0.932] 2477  
cut off  
[0.9972] 253  
[0.9822] 914  
[0.9541] 1562  
[0.9779] 2366  
cut off
```







```
[22]: #3d  
# training  
c = 10  
d = 20  
s = 15  
w = cp.Variable(2500, boolean = True)  
objective = cp.Minimize( 10 * cp.sum(w) + d * cp.sum(cp.multiply((1-w),  
shirt_prob))  
- 15 * cp.sum(cp.multiply(w, shirt_prob)))  
constraint = [ cp.sum(w) <=inspection_capacity_train]  
problem5 = cp.Problem(objective, constraint)  
problem5.solve(solver = cp.SCIPY)  
wsol = w.value
```

```
print("expected cost train:", problem5.objective.value)
print(wsol)
```

```
/opt/conda/lib/python3.11/site-
packages/cvxpy/reductions/solvers/solving_chain.py:407: UserWarning: The problem
includes expressions that don't support CPP backend. Defaulting to the SCIPY
backend for canonicalization.
    warnings.warn(UserWarning(
expected cost train: 7482.488318449875
[0. 0. 0. ... 1. 0. 0.]
```

```
[139]: #3d
# testing
shirt_prob2 = []
for i in range(0, 500):
    f = -(X_shirt_test[i] @ asol[5] + bsol[5])
    o = 1 / (1 + np.exp(-f))
    shirt_prob2.append(o)

c = 10
d = 20
s = 15
w = cp.Variable(500, boolean = True)
objective = cp.Minimize( 10 * cp.sum(w) + d * cp.sum(cp.multiply((1-w), shirt_prob2))
                           - 15 * cp.sum(cp.multiply(w, shirt_prob2)))
constraint = [ cp.sum(w) <=inspection_capacity_test]
problem5 = cp.Problem(objective, constraint)
problem5.solve(solver = cp.SCIPY)
print("expected cost test:", problem5.objective.value)
wsol = w.value
print(wsol)
```

```
1328.7581449199374
[1. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 1.
 0. 1. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 1. 0. 0. 0. 0. 1. 1.
 0. 1. 0. 0. 1. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 1. 1. 0.
 0. 1. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 1. 0. 0. 0. 1. 1.
 1. 1. 0. 0. 0. 0. 1. 1. 0. 1. 0. 1. 1. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 1. 1. 0.
 1. 1. 0. 1. 1. 0. 1. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 1. 1. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 1. 1.
 0. 0. 1. 0. 0. 1. 1. 1. 0. 0. 1. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0.
 0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 1. 1. 1. 0. 1. 1. 0. 1. 0. 1. 0. 1. 0. 0. 0. 1. 0. 0. 1. 0. 1. 0. 0. 0. 1. 0. 0. 0. 1.
 1. 1. 1. 0. 1. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 1. 1. 0. 0. 0. 1. 1. 0. 0. 1. 1. 0.
 0. 1. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 1. 0. 1. 0. 0. 1. 0. 1. 1. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 1.
 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 1. 0. 0. 1. 0. 1.
```

```
0. 0. 1. 0. 0. 1. 0. 0. 0. 1. 0. 1. 1. 0. 1. 0. 0. 0. 1. 0. 0.  
1. 0. 1. 1. 1. 0. 0. 0. 0. 1. 0. 0. 0. 0. 1. 1. 0. 0. 0. 0. 0. 1. 1.  
1. 0. 0. 1. 0. 0. 0. 0. 1. 1. 0. 0. 0. 0. 1. 0. 0. 1. 1. 0. 0. 0. 0. 0.  
0. 0. 1. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 1. 1. 0. 1. 0. 0.  
0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 1. 0. 1. 1. 0. 1. 0.  
0. 0. 0. 0. 1. 1. 0. 0. 0. 0. 1. 0. 0. 0. 1. 1. 1. 1. 0. 0. 0. 0. 1.  
0. 0. 1. 1. 0. 1. 1. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0. 0.  
1. 0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0. 0. 1. 1. 0. 0. 0. 0. 1.]
```

[ ]: