Laboratorium 7: Restricted Boltzmann Machines i Deep Belief Networks

5 Ekstrakcja cech za pomocą Restricted Boltzmann Machine

- Wczytaj zbiór danych. Są to obrazy w skali szarości, przypisane do jednej z wielu klas, z pre-definiowanym podziałem na zbiór treningowy i testowy (w przypadku MNIST oraz Fashion-MNIST jest to 60000 rekordów treningowych i 10000 testowych).

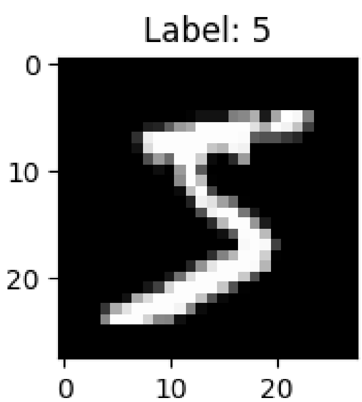
```
import matplotlib.pyplot as plt
import tensorflow as tf
import numpy as np

(x_train, y_train), (x_test, y_test) =
tf.keras.datasets.mnist.load_data()
(f_x_train, f_y_train), (f_x_test, f_y_test) =
tf.keras.datasets.fashion_mnist.load_data()

k_x_train = np.load("kmnist-train-imgs.npz")['arr_0']
k_y_train = np.load("kmnist-train-labels.npz")['arr_0']
k_x_test = np.load("kmnist-test-imgs.npz")['arr_0']
k_y_test = np.load("kmnist-test-labels.npz")['arr_0']

# data for MNIST
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
print(f"Labels: {np.unique(y_train)}")

(60000, 28, 28)
(60000,)
(10000, 28, 28)
(10000,)
Labels: [0 1 2 3 4 5 6 7 8 9]

# data for FASHION-MNIST
print(f_x_train.shape)
print(f_y_train.shape)
print(f_x_test.shape)
print(f_y_test.shape)
print(f"Labels: {np.unique(f_y_train)}")

(60000, 28, 28)
(60000,)
(10000, 28, 28)
```

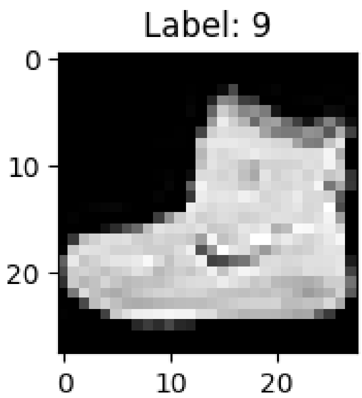
```
(10000,)
Labels: [0 1 2 3 4 5 6 7 8 9]
```

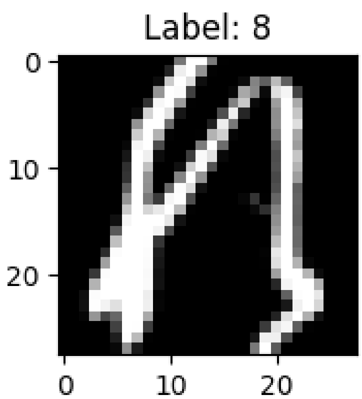
```
# data for Kuzushiji-MNIST
print(k_x_train.shape)
print(k_y_train.shape)
print(k_x_test.shape)
print(k_y_test.shape)
print(f"Labels: {np.unique(k_y_train)}")
```

```
(60000, 28, 28)
(60000,)
(10000, 28, 28)
(10000,)
Labels: [0 1 2 3 4 5 6 7 8 9]
```

```
plt.figure(figsize=(2,2))
plt.imshow(x_train[0], cmap='gray')
plt.title(f"Label: {y_train[0]}")
plt.show()

plt.figure(figsize=(2,2))
plt.imshow(f_x_train[0], cmap='gray')
plt.title(f"Label: {f_y_train[0]}")
plt.show()

plt.figure(figsize=(2,2))
plt.imshow(k_x_train[0], cmap='gray')
plt.title(f"Label: {k_y_train[0]}")
plt.show()
```



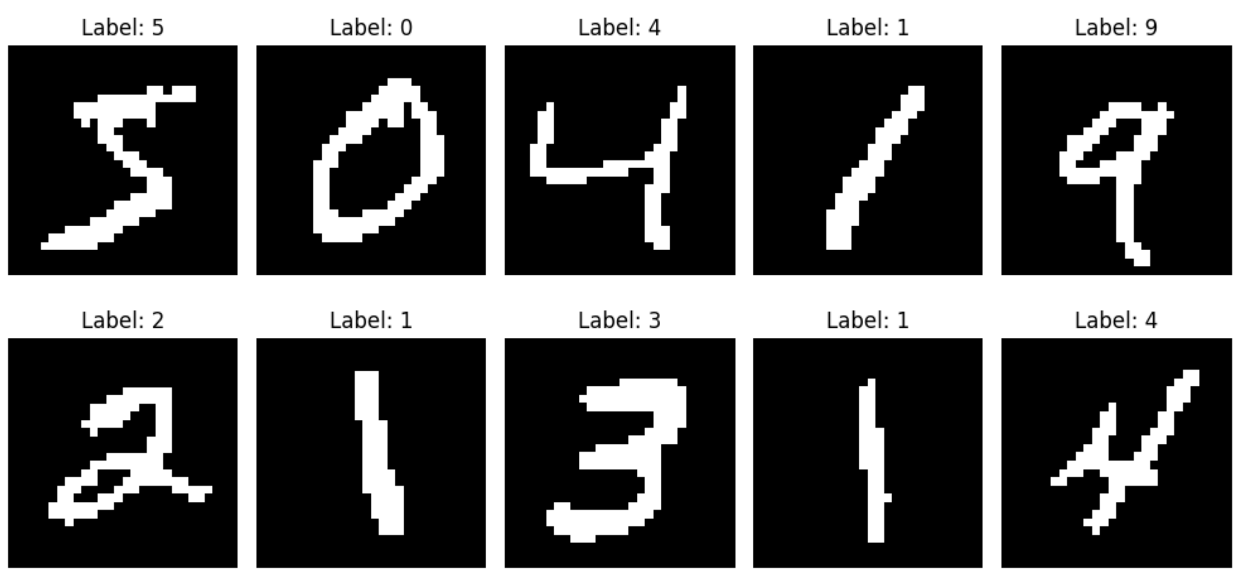




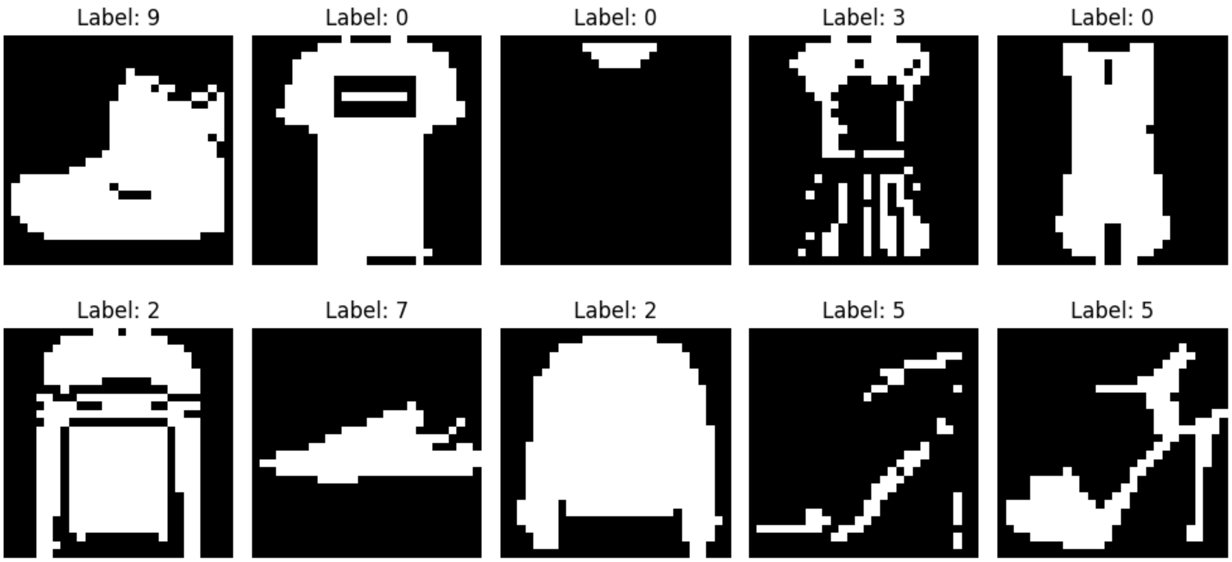
- Dokonaj binaryzacji[1] obrazów (zarówno zbiór treningowy, jak i testowy), a następnie wyświel 10 przykładowych rekordów ze zbioru treningowego.
- Dokonaj konwersji danych na tablice numpy

```
from sklearn.preprocessing import binarize

def binarize_mnist(data):
  result = []
  for image in data:
    result.append(binarize(image, threshold=127))
  return result

def binarize_for_mnist():
  b_x_train = binarize_mnist(x_train)
  b_x_test = binarize_mnist(x_test)
  return np.array(b_x_train).astype(np.uint8),
np.array(b_x_test).astype(np.uint8)

def binarize_for_f_mnist():
  b_f_x_train = binarize_mnist(f_x_train)
  b_f_x_test = binarize_mnist(f_x_test)
  return np.array(b_f_x_train).astype(np.uint8),
np.array(b_f_x_test).astype(np.uint8)
```

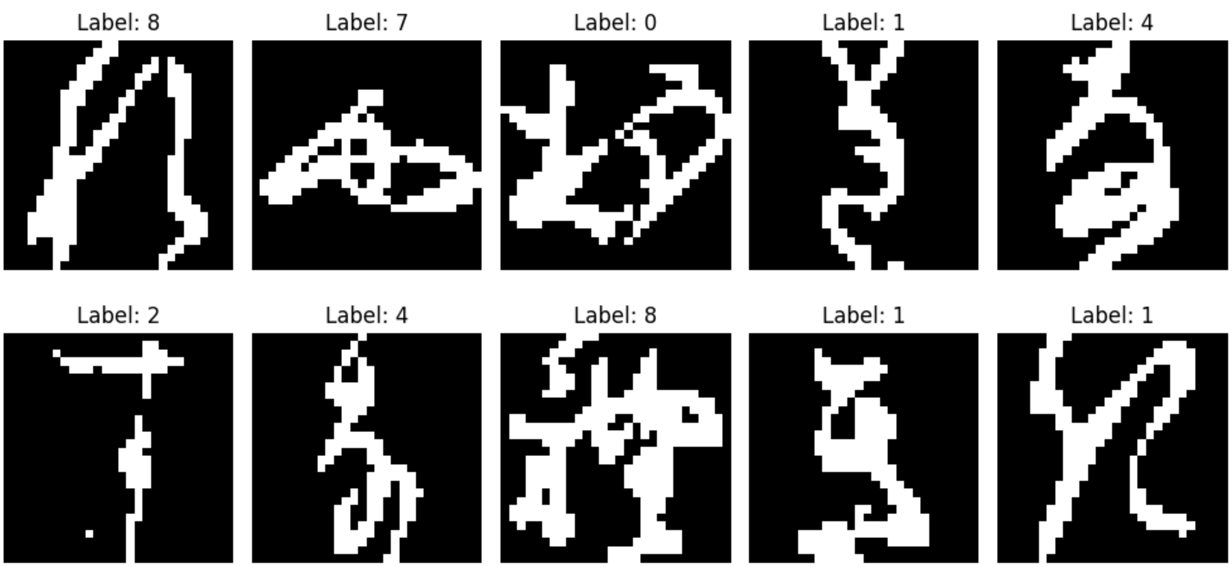
```
def binarize_for_k_mnist():
  b_k_x_train = binarize_mnist(k_x_train)
  b_k_x_test = binarize_mnist(k_x_test)
  return np.array(b_k_x_train).astype(np.uint8),
np.array(b_k_x_test).astype(np.uint8)

b_x_train, b_x_test = binarize_for_mnist()
b_f_x_train, b_f_x_test = binarize_for_f_mnist()
b_k_x_train, b_k_x_test = binarize_for_k_mnist()

y_train = np.array(y_train).astype(np.uint8)
y_test = np.array(y_test).astype(np.uint8)

f_y_train = np.array(f_y_train).astype(np.uint8)
f_y_test = np.array(f_y_test).astype(np.uint8)

k_y_train = np.array(k_y_train).astype(np.uint8)
k_y_test = np.array(k_y_test).astype(np.uint8)

def plot_ten_images(x_data, y_data, lbl='Label'):
  plt.figure(figsize=(10, 5))
  for i in range(10):
      plt.subplot(2, 5, i + 1)
      plt.imshow(x_data[i], cmap='gray')
      plt.title(f"{lbl}: {y_data[i]}")
      plt.axis('off')

  plt.tight_layout()
  plt.show()

plot_ten_images(b_x_train, y_train)
```



```
plot_ten_images(b_f_x_train, f_y_train)
```




```
plot_ten_images(b_k_x_train, k_y_train)
```




```
# Prepare data
# Flatten images
b_x_train = b_x_train.reshape(-1, 28 * 28)
b_x_test = b_x_test.reshape(-1, 28 * 28)

b_f_x_train = b_f_x_train.reshape(-1, 28 * 28)
b_f_x_test = b_f_x_test.reshape(-1, 28 * 28)

b_k_x_train = b_k_x_train.reshape(-1, 28 * 28)
```

```
b_k_x_test = b_k_x_test.reshape(-1, 28 * 28)

# Scale images to [0, 1]
x_train = x_train.astype(np.float32)/255.0
x_train = x_train.reshape(-1, 28*28)

f_x_train = f_x_train.astype(np.float32)/255.0
f_x_train = f_x_train.reshape(-1, 28*28)

k_x_train = k_x_train.astype(np.float32)/255.0
k_x_train = k_x_train.reshape(-1, 28*28)

x_test = x_test.astype(np.float32) / 255.0
x_test = x_test.reshape(-1, 28*28)

f_x_test = f_x_test.astype(np.float32) / 255.0
f_x_test = f_x_test.reshape(-1, 28*28)

k_x_test = k_x_test.astype(np.float32) / 255.0
k_x_test = k_x_test.reshape(-1, 28*28)
```

- Zbuduj Pipeline złożony z: – BernoulliRBM do ekstrakcji cech – LogisticRegression jako klasyfikatora

```
from sklearn.neural_network import BernoulliRBM
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV

baseline_classifier = LogisticRegression()
pipe = Pipeline([('rbm', BernoulliRBM(n_components=50, n_iter=2)),
('regression', LogisticRegression())])
f_pipe = Pipeline([('rbm', BernoulliRBM(n_components=50, n_iter=2)),
('regression', LogisticRegression())])
k_pipe = Pipeline([('rbm', BernoulliRBM(n_components=50, n_iter=2)),
('regression', LogisticRegression())])

pipe.fit(b_x_train, y_train).score(b_x_test, y_test)
```

```
/home/adrian/dev/um-labs/lab_RBM/.venv/lib/python3.11/site-packages/
sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
```

```
regression
  n_iter_i = _check_optimize_result(

0.8947

pipe2 = Pipeline([('rbm', BernoulliRBM(n_components=50, n_iter=10)),
('regression', LogisticRegression())])
pipe2.fit(b_x_train, y_train).score(b_x_test, y_test)

/home/adrian/dev/um-labs/lab_RBM/.venv/lib/python3.11/site-packages/
sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

0.8961

f_pipe.fit(b_f_x_train, f_y_train).score(b_f_x_test, f_y_test)

/home/adrian/dev/um-labs/lab_RBM/.venv/lib/python3.11/site-packages/
sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

0.7227

k_pipe.fit(b_f_x_train, f_y_train).score(b_f_x_test, f_y_test)

/home/adrian/dev/um-labs/lab_RBM/.venv/lib/python3.11/site-packages/
sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
```

```
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

0.7144
```

- Dostrój hiperparametry modelu korzystając z wyszukiwania siatkowego i walidacji krzyżowej (GridSearchCV). Siatkę parametrów możesz dobrać stosowanie do zbioru danych i dostępnych zasobów obliczeniowych. Przykładowa siatka znajduje się poniżej.

```
param_grid = {
    'rbm__n_components': [70, 80, 90],
    'rbm__learning_rate': [0.05, 0.1],
    'rbm__batch_size': [10, 20],
    'rbm__n_iter': [5],
    'regression__C': [0.1, 0.5, 1.0]
}

grid_search = GridSearchCV(
    estimator=pipe,
    param_grid=param_grid,
    scoring='accuracy',
    cv=5,
    verbose=2,
    n_jobs=5
)

grid_search.fit(b_x_train, y_train)

print("Best params:", grid_search.best_params_)
print("Best score:", grid_search.best_score_)

print("Best params:", grid_search.best_params_)
print("Best score:", grid_search.best_score_)

Best params: {'rbm__batch_size': 20, 'rbm__learning_rate': 0.05,
'rbm__n_components': 90, 'rbm__n_iter': 5, 'regression__C': 1.0}
Best score: 0.9215833333333332

f_grid_search = GridSearchCV(
    estimator=f_pipe,
    param_grid=param_grid,
    scoring='accuracy',
    cv=5,
    verbose=2,
    n_jobs=5
)
```

```
f_grid_search.fit(b_f_x_train, f_y_train)

print("Best params:", f_grid_search.best_params_)
print("Best score:", f_grid_search.best_score_)

Best params: {'rbm__batch_size': 20, 'rbm__learning_rate': 0.05,
'rbm__n_components': 90, 'rbm__n_iter': 5, 'regression__C': 1.0}
Best score: 0.7785833333333334

k_grid_search = GridSearchCV(
    estimator=k_pipe,
    param_grid=param_grid,
    scoring='accuracy',
    cv=5,
    verbose=2,
    n_jobs=5
)

k_grid_search.fit(b_k_x_train, k_y_train)

print("Best params:", k_grid_search.best_params_)
print("Best score:", k_grid_search.best_score_)

Best params: {'rbm__batch_size': 10, 'rbm__learning_rate': 0.1,
'rbm__n_components': 90, 'rbm__n_iter': 5, 'regression__C': 0.5}
Best score: 0.8454666666666666
```

- Przedstaw i skomentuj otrzymane wartości hiperparametrów, a następnie wytrenuj zgodnie z nimi RBM i klasyfikator.

Komentarz do wyników hiperparametrów:

Dla zbiorów MNIST i F-MNIST batch-size zostały wybrany większy co daje większą stabilizację obliczeń, a learning-rate mniejszy więc uczenie będzie dokładniejsze. Ilość n_components dla każdego z przypadków została wybrana największa. Łatwiej dokonać ekstrakcji cech przy większej ilości komponentów. Wtedy uczenie staje się \dokładniejsze. Ilość iteracji została ustalona na 5, ponieważ wtedy są szybsze obliczenia. Domyślna wartość to 10 i dla ostatecznych wyników taka została ustalona. Dla K-MNIST parametry batch-size, learning-rate i regression_C zostały wybrane nieco inne i dla nich best score wyszedł większy, ale po testowaniu tych parametrów to nie potwierdza się w poniższych wynikach (tutaj best score 0.845, a poniżej 0.7285), dlatego nie rozumiem jak to się stało.

```
pipe = Pipeline([('rbm',
BernoulliRBM(n_components=grid_search.best_params_['rbm__n_components'
], batch_size=grid_search.best_params_['rbm__batch_size'],
learning_rate=grid_search.best_params_['rbm__learning_rate'],
n_iter=10)), ('regression',
LogisticRegression(C=grid_search.best_params_['regression__C']))])
f_pipe = Pipeline([('rbm',
```

```
BernoulliRBM(n_components=f_grid_search.best_params_['rbm__n_component
s'], batch_size=f_grid_search.best_params_['rbm__batch_size'],
learning_rate=f_grid_search.best_params_['rbm__learning_rate'],
n_iter=10)), ('regression',
LogisticRegression(C=f_grid_search.best_params_['regression__C']))])
k_pipe = Pipeline([('rbm',
BernoulliRBM(n_components=k_grid_search.best_params_['rbm__n_component
s'], batch_size=k_grid_search.best_params_['rbm__batch_size'],
learning_rate=k_grid_search.best_params_['rbm__learning_rate'],
n_iter=10)), ('regression',
LogisticRegression(C=k_grid_search.best_params_['regression__C']))])
```

```
pipe.fit(b_x_train, y_train).score(b_x_test, y_test)
```

```
/home/adrian/dev/um-labs/lab_RBM/.venv/lib/python3.11/site-packages/
sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs
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Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
0.9266
```

```
f_pipe.fit(b_f_x_train, f_y_train).score(b_f_x_test, f_y_test)
```

```
/home/adrian/dev/um-labs/lab_RBM/.venv/lib/python3.11/site-packages/
sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs
failed to converge (status=1):
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Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
0.779
```

```
k_pipe.fit(b_k_x_train, k_y_train).score(b_k_x_test, k_y_test)
```

```
0.7285
```

```
k_pipe_from_grid = k_grid_search.best_estimator_
k_pipe_from_grid.score(b_k_x_test, k_y_test)

0.7238
```

- Dokonaj klasyfikacji na zbiorze testowym i przedstaw szczegółowo wyniki (accuracy, precision, recall, f1-score): – Na poziomie każdej klasy – Zbiorcze

```
from sklearn.metrics import accuracy_score, recall_score, f1_score,
precision_score

def result_scores(y_true, y_pred):
  res_acc = accuracy_score(y_true, y_pred, )
  res_recall = recall_score(y_true, y_pred, average='micro')
  res_f1 = f1_score(y_true, y_pred, average='micro')
  res_prec = precision_score(y_true, y_pred, average='micro')

  print(f"Results: ")
  print(f"\tAccuracy: {res_acc}")
  print(f"\tRecall: {res_recall}")
  print(f"\tF1-score: {res_f1}")
  print(f"\tPrecision: {res_prec}")

# Extract classes
def extract_classes(y_data):
  mnist_classes = np.unique(y_data)
  indices_of_mnist_classes = {
      "0": [],
      "1": [],
      "2": [],
      "3": [],
      "4": [],
      "5": [],
      "6": [],
      "7": [],
      "8": [],
      "9": []
  }

  amount_of_elements = 0
  for nr_class in mnist_classes:
      indices_of_mnist_classes[str(nr_class)] = np.argwhere(y_data ==
nr_class).reshape(-1)
      amount_of_elements +=
len(indices_of_mnist_classes[str(nr_class)])

  assert amount_of_elements == len(y_data)

  return indices_of_mnist_classes
```

```python
y_test_classes = extract_classes(y_test)
f_y_test_classes = extract_classes(f_y_test)
k_y_test_classes = extract_classes(k_y_test)

def results_for_every_class(model, x_data, y_data):
  data_classes = np.unique(y_data)
  indices_classes = extract_classes(y_data)

  for single_class in data_classes:
    print(f"Class: {single_class}")
    y_pred = model.predict(x_data[indices_classes[str(single_class)]])
    result_scores(y_data[indices_classes[str(single_class)]], y_pred)

print(f"For MNIST dataset:")
print(f"Baseline: ")
baseline_classifier.fit(x_train, y_train)
y_pred_baseline = baseline_classifier.predict(x_test)
result_scores(y_test, y_pred_baseline)

print(f"For classes: ")
results_for_every_class(pipe, b_x_test, y_test)

print(f"For all:")
y_pred_all = pipe.predict(b_x_test)
result_scores(y_test, y_pred_all)
```

```
For MNIST dataset:
Baseline:

/home/adrian/dev/um-labs/lab_RBM/.venv/lib/python3.11/site-packages/
sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

Results:
      Accuracy: 0.9256
      Recall: 0.9256
      F1-score: 0.9256
      Precision: 0.9256
For classes:
Class: 0
Results:
```

```
     Accuracy: 0.9744897959183674
     Recall: 0.9744897959183674
     F1-score: 0.9744897959183674
     Precision: 0.9744897959183674
Class: 1
Results:
     Accuracy: 0.9823788546255506
     Recall: 0.9823788546255506
     F1-score: 0.9823788546255506
     Precision: 0.9823788546255506
Class: 2
Results:
     Accuracy: 0.9127906976744186
     Recall: 0.9127906976744186
     F1-score: 0.9127906976744186
     Precision: 0.9127906976744186
Class: 3
Results:
     Accuracy: 0.9089108910891089
     Recall: 0.9089108910891089
     F1-score: 0.9089108910891089
     Precision: 0.9089108910891089
Class: 4
Results:
     Accuracy: 0.9276985743380856
     Recall: 0.9276985743380856
     F1-score: 0.9276985743380856
     Precision: 0.9276985743380856
Class: 5
Results:
     Accuracy: 0.874439461883408
     Recall: 0.874439461883408
     F1-score: 0.874439461883408
     Precision: 0.874439461883408
Class: 6
Results:
     Accuracy: 0.9561586638830898
     Recall: 0.9561586638830898
     F1-score: 0.9561586638830898
     Precision: 0.9561586638830898
Class: 7
Results:
     Accuracy: 0.919260700389105
     Recall: 0.919260700389105
     F1-score: 0.919260700389105
     Precision: 0.919260700389105
Class: 8
Results:
     Accuracy: 0.893223819301848
```

```
      Recall: 0.893223819301848
      F1-score: 0.893223819301848
      Precision: 0.893223819301848
Class: 9
Results:
      Accuracy: 0.9058473736372646
      Recall: 0.9058473736372646
      F1-score: 0.9058473736372646
      Precision: 0.9058473736372646
For all:
Results:
      Accuracy: 0.9266
      Recall: 0.9266
      F1-score: 0.9266
      Precision: 0.9266
```

```
print(f"For FASHION-MNIST dataset:")
print(f"Baseline: ")
baseline_classifier.fit(f_x_train, f_y_train)
f_y_pred_baseline = baseline_classifier.predict(f_x_test)
result_scores(f_y_test, f_y_pred_baseline)

print(f"For classes: ")
results_for_every_class(f_pipe, b_f_x_test, f_y_test)

print(f"For all:")
f_y_pred_all = f_pipe.predict(b_f_x_test)
result_scores(f_y_test, f_y_pred_all)
```

```
For FASHION-MNIST dataset:
Baseline:

/home/adrian/dev/um-labs/lab_RBM/.venv/lib/python3.11/site-packages/
sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

Results:
      Accuracy: 0.8438
      Recall: 0.8438
      F1-score: 0.8438
      Precision: 0.8438
```

```
For classes:
Class: 0
Results:
	Accuracy: 0.744
	Recall: 0.744
	F1-score: 0.744
	Precision: 0.744
Class: 1
Results:
	Accuracy: 0.946
	Recall: 0.946
	F1-score: 0.946
	Precision: 0.946
Class: 2
Results:
	Accuracy: 0.623
	Recall: 0.623
	F1-score: 0.623
	Precision: 0.623
Class: 3
Results:
	Accuracy: 0.813
	Recall: 0.813
	F1-score: 0.813
	Precision: 0.813
Class: 4
Results:
	Accuracy: 0.738
	Recall: 0.738
	F1-score: 0.738
	Precision: 0.738
Class: 5
Results:
	Accuracy: 0.869
	Recall: 0.869
	F1-score: 0.869
	Precision: 0.869
Class: 6
Results:
	Accuracy: 0.4
	Recall: 0.4
	F1-score: 0.4
	Precision: 0.4
Class: 7
Results:
	Accuracy: 0.834
	Recall: 0.834
	F1-score: 0.834
	Precision: 0.834
```

```
Class: 8
Results:
	Accuracy: 0.914
	Recall: 0.914
	F1-score: 0.914
	Precision: 0.914
Class: 9
Results:
	Accuracy: 0.909
	Recall: 0.909
	F1-score: 0.909
	Precision: 0.909
For all:
Results:
	Accuracy: 0.779
	Recall: 0.779
	F1-score: 0.779
	Precision: 0.779
```

```
print(f"For K-MNIST dataset:")
print(f"Baseline: ")
baseline_classifier.fit(k_x_train, k_y_train)
k_y_pred_baseline = baseline_classifier.predict(k_x_test)
result_scores(k_y_test, k_y_pred_baseline)

print(f"For classes: ")
results_for_every_class(k_pipe, b_k_x_test, k_y_test)

print(f"For all:")
k_y_pred_all = k_pipe.predict(b_k_x_test)
result_scores(k_y_test, k_y_pred_all)
```

```
For K-MNIST dataset:
Baseline:

/home/adrian/dev/um-labs/lab_RBM/.venv/lib/python3.11/site-packages/
sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

Results:
	Accuracy: 0.6965
```

```
      Recall: 0.6965
      F1-score: 0.6965
      Precision: 0.6965
For classes:
Class: 0
Results:
      Accuracy: 0.785
      Recall: 0.785
      F1-score: 0.785
      Precision: 0.785
Class: 1
Results:
      Accuracy: 0.733
      Recall: 0.733
      F1-score: 0.733
      Precision: 0.733
Class: 2
Results:
      Accuracy: 0.642
      Recall: 0.642
      F1-score: 0.642
      Precision: 0.642
Class: 3
Results:
      Accuracy: 0.777
      Recall: 0.777
      F1-score: 0.777
      Precision: 0.777
Class: 4
Results:
      Accuracy: 0.694
      Recall: 0.694
      F1-score: 0.694
      Precision: 0.694
Class: 5
Results:
      Accuracy: 0.742
      Recall: 0.742
      F1-score: 0.742
      Precision: 0.742
Class: 6
Results:
      Accuracy: 0.762
      Recall: 0.762
      F1-score: 0.762
      Precision: 0.762
Class: 7
Results:
      Accuracy: 0.666
```

```
     Recall: 0.666
     F1-score: 0.666
     Precision: 0.666
Class: 8
Results:
     Accuracy: 0.752
     Recall: 0.752
     F1-score: 0.752
     Precision: 0.752
Class: 9
Results:
     Accuracy: 0.732
     Recall: 0.732
     F1-score: 0.732
     Precision: 0.732
For all:
Results:
     Accuracy: 0.7285
     Recall: 0.7285
     F1-score: 0.7285
     Precision: 0.7285
```

- Czy nieliniowa ekstrakcja cech za pomocą RBM poprawia wyniki klasyfikacji w porównaniu z baseline (regresja logistyczna na surowych pikselach)?

Odpowiedź:

Dla zbiorów danych MNIST i K-MNIST wyniki klasyfikacji zostały poprawione. Dla F-MNIST nie udało się poprawić wyników. Dla poszczególnych cech było różnie, czasami były poprawy względem baseline-u, a czasami nie.

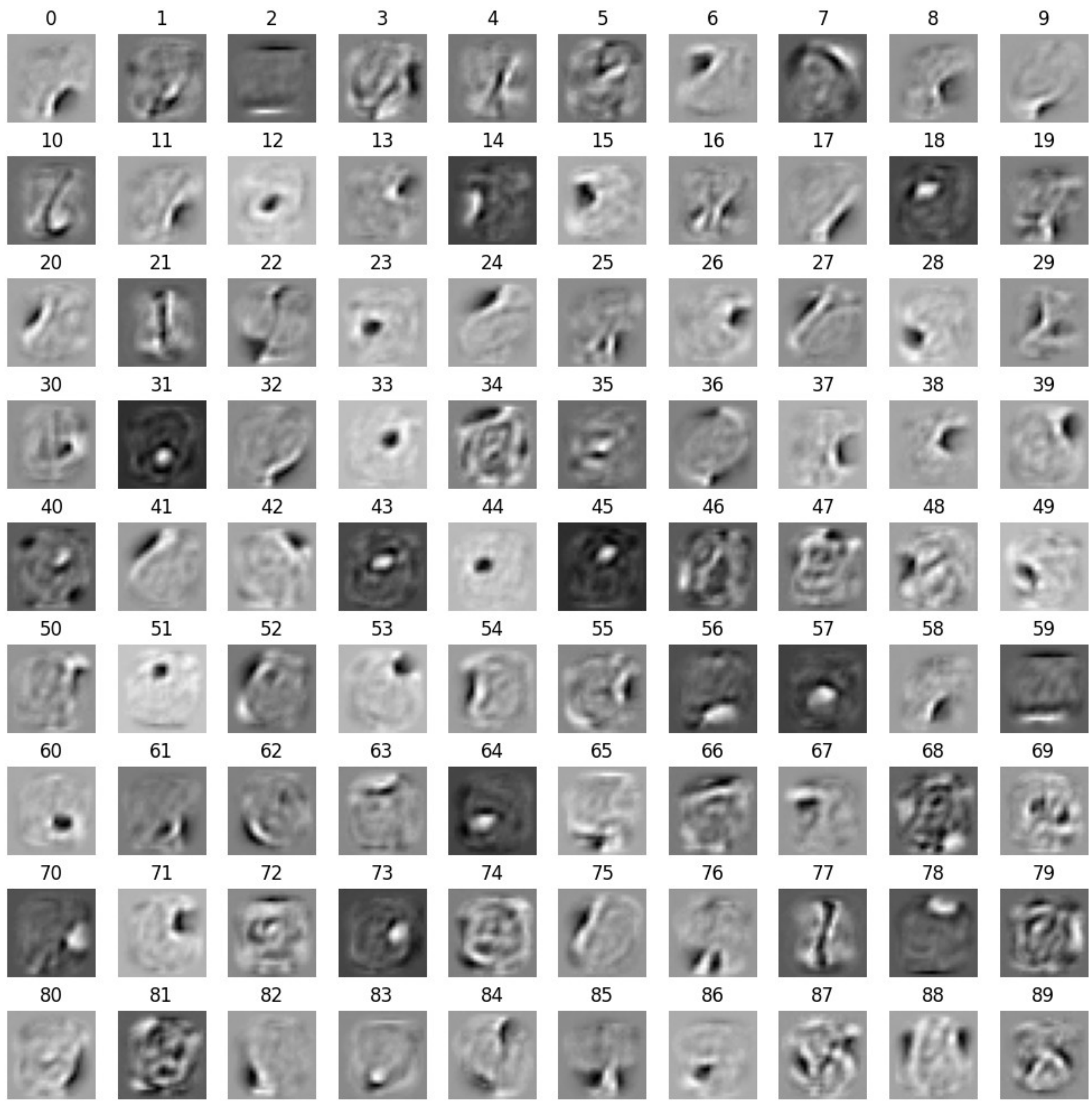
- Przedstaw wizualizację wszystkich ekstrachowanych cech ukrytych (n components obrazów odpowiadających wyuczonym wagom łączącym się z określonym elementem warstwy ukrytej). Spróbuj rozpoznać jakie wysokopoziomowe cechy obrazu są wzmacniane przez określony komponent.

```python
def visualize_features(components):
  print(components.shape)
  image_shape = (28, 28)
  reshaped_components = components.reshape(-1, *image_shape)
  plt.figure(figsize=(10, 10))
  for i in range(reshaped_components.shape[0]):
      plt.subplot(reshaped_components.shape[0]//10, 10, i + 1)
      plt.imshow(reshaped_components[i], cmap='gray')
      plt.title(f"{i}")
      plt.axis('off')

  plt.tight_layout()
  plt.show()
```

Components for MNIST dataset:

```
visualize_features(pipe['rbm'].components_)
```

```
(90, 784)
```



Components for F-MNIST dataset:

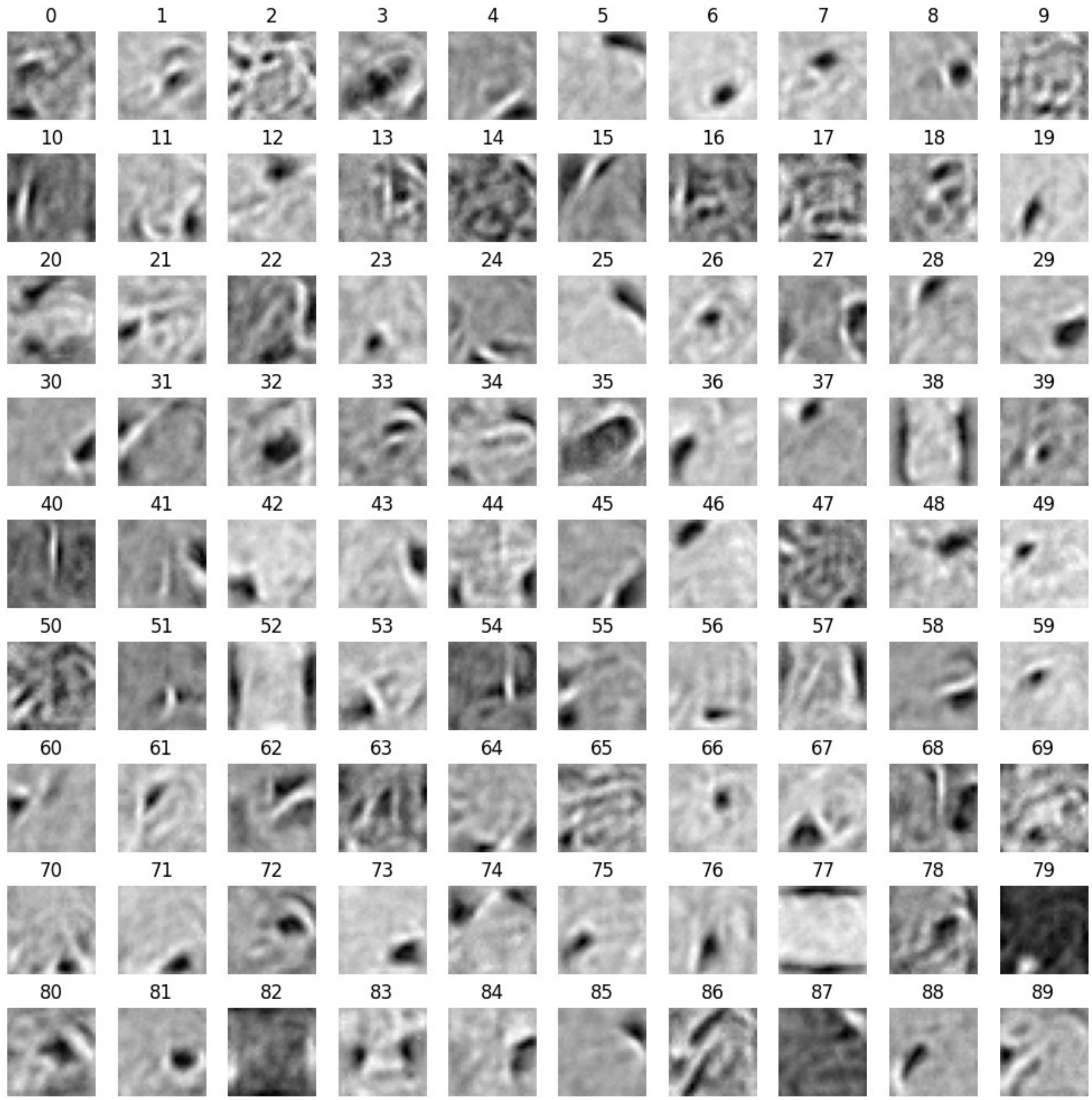
```
visualize_features(f_pipe['rbm'].components_)
```

```
(90, 784)
```

Components for K-MNIST dataset:

```
visualize_features(k_pipe['rbm'].components_)
```

```
(90, 784)
```



Dla poszczególnych komponentów widać czasami cechy jakie są wykrywane przez model np. są to ubrania jak koszule.

6 Hierarchiczna ekstrakcja cech za pomocą Deep Belief Network

1. Skonfiguruj 3 RBM w ten sposób, że warstwa ekstrakcji cech (hidden layer) RBM(i) staje się warstwą wejściową (visible layer) BRM(i + 1). RBMy trenowane są w sekwencyjnie: 1, 2, 3.

1. Rozmiar warstwy ukrytej jest pre-definiowany, przykładowo dla MNIST proponujemy kolejno: 256, 128, 64. Dla innych zbiorów danych rozmiary te możesz dopasować empirycznie, przy czym nie jest wymagane zastosowanie wyszukiwania siatkowego (duże wymagania obliczeniowe). Wartości pozostałych hiperparametrów mogą być podobne jak w poprzednim zadaniu.

```
def dbn_for_dataset(x_train_data, y_train_data, x_test_data,
y_test_data):
  rbm1 = BernoulliRBM(n_components=256, learning_rate=0.05, n_iter=7,
random_state=42)
  rbm2 = BernoulliRBM(n_components=128, learning_rate=0.05, n_iter=7,
random_state=42)
  rbm3 = BernoulliRBM(n_components=64, learning_rate=0.05, n_iter=7,
random_state=42)
  regression_classifier = LogisticRegression(max_iter=1000,
random_state=42)

  rbm1.fit(x_train_data)
  x_rbm1 = rbm1.transform(x_train_data)

  x_test_rbm1 = rbm1.transform(x_test_data)
  regression_classifier.fit(x_rbm1, y_train_data)
  y_pred_rbm1 = regression_classifier.predict(x_test_rbm1)

  rbm2.fit(x_rbm1)
  x_rbm2 = rbm2.transform(x_rbm1)

  x_test_rbm2 = rbm2.transform(x_test_rbm1)
  regression_classifier.fit(x_rbm2, y_train_data)
  y_pred_rbm2 = regression_classifier.predict(x_test_rbm2)

  rbm3.fit(x_rbm2)
  x_rbm3 = rbm3.transform(x_rbm2)

  x_test_rbm3 = rbm3.transform(x_test_rbm2)
  regression_classifier.fit(x_rbm3, y_train_data)
  y_pred_rbm3 = regression_classifier.predict(x_test_rbm3)

  print(f"Scores for first RBM: ")
  result_scores(y_test_data, y_pred_rbm1)
  print(f"Scores for first & second RBM: ")
  result_scores(y_test_data, y_pred_rbm2)
  print(f"Scores for DBN: ")
  result_scores(y_test_data, y_pred_rbm3)
```

1. Porównaj wyniki klasyfikacji uzyskane z zastosowaniem regresji logistycznej, dla poniższych wariantów ekstrakcji cech: • Baseline - regresja logistyczna na surowych pikselach • Pełna hierarchiczna ekstrakcja (wszystkie 3 RBMy) • Pierwszy RBM • Pierwszy i drugi RBM

```python
def baseline(x_train_data, y_train_data, x_test_data, y_test_data):
  regression_classifier = LogisticRegression(max_iter=1000,
random_state=42)
  regression_classifier.fit(x_train_data, y_train_data)

  y_pred = regression_classifier.predict(x_test_data)
  print(f"Scores for baseline: ")
  result_scores(y_test_data, y_pred)

print(f"Baseline for MNIST:")
baseline(x_train, y_train, x_test, y_test)
print(f"Results for MNIST dataset: ")
dbn_for_dataset(b_x_train, y_train, b_x_test, y_test)

print(f"Baseline for F-MNIST:")
baseline(f_x_train, f_y_train, f_x_test, f_y_test)
print(f"Results for FASHION-MNIST dataset: ")
dbn_for_dataset(b_f_x_train, f_y_train, b_f_x_test, f_y_test)

print(f"Baseline for K-MNIST:")
baseline(k_x_train, k_y_train, k_x_test, k_y_test)
print(f"Results for K-MNIST dataset: ")
dbn_for_dataset(b_k_x_train, k_y_train, b_k_x_test, k_y_test)
```

```
Baseline for MNIST:
Scores for baseline:
Results:
	Accuracy: 0.9263
	Recall: 0.9263
	F1-score: 0.9263
	Precision: 0.9263
Results for MNIST dataset:
Scores for first RBM:
Results:
	Accuracy: 0.9595
	Recall: 0.9595
	F1-score: 0.9595
	Precision: 0.9595
Scores for first & second RBM:
Results:
	Accuracy: 0.958
	Recall: 0.958
	F1-score: 0.958
	Precision: 0.958
Scores for DBN:
Results:
	Accuracy: 0.943
	Recall: 0.943
	F1-score: 0.943
	Precision: 0.943
```

```
Baseline for F-MNIST:
Scores for baseline:
Results:
      Accuracy: 0.8432
      Recall: 0.8432
      F1-score: 0.8432
      Precision: 0.8432
Results for FASHION-MNIST dataset:
Scores for first RBM:
Results:
      Accuracy: 0.802
      Recall: 0.802
      F1-score: 0.802
      Precision: 0.802
Scores for first & second RBM:
Results:
      Accuracy: 0.7647
      Recall: 0.7647
      F1-score: 0.7647
      Precision: 0.7647
Scores for DBN:
Results:
      Accuracy: 0.7232
      Recall: 0.7232
      F1-score: 0.7232
      Precision: 0.7232
Baseline for K-MNIST:
Scores for baseline:
Results:
      Accuracy: 0.6934
      Recall: 0.6934
      F1-score: 0.6934
      Precision: 0.6934
Results for K-MNIST dataset:
Scores for first RBM:
Results:
      Accuracy: 0.8073
      Recall: 0.8073
      F1-score: 0.8073
      Precision: 0.8073
Scores for first & second RBM:
Results:
      Accuracy: 0.7923
      Recall: 0.7923
      F1-score: 0.7923
      Precision: 0.7923
Scores for DBN:
Results:
      Accuracy: 0.7796
```

```
    Recall: 0.7796
    F1-score: 0.7796
    Precision: 0.7796
```

1. Czy ustawianie ekstraktorów RBM jest korzystne dla każdego ze zbiorów danych? W jaki przypadku hierarchiczna ekstrakcja cech może być przydatna?

Ustawienie ekstraktorów jest korzystne dla zbiorów danych MNIST i K-MNIST. Nawet jeden RBM już znacząco poprawiał wyniki. Hierarchiczna ekstrakcja cech jest przydatna, gdy potrzebujemy badać cechy juz w znalezionych cechach w danych.

7 ⋆ Restricted Boltzmann Machines: implementacja, testy rekonstrukcji

1. Zaimplementuj RBM wraz z algorytmem trenowania Contrastive Divergence. Możesz użyć następującego szablonu:

```
import time

def sigmoid(x):
  return 1.0 / (1.0 + np.exp(-x))

class RBM():
  def __init__(self, visible_dim, hidden_dim, learning_rate,
gifname='./images/rbm_training.gif'):
    self.visible_dim = visible_dim
    self.hidden_dim = hidden_dim
    self.learning_rate = learning_rate
    self.gif_name = gifname
    self.K = 1

    self.W = np.random.normal(0, 0.01, (visible_dim,
hidden_dim)).astype(np.float32)
    self.b = np.zeros(visible_dim)
    self.a = np.zeros(hidden_dim)

  def wake_phase(self, visible):
    preactivation = visible @ self.W
    preactivation = preactivation + np.broadcast_to(self.a,
preactivation.shape)
    activation = sigmoid(preactivation)
    binary_activation = activation >
np.random.rand(*activation.shape).astype(np.float32)
    return activation, binary_activation

  def dream_phase(self, hidden):
    preactivation = hidden @ self.W.T
    preactivation = preactivation + np.broadcast_to(self.b,
```

```
preactivation.shape)
    activation = sigmoid(preactivation)
    binary_activation = activation >
np.random.rand(*activation.shape).astype(np.float32)
    return activation, binary_activation

  def train(self, batch):
    positive_visible = batch
    positive_hidden, negative_hidden = self.wake_phase(batch)
    negative_visible = self.dream_phase(negative_hidden)[1]

    for k in range(self.K):
      negative_hidden = self.wake_phase(negative_visible)[1]
      negative_visible = self.dream_phase(negative_hidden)[1]

    negative_hidden = self.wake_phase(negative_visible)[0]

    grad_positive = (positive_visible.T @ positive_hidden) /
batch.shape[0]
    grad_negative = (negative_visible.T @ negative_hidden) /
batch.shape[0]

    self.W += self.learning_rate * (grad_positive - grad_negative)
    return np.mean(np.abs(positive_visible[positive_visible >= 0] -
negative_visible[positive_visible >= 0]))

  def fit(self, X, epochs=50, batch_dim=128, lr=0.1):
    self.learning_rate = lr
    test_set = X[0:2*batch_dim]
    for epoch in range(epochs):

      start = time.time()
      train_loss = 0
      s = 0
      for i in range(0, len(X) - batch_dim, batch_dim):
        batch = X[i:i+batch_dim]
        train_loss += self.train(batch)
        s+=1
      stop = time.time()

      reconstruction_error = self.reconstruction_error(test_set)
      print(f"Epoch {epoch+1}, time: {stop - start},
reconstruction_error: {reconstruction_error}, train_loss:
{train_loss/s}")
      self.plot_weights(epoch)

  def reconstruction_error(self, X):
    error = X - self.reconstruct(X)
    return np.sum(np.square(error))/X.shape[0]
```

```
  def reconstruct(self, X):
    preactivation = X @ self.W
    preactivation += np.broadcast_to(self.a, preactivation.shape)
    hidden = sigmoid(preactivation)
    hidden = hidden > np.random.rand(*hidden.shape).astype(np.float64)
    preactivation = hidden @ self.W.T
    preactivation += np.broadcast_to(self.b, preactivation.shape)
    visible = sigmoid(preactivation)
    return visible

  def plot_weights(self, epoch):
    filters = np.reshape(np.transpose(self.W),
newshape=(self.hidden_dim, 28, 28))
    filters = np.clip(filters, -1, 1)
    fig = plt.figure(figsize=(5, 5))

    for i in range(self.hidden_dim):
      plt.subplot(8, self.hidden_dim//8, i + 1)
      plt.imshow(filters[i], cmap='gray')
      plt.axis('off')

    plt.tight_layout()
    plt.savefig(f'./images/image_at_epoch_{epoch:04d}.png')
    # plt.show()
    plt.close(fig)
```

1. Wytrenuj RBM na zbiorze Fashion-MNIST (część treningowa) dla warstwy ukrytej (hidden dim) o rozmiarze 40. Zastosuj domyślne wartości parametrów metody fit().

```
rbm_f_mnist = RBM(28*28, 40, 0.1)
rbm_f_mnist.fit(b_f_x_train, epochs=30, batch_dim=128)

/tmp/ipykernel_5746/441891556.py:4: RuntimeWarning: overflow
encountered in exp
  return 1.0 / (1.0 + np.exp(-x))

Epoch 1, time: 9.231838703155518, reconstruction_error:
77.62876892089844, train_loss: 37.321746341765895
Epoch 2, time: 9.52246880531311, reconstruction_error:
71.9843521118164, train_loss: 29.099820788942576
Epoch 3, time: 13.405994176864624, reconstruction_error:
69.47746276855469, train_loss: 27.572250060130212
Epoch 4, time: 12.423358917236328, reconstruction_error:
68.17606353759766, train_loss: 26.806279864960807
Epoch 5, time: 10.08058476448059, reconstruction_error:
66.76380157470703, train_loss: 26.355702223046677
Epoch 6, time: 9.121027708053589, reconstruction_error:
66.30818176269531, train_loss: 25.963610888816664
Epoch 7, time: 8.778710126876831, reconstruction_error:
```

```
66.05725860595703, train_loss: 25.653657565540264
Epoch 8, time: 10.14504861831665, reconstruction_error:
65.95828247070312, train_loss: 25.503535248233934
Epoch 9, time: 11.130028009414673, reconstruction_error:
65.7374267578125, train_loss: 25.414321438962197
Epoch 10, time: 6.259296655654907, reconstruction_error:
66.0661849975586, train_loss: 25.30433257412539
Epoch 11, time: 5.841235876083374, reconstruction_error:
65.78767395019531, train_loss: 25.25900343611003
Epoch 12, time: 5.721011161804199, reconstruction_error:
65.65464782714844, train_loss: 25.226255226900445
Epoch 13, time: 11.770118474960327, reconstruction_error:
65.73456573486328, train_loss: 25.19484576683237
Epoch 14, time: 14.629521608352661, reconstruction_error:
65.1994400024414, train_loss: 25.162717703768234
Epoch 15, time: 11.65986943244934, reconstruction_error:
65.46661376953125, train_loss: 25.15456944120796
Epoch 16, time: 9.923290491104126, reconstruction_error:
65.24038696289062, train_loss: 25.107378544616967
Epoch 17, time: 9.647526741027832, reconstruction_error:
65.67645263671875, train_loss: 25.112819478001544
Epoch 18, time: 11.533295631408691, reconstruction_error:
65.80133819580078, train_loss: 25.06313060079801
Epoch 19, time: 10.197265148162842, reconstruction_error:
66.16260528564453, train_loss: 25.10699702432055
Epoch 20, time: 11.775666952133179, reconstruction_error:
66.6102066040039, train_loss: 25.16769861114521
Epoch 21, time: 11.13505506515503, reconstruction_error:
66.48805236816406, train_loss: 25.23518558690504
Epoch 22, time: 9.345412969589233, reconstruction_error:
66.26042938232422, train_loss: 25.23296922184339
Epoch 23, time: 9.32714295387268, reconstruction_error:
66.40379333496094, train_loss: 25.275643836260485
Epoch 24, time: 11.3136146068573, reconstruction_error:
66.45555877685547, train_loss: 25.30430649072528
Epoch 25, time: 11.55119252204895, reconstruction_error:
66.61209869384766, train_loss: 25.34479380444087
Epoch 26, time: 22.16575002670288, reconstruction_error:
66.93470001220703, train_loss: 25.36642882438434
Epoch 27, time: 10.273731470108032, reconstruction_error:
66.44853973388672, train_loss: 25.364823492247453
Epoch 28, time: 6.184662342071533, reconstruction_error:
67.05076599121094, train_loss: 25.37330455770048
Epoch 29, time: 7.593412399291992, reconstruction_error:
66.68024444580078, train_loss: 25.34871210603632
Epoch 30, time: 6.177523612976074, reconstruction_error:
66.87451171875, train_loss: 25.346356125583245
```

1. Zwizualizuj jak zmieniają się wagi w kolejnych epokach treningu. W tym celi wywołuj metodę plot weights() w metodzie fit(). Przedstaw wyniki w formie animowanego pliku GIF. Zapisz obserwacje dotyczące postępów treningu.

```
import imageio
import glob
import embed
def create_gif():
  with imageio.get_writer('images/rbm_training.gif', mode='I') as
writer:
    filenames = glob.glob('images/image*.png')
    filenames = sorted(filenames)
    for filename in filenames:
      image = imageio.imread(filename)
      writer.append_data(image)
    image = imageio.imread(filename)
    writer.append_data(image)
create_gif()
```

```
/tmp/ipykernel_7783/1815423369.py:9: DeprecationWarning: Starting with
ImageIO v3 the behavior of this function will switch to that of
iio.v3.imread. To keep the current behavior (and make this warning
disappear) use `import imageio.v2 as imageio` or call
`imageio.v2.imread` directly.
  image = imageio.imread(filename)
/tmp/ipykernel_7783/1815423369.py:11: DeprecationWarning: Starting
with ImageIO v3 the behavior of this function will switch to that of
iio.v3.imread. To keep the current behavior (and make this warning
disappear) use `import imageio.v2 as imageio` or call
`imageio.v2.imread` directly.
  image = imageio.imread(filename)
```

"RBM training"

Obserwacje:

Podczas treningu kształty na obrazkach są coraz smuklejsze i dokładniejsze, a cechy coraz bardziej się uwidaczniają.

Wnioski:

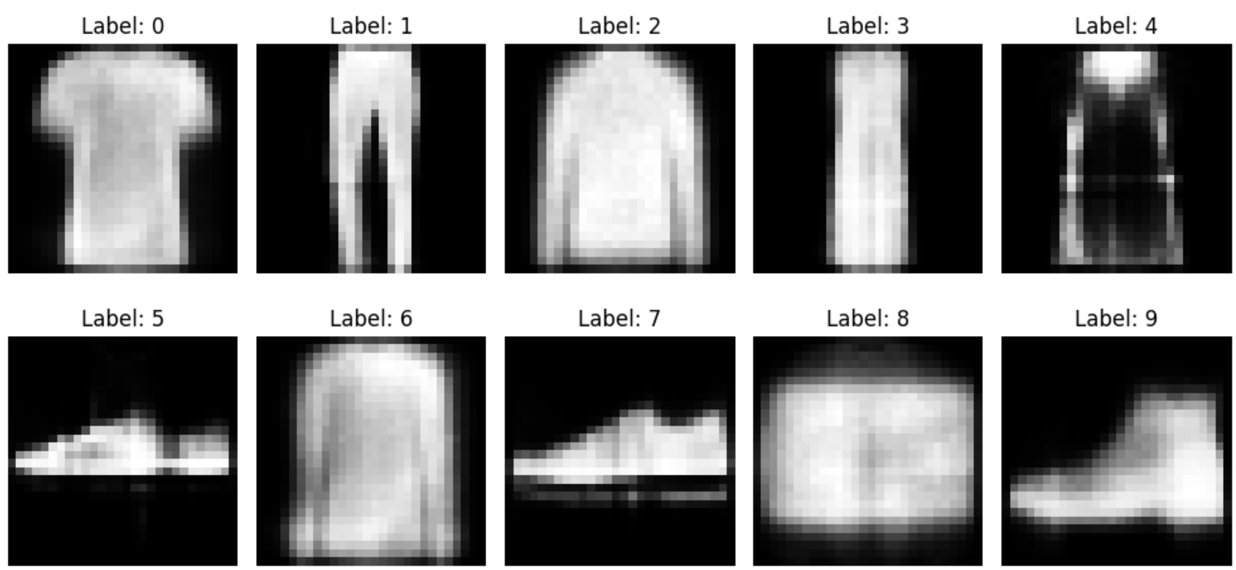
Podczas trenowania dochodzi do ekstrakcji cech i kształty są coraz lepiej rozpoznawane.

1. Wybierz 10 przykładów ze zbioru testowego (po jedynym dla każdej klasy). Następnie, użyj RBM do rekonstrukcji obrazu testowego. Porównaj otrzymaną rekonstrukcję z obrazem oryginalnym: • Przedstaw wizualizację: obraz oryginalny vs. obraz odtworzony na podstawie wyuczonych wag RBM (dla każdej klasy) • Ilościowo: zastosuj Structural Similarity Index (SSIM).

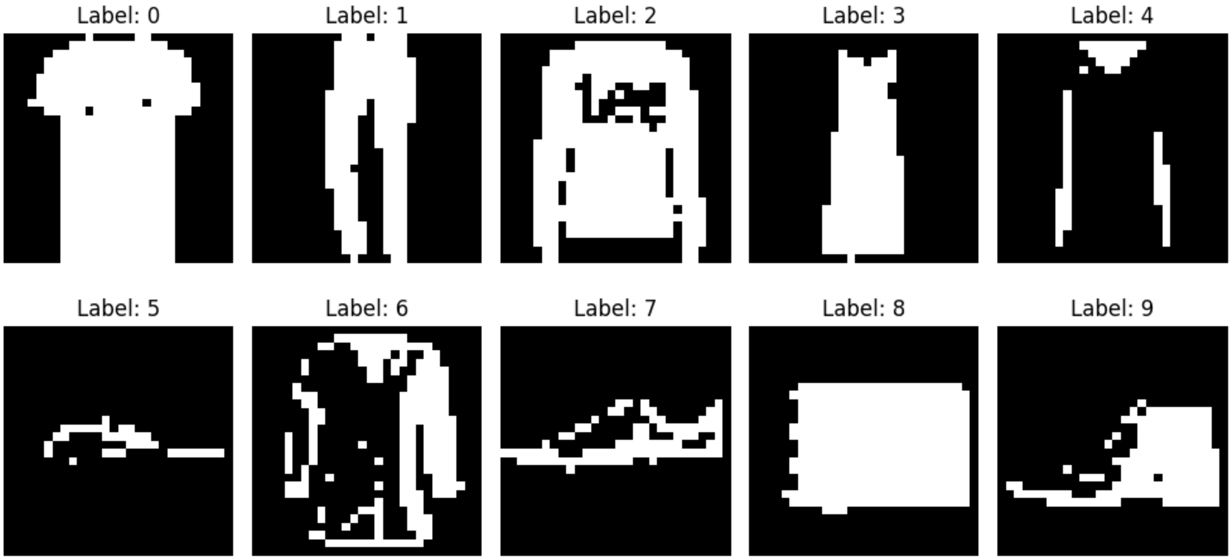
```
from skimage.metrics import structural_similarity as ssim
```

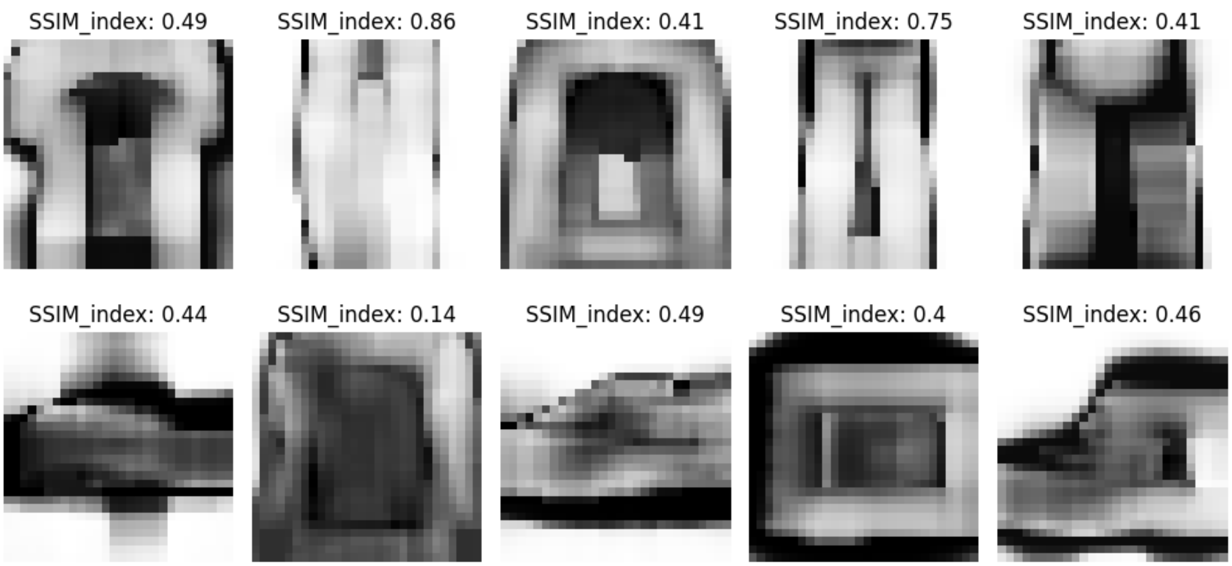
```
f_y_test_classes = extract_classes(f_y_test)

def show_examples(different_classes, x_dataset, y_dataset):
    indices = [different_classes[str(i)][0] for i in range(10)]
    labels = y_dataset[indices]
    reconstructions = rbm_f_mnist.reconstruct(x_dataset[indices])
    reconstructions = np.reshape(reconstructions, newshape=(10, 28,
28))
    reconstructions = np.clip(reconstructions, -1, 1)
    original = np.reshape(x_dataset[indices], newshape=(10, 28, 28))
    print(f"Reconstructed images: ")
    plot_ten_images(reconstructions, labels)
    print(f"Original images: ")
    plot_ten_images(original, labels)
    ssim_indices = []
    differences = []
    for i in range(10):
        ssim_index, diff = ssim(reconstructions[i], original[i],
data_range=1, full=True)
        ssim_indices.append(round(ssim_index, 2))
        differences.append(diff)
    plot_ten_images(differences, ssim_indices, "SSIM_index")



show_examples(f_y_test_classes, b_f_x_test, f_y_test)
```

```
/tmp/ipykernel_5746/441891556.py:4: RuntimeWarning: overflow
encountered in exp
  return 1.0 / (1.0 + np.exp(-x))

Reconstructed images:
```



```
Original images:
```





1. Skomentuj uzyskane wyniki.

Komentarz:

Uzyskane wyniki przypominają kształty orginalnych obrazków. Posiadają ich zarys, ale nie są w stanie odzwierciedlać dokładnych szczegółów. SSIM wykazuje podobieństwo na poziomie 0.4 - 0.5, więc są to podobne obrazy, ale tylko do pewnego stopnia.

8 Ekstrakcja cech za pomocą Autoencodera

1. Wczytaj zbiór danych. Dokonaj skalowania cech do przedziału [0, 1] oraz konwersji na tablice numpy (zarówno dane treningowe, jak i testowe).

```
from sklearn.model_selection import train_test_split
l = len(x_train)
ratio = 1
t_x_train, t_x_val, t_y_train, t_y_val =
train_test_split(x_train[:int(ratio*l)], y_train[:int(ratio*l)],
test_size=0.2, random_state=41)
t_f_x_train, t_f_x_val, t_f_y_train, t_f_y_val =
train_test_split(f_x_train, f_y_train, test_size=0.2, random_state=41)
t_k_x_train, t_k_x_val, t_k_y_train, t_k_y_val =
train_test_split(k_x_train, k_y_train, test_size=0.2, random_state=41)
```

1. Zbuduj i wytrenuj prosty Autoencoder. Przykładowa konfiguracja prostego Autoencodera: • Kodowanie: aktywacja ReLU • Dekodowanie: aktywacja sigmoidalna • Adam optimizer • Loss function: binary crossentropy • Encoding dimension: 196 (liczba ekstrachowanych cech) • Liczba epok treningu: > 30

```
class Autoencoder(tf.keras.Model):
  def __init__(self, encoding_dimension):
    super(Autoencoder, self).__init__()
    self.encoding_dimension = encoding_dimension

    self.encoder = tf.keras.Sequential(
        [
            # tf.keras.layers.Flatten(input_shape=input_shape),
            tf.keras.layers.Dense(784, activation='relu'),
            tf.keras.layers.Dense(128, activation='relu'),
            tf.keras.layers.Dense(64, activation='relu'),
            tf.keras.layers.Dense(32, activation='relu'),
            tf.keras.layers.Dense(self.encoding_dimension)
        ]
    )

    self.decoder = tf.keras.Sequential(
        [
            tf.keras.layers.Dense(self.encoding_dimension,
activation='relu'),
            tf.keras.layers.Dense(32, activation='relu'),
            tf.keras.layers.Dense(64, activation='relu'),
            tf.keras.layers.Dense(128, activation='relu'),
            tf.keras.layers.Dense(784, activation='sigmoid'),
            # tf.keras.layers.Reshape(target_shape=input_shape)
        ]
    )
```

```
  def call(self, x):
    encoded = self.encoder(x)
    decoded = self.decoder(encoded)
    return decoded

latent_dim = 196
batch_size = 32
epochs = 35

autoencoder = Autoencoder(latent_dim)
autoencoder.compile(optimizer='adam',
loss=tf.keras.losses.BinaryCrossentropy(from_logits=False),
metrics=[tf.keras.metrics.Accuracy])

2025-01-03 19:49:19.271215: E
external/local_xla/xla/stream_executor/cuda/cuda_driver.cc:152] failed
call to cuInit: INTERNAL: CUDA error: Failed call to cuInit: UNKNOWN
ERROR (303)

f_autoencoder = Autoencoder(latent_dim)
f_autoencoder.compile(optimizer='adam',
loss=tf.keras.losses.BinaryCrossentropy(from_logits=False),
metrics=[tf.keras.metrics.Accuracy])

k_autoencoder = Autoencoder(latent_dim)
k_autoencoder.compile(optimizer='adam',
loss=tf.keras.losses.BinaryCrossentropy(from_logits=False),
metrics=[tf.keras.metrics.Accuracy])
```

1. Przedstaw postępy trenowania wyświetlając wartości funkcji strat (loss) na zbiorach treningowych i testowych dla kolejnych epok.

```
autoencoder.fit(x_train, x_train,
                epochs=epochs,
                shuffle=True,
                batch_size=batch_size,
                validation_data=(x_test, x_test))

2025-01-03 19:50:10.130263: W
external/local_xla/xla/tsl/framework/cpu_allocator_impl.cc:83]
Allocation of 188160000 exceeds 10% of free system memory.
2025-01-03 19:50:10.361451: W
external/local_xla/xla/tsl/framework/cpu_allocator_impl.cc:83]
Allocation of 188160000 exceeds 10% of free system memory.

Epoch 1/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 38s 18ms/step - accuracy: 0.0000e+00 -
loss: 0.2235 - val_accuracy: 0.0000e+00 - val_loss: 0.1367
Epoch 2/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 0.0000e+00 -
loss: 0.1349 - val_accuracy: 0.0000e+00 - val_loss: 0.1241
```

```
Epoch 3/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 37s 20ms/step - accuracy: 2.7851e-08 -
loss: 0.1223 - val_accuracy: 0.0000e+00 - val_loss: 0.1142
Epoch 4/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 35s 18ms/step - accuracy: 0.0000e+00 -
loss: 0.1130 - val_accuracy: 0.0000e+00 - val_loss: 0.1096
Epoch 5/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 7.0394e-08 -
loss: 0.1075 - val_accuracy: 2.5510e-07 - val_loss: 0.1048
Epoch 6/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 31s 17ms/step - accuracy: 8.7345e-09 -
loss: 0.1044 - val_accuracy: 0.0000e+00 - val_loss: 0.1025
Epoch 7/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 0.0000e+00 -
loss: 0.1025 - val_accuracy: 1.2755e-07 - val_loss: 0.1008
Epoch 8/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 32s 17ms/step - accuracy: 1.4384e-07 -
loss: 0.1010 - val_accuracy: 3.8265e-07 - val_loss: 0.0993
Epoch 9/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 32s 17ms/step - accuracy: 1.1853e-07 -
loss: 0.0996 - val_accuracy: 1.2755e-07 - val_loss: 0.0986
Epoch 10/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 41s 17ms/step - accuracy: 1.3909e-07 -
loss: 0.0983 - val_accuracy: 8.9286e-07 - val_loss: 0.0972
Epoch 11/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 31s 17ms/step - accuracy: 3.6967e-07 -
loss: 0.0973 - val_accuracy: 3.8265e-07 - val_loss: 0.0964
Epoch 12/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 33s 17ms/step - accuracy: 1.1794e-06 -
loss: 0.0963 - val_accuracy: 2.4235e-06 - val_loss: 0.0960
Epoch 13/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 32s 17ms/step - accuracy: 1.3490e-06 -
loss: 0.0954 - val_accuracy: 1.5306e-06 - val_loss: 0.0949
Epoch 14/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 32s 17ms/step - accuracy: 3.6246e-06 -
loss: 0.0947 - val_accuracy: 1.6582e-06 - val_loss: 0.0945
Epoch 15/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 31s 16ms/step - accuracy: 4.1669e-06 -
loss: 0.0938 - val_accuracy: 4.3367e-06 - val_loss: 0.0942
Epoch 16/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 33s 17ms/step - accuracy: 5.9225e-06 -
loss: 0.0935 - val_accuracy: 5.8673e-06 - val_loss: 0.0930
Epoch 17/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 32s 17ms/step - accuracy: 8.1361e-06 -
loss: 0.0930 - val_accuracy: 4.9745e-06 - val_loss: 0.0927
Epoch 18/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 9.9479e-06 -
loss: 0.0925 - val_accuracy: 3.6990e-06 - val_loss: 0.0926
Epoch 19/35
```

```
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 35s 19ms/step - accuracy: 1.3450e-05 -
loss: 0.0922 - val_accuracy: 2.3342e-05 - val_loss: 0.0922
Epoch 20/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 1.7051e-05 -
loss: 0.0918 - val_accuracy: 1.8240e-05 - val_loss: 0.0935
Epoch 21/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 2.0425e-05 -
loss: 0.0914 - val_accuracy: 5.9694e-05 - val_loss: 0.0929
Epoch 22/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 2.7709e-05 -
loss: 0.0913 - val_accuracy: 2.7041e-05 - val_loss: 0.0913
Epoch 23/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 35s 18ms/step - accuracy: 3.3794e-05 -
loss: 0.0909 - val_accuracy: 3.0102e-05 - val_loss: 0.0915
Epoch 24/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 3.9096e-05 -
loss: 0.0907 - val_accuracy: 4.2219e-05 - val_loss: 0.0913
Epoch 25/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 4.3014e-05 -
loss: 0.0905 - val_accuracy: 5.6505e-05 - val_loss: 0.0911
Epoch 26/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 35s 18ms/step - accuracy: 5.3975e-05 -
loss: 0.0900 - val_accuracy: 5.9184e-05 - val_loss: 0.0908
Epoch 27/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 5.8900e-05 -
loss: 0.0898 - val_accuracy: 6.0714e-05 - val_loss: 0.0901
Epoch 28/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 6.6200e-05 -
loss: 0.0896 - val_accuracy: 5.7398e-05 - val_loss: 0.0894
Epoch 29/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 35s 19ms/step - accuracy: 6.5761e-05 -
loss: 0.0893 - val_accuracy: 5.5357e-05 - val_loss: 0.0901
Epoch 30/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 7.7039e-05 -
loss: 0.0892 - val_accuracy: 5.3571e-05 - val_loss: 0.0895
Epoch 31/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 26s 14ms/step - accuracy: 8.1733e-05 -
loss: 0.0889 - val_accuracy: 8.7117e-05 - val_loss: 0.0906
Epoch 32/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 25s 13ms/step - accuracy: 8.1336e-05 -
loss: 0.0889 - val_accuracy: 4.8980e-05 - val_loss: 0.0891
Epoch 33/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 24s 13ms/step - accuracy: 9.4896e-05 -
loss: 0.0885 - val_accuracy: 6.3776e-05 - val_loss: 0.0890
Epoch 34/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 23s 12ms/step - accuracy: 1.0104e-04 -
loss: 0.0884 - val_accuracy: 8.2398e-05 - val_loss: 0.0889
Epoch 35/35
```

```
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 25s 13ms/step - accuracy: 1.1041e-04 -
loss: 0.0882 - val_accuracy: 8.2781e-05 - val_loss: 0.0886

<keras.src.callbacks.history.History at 0x7f488af36910>
```

```
f_autoencoder.fit(f_x_train, f_x_train,
                epochs=epochs,
                shuffle=True,
                batch_size=batch_size,
                validation_data=(f_x_test, f_x_test))
```

```
2025-01-03 20:44:17.879751: W
external/local_xla/xla/tsl/framework/cpu_allocator_impl.cc:83]
Allocation of 188160000 exceeds 10% of free system memory.

Epoch 1/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 17ms/step - accuracy: 7.8733e-08 -
loss: 0.3602 - val_accuracy: 1.2755e-07 - val_loss: 0.3042
Epoch 2/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 36s 19ms/step - accuracy: 3.7592e-06 -
loss: 0.2998 - val_accuracy: 5.1020e-06 - val_loss: 0.2968
Epoch 3/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 38s 20ms/step - accuracy: 3.1669e-05 -
loss: 0.2946 - val_accuracy: 3.2270e-05 - val_loss: 0.2940
Epoch 4/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 38s 20ms/step - accuracy: 5.6528e-05 -
loss: 0.2909 - val_accuracy: 1.3265e-05 - val_loss: 0.2920
Epoch 5/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 37s 20ms/step - accuracy: 4.3741e-05 -
loss: 0.2884 - val_accuracy: 3.3163e-06 - val_loss: 0.2889
Epoch 6/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 1.2906e-05 -
loss: 0.2863 - val_accuracy: 7.6531e-07 - val_loss: 0.2867
Epoch 7/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 4.7483e-06 -
loss: 0.2839 - val_accuracy: 1.7857e-06 - val_loss: 0.2854
Epoch 8/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 29s 16ms/step - accuracy: 3.4578e-06 -
loss: 0.2823 - val_accuracy: 2.1684e-06 - val_loss: 0.2844
Epoch 9/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 39s 21ms/step - accuracy: 5.3652e-06 -
loss: 0.2819 - val_accuracy: 3.4439e-06 - val_loss: 0.2835
Epoch 10/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 37s 20ms/step - accuracy: 2.8862e-06 -
loss: 0.2809 - val_accuracy: 5.1020e-07 - val_loss: 0.2825
Epoch 11/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 4.5398e-06 -
loss: 0.2794 - val_accuracy: 2.5510e-07 - val_loss: 0.2819
Epoch 12/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 5.2639e-06 -
```

```
loss: 0.2792 - val_accuracy: 3.4439e-06 - val_loss: 0.2815
Epoch 13/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 3.9119e-06 -
loss: 0.2790 - val_accuracy: 1.2755e-06 - val_loss: 0.2810
Epoch 14/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 4.6298e-06 -
loss: 0.2784 - val_accuracy: 2.5510e-07 - val_loss: 0.2810
Epoch 15/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 29s 16ms/step - accuracy: 4.3416e-06 -
loss: 0.2781 - val_accuracy: 8.9286e-07 - val_loss: 0.2799
Epoch 16/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 31s 16ms/step - accuracy: 6.2480e-06 -
loss: 0.2780 - val_accuracy: 1.1480e-06 - val_loss: 0.2804
Epoch 17/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 6.3066e-06 -
loss: 0.2770 - val_accuracy: 1.9133e-06 - val_loss: 0.2800
Epoch 18/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 7.7761e-06 -
loss: 0.2766 - val_accuracy: 2.5510e-06 - val_loss: 0.2789
Epoch 19/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 37s 20ms/step - accuracy: 1.0817e-05 -
loss: 0.2761 - val_accuracy: 2.0408e-06 - val_loss: 0.2788
Epoch 20/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 41s 22ms/step - accuracy: 8.5414e-06 -
loss: 0.2767 - val_accuracy: 4.8469e-06 - val_loss: 0.2785
Epoch 21/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 7.7074e-06 -
loss: 0.2751 - val_accuracy: 1.5306e-06 - val_loss: 0.2786
Epoch 22/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 1.4433e-05 -
loss: 0.2769 - val_accuracy: 2.6786e-06 - val_loss: 0.2786
Epoch 23/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 1.5450e-05 -
loss: 0.2761 - val_accuracy: 8.4184e-06 - val_loss: 0.2776
Epoch 24/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 2.3432e-05 -
loss: 0.2749 - val_accuracy: 1.9388e-05 - val_loss: 0.2782
Epoch 25/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 2.7979e-05 -
loss: 0.2753 - val_accuracy: 2.8699e-05 - val_loss: 0.2774
Epoch 26/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 3.6084e-05 -
loss: 0.2745 - val_accuracy: 2.0281e-05 - val_loss: 0.2776
Epoch 27/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 4.1789e-05 -
loss: 0.2744 - val_accuracy: 3.7883e-05 - val_loss: 0.2776
Epoch 28/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 3.5832e-05 -
loss: 0.2739 - val_accuracy: 1.9260e-05 - val_loss: 0.2774
```

```
Epoch 29/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 4.2334e-05 -
loss: 0.2744 - val_accuracy: 1.2372e-05 - val_loss: 0.2770
Epoch 30/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 3.9478e-05 -
loss: 0.2749 - val_accuracy: 2.0153e-05 - val_loss: 0.2770
Epoch 31/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 29s 16ms/step - accuracy: 5.1228e-05 -
loss: 0.2736 - val_accuracy: 1.5561e-05 - val_loss: 0.2768
Epoch 32/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 5.3395e-05 -
loss: 0.2734 - val_accuracy: 2.0918e-05 - val_loss: 0.2769
Epoch 33/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 5.2796e-05 -
loss: 0.2738 - val_accuracy: 2.3597e-05 - val_loss: 0.2770
Epoch 34/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 4.2895e-05 -
loss: 0.2736 - val_accuracy: 1.4031e-05 - val_loss: 0.2764
Epoch 35/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 30s 16ms/step - accuracy: 5.4191e-05 -
loss: 0.2736 - val_accuracy: 2.0026e-05 - val_loss: 0.2765

<keras.src.callbacks.history.History at 0x7f48582c6910>
```

```
k_autoencoder.fit(k_x_train, k_x_train,
                epochs=epochs,
                shuffle=True,
                batch_size=batch_size,
                validation_data=(k_x_test, k_x_test))
```

```
Epoch 1/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 36s 19ms/step - accuracy: 0.0000e+00 -
loss: 0.2981 - val_accuracy: 0.0000e+00 - val_loss: 0.2867
Epoch 2/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 41s 19ms/step - accuracy: 0.0000e+00 -
loss: 0.2672 - val_accuracy: 0.0000e+00 - val_loss: 0.2696
Epoch 3/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 33s 18ms/step - accuracy: 6.8010e-09 -
loss: 0.2516 - val_accuracy: 0.0000e+00 - val_loss: 0.2600
Epoch 4/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 37s 20ms/step - accuracy: 0.0000e+00 -
loss: 0.2419 - val_accuracy: 0.0000e+00 - val_loss: 0.2515
Epoch 5/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 0.0000e+00 -
loss: 0.2342 - val_accuracy: 0.0000e+00 - val_loss: 0.2485
Epoch 6/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 1.5823e-08 -
loss: 0.2308 - val_accuracy: 0.0000e+00 - val_loss: 0.2441
Epoch 7/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 33s 18ms/step - accuracy: 0.0000e+00 -
```

```
loss: 0.2265 - val_accuracy: 0.0000e+00 - val_loss: 0.2439
Epoch 8/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 0.0000e+00 -
loss: 0.2241 - val_accuracy: 0.0000e+00 - val_loss: 0.2402
Epoch 9/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 0.0000e+00 -
loss: 0.2222 - val_accuracy: 0.0000e+00 - val_loss: 0.2375
Epoch 10/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 0.0000e+00 -
loss: 0.2198 - val_accuracy: 0.0000e+00 - val_loss: 0.2356
Epoch 11/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 35s 19ms/step - accuracy: 6.3127e-08 -
loss: 0.2181 - val_accuracy: 1.2755e-07 - val_loss: 0.2345
Epoch 12/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 34s 18ms/step - accuracy: 1.2266e-08 -
loss: 0.2174 - val_accuracy: 0.0000e+00 - val_loss: 0.2343
Epoch 13/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 35s 19ms/step - accuracy: 0.0000e+00 -
loss: 0.2158 - val_accuracy: 0.0000e+00 - val_loss: 0.2321
Epoch 14/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 35s 19ms/step - accuracy: 0.0000e+00 -
loss: 0.2148 - val_accuracy: 0.0000e+00 - val_loss: 0.2307
Epoch 15/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 35s 19ms/step - accuracy: 3.6927e-09 -
loss: 0.2133 - val_accuracy: 0.0000e+00 - val_loss: 0.2293
Epoch 16/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 33s 18ms/step - accuracy: 0.0000e+00 -
loss: 0.2121 - val_accuracy: 0.0000e+00 - val_loss: 0.2291
Epoch 17/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 31s 17ms/step - accuracy: 1.0218e-07 -
loss: 0.2110 - val_accuracy: 0.0000e+00 - val_loss: 0.2283
Epoch 18/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 36s 19ms/step - accuracy: 2.9603e-08 -
loss: 0.2103 - val_accuracy: 0.0000e+00 - val_loss: 0.2274
Epoch 19/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 54s 29ms/step - accuracy: 0.0000e+00 -
loss: 0.2099 - val_accuracy: 0.0000e+00 - val_loss: 0.2285
Epoch 20/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 55s 29ms/step - accuracy: 5.4110e-08 -
loss: 0.2088 - val_accuracy: 1.2755e-07 - val_loss: 0.2270
Epoch 21/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 52s 28ms/step - accuracy: 0.0000e+00 -
loss: 0.2080 - val_accuracy: 0.0000e+00 - val_loss: 0.2275
Epoch 22/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 54s 29ms/step - accuracy: 1.0257e-07 -
loss: 0.2081 - val_accuracy: 0.0000e+00 - val_loss: 0.2262
Epoch 23/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 54s 29ms/step - accuracy: 3.3156e-08 -
loss: 0.2082 - val_accuracy: 0.0000e+00 - val_loss: 0.2263
```

```
Epoch 24/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 53s 28ms/step - accuracy: 1.3005e-08 -
loss: 0.2077 - val_accuracy: 0.0000e+00 - val_loss: 0.2258
Epoch 25/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 54s 29ms/step - accuracy: 0.0000e+00 -
loss: 0.2071 - val_accuracy: 0.0000e+00 - val_loss: 0.2256
Epoch 26/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 53s 28ms/step - accuracy: 5.4650e-08 -
loss: 0.2071 - val_accuracy: 0.0000e+00 - val_loss: 0.2251
Epoch 27/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 54s 29ms/step - accuracy: 4.1283e-08 -
loss: 0.2065 - val_accuracy: 0.0000e+00 - val_loss: 0.2253
Epoch 28/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 54s 29ms/step - accuracy: 0.0000e+00 -
loss: 0.2059 - val_accuracy: 0.0000e+00 - val_loss: 0.2246
Epoch 29/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 54s 29ms/step - accuracy: 0.0000e+00 -
loss: 0.2059 - val_accuracy: 0.0000e+00 - val_loss: 0.2248
Epoch 30/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 55s 29ms/step - accuracy: 3.7958e-09 -
loss: 0.2053 - val_accuracy: 0.0000e+00 - val_loss: 0.2261
Epoch 31/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 54s 29ms/step - accuracy: 0.0000e+00 -
loss: 0.2049 - val_accuracy: 0.0000e+00 - val_loss: 0.2243
Epoch 32/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 55s 29ms/step - accuracy: 0.0000e+00 -
loss: 0.2052 - val_accuracy: 0.0000e+00 - val_loss: 0.2238
Epoch 33/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 54s 29ms/step - accuracy: 6.2936e-08 -
loss: 0.2045 - val_accuracy: 0.0000e+00 - val_loss: 0.2241
Epoch 34/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 54s 29ms/step - accuracy: 1.3434e-07 -
loss: 0.2040 - val_accuracy: 0.0000e+00 - val_loss: 0.2234
Epoch 35/35
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 56s 30ms/step - accuracy: 1.0019e-07 -
loss: 0.2041 - val_accuracy: 0.0000e+00 - val_loss: 0.2234

<keras.src.callbacks.history.History at 0x7f48908f1210>
```

1. Hiperparametry Autoencodera możesz dobrać wykorzystując wyszukiwanie siatkowe (grid search).

```
from sklearn.model_selection import GridSearchCV
from scikeras.wrappers import KerasRegressor, KerasClassifier

param_grid = {
    'encoding_dimension': [32, 196],
    'batch_size': [32, 64, 128],
    'epochs': [30, 40, 50]
}
```

```
kerasClassifier = KerasClassifier(build_fn=autoencoder, verbose=0)
grid_search = GridSearchCV(estimator=kerasClassifier,
param_grid=param_grid, cv=3)

grid_search.fit(t_x_train, t_x_train)

print("Best Hyperparameters:", grid_search.best_params_)
```

Wyszukiwanie siatkowe nie zadziałało, dlatego opóściłem ten podpunkt.

1. Korzystając w wytrenowanego Autoencodera wygeneruj nowe cechy dla zbioru treningowego oraz zbioru testowego.

```
reconstructions_x_train = autoencoder.predict(x_train)
reconstructions_x_test = autoencoder.predict(x_test)

reconstructions_f_x_train = f_autoencoder.predict(f_x_train)
reconstructions_f_x_test = f_autoencoder.predict(f_x_test)

reconstructions_k_x_train = k_autoencoder.predict(k_x_train)
reconstructions_k_x_test = k_autoencoder.predict(k_x_test)

1875/1875 ━━━━━━━━━━━━━━━━━━━━ 13s 7ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step
```

1. Wytrenuj klasyfikator LogisticRegression ustawiając solver='newton-cg'. Dokonaj predykcji na zbiorze testowym oraz porównaj uzyskane wyniki z wynikami z sekcji 5 i 6. Czy zmiana klasyfikatora na RandomForestClassifier poprawi dokładność klasyfikacji? Przedstaw swój komentarz do całościowych wyników klasyfikacji.

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

Dla mnist:

```
classifier = LogisticRegression(solver='newton-cg')
classifier.fit(x_train, y_train)

y_pred = classifier.predict(x_test)
y_pred_recon = classifier.predict(reconstructions_x_test)
print(f"accuracy_score baseline: {accuracy_score(y_pred, y_test)},
accuracy_score reconstructions: {accuracy_score(y_pred_recon,
y_test)}")

accuracy_score baseline: 0.926, accuracy_score reconstructions: 0.9308
```

Dla F-mnist:

```
f_classifier = LogisticRegression(solver='newton-cg')
f_classifier.fit(f_x_train, f_y_train)

y_pred = f_classifier.predict(f_x_test)
y_pred_recon = f_classifier.predict(reconstructions_f_x_test)
print(f"accuracy_score baseline: {accuracy_score(y_pred, f_y_test)},
accuracy_score reconstructions: {accuracy_score(y_pred_recon,
f_y_test)}")
```

```
accuracy_score baseline: 0.8434, accuracy_score reconstructions:
0.8336
```

Dla K-mnist:

```
k_classifier = LogisticRegression(solver='newton-cg')
k_classifier.fit(k_x_train, k_y_train)

y_pred = k_classifier.predict(k_x_test)
y_pred_recon = k_classifier.predict(reconstructions_k_x_test)
print(f"accuracy_score baseline: {accuracy_score(y_pred, k_y_test)},
accuracy_score reconstructions: {accuracy_score(y_pred_recon,
k_y_test)}")
```

```
accuracy_score baseline: 0.694, accuracy_score reconstructions: 0.7015
```

```
rf_classifier = RandomForestClassifier()
rf_classifier.fit(x_train, y_train)

y_pred_rf = rf_classifier.predict(x_test)
y_pred_rf_recon = rf_classifier.predict(reconstructions_x_test)
print(f"accuracy_score baseline: {accuracy_score(y_pred_rf, y_test)},
accuracy_score reconstructions: {accuracy_score(y_pred_rf_recon,
y_test)}")
```

```
accuracy_score baseline: 0.969, accuracy_score reconstructions: 0.9285
```

```
f_rf_classifier = RandomForestClassifier()
f_rf_classifier.fit(f_x_train, f_y_train)
y_pred_rf = f_rf_classifier.predict(f_x_test)
y_pred_rf_recon = f_rf_classifier.predict(reconstructions_f_x_test)
print(f"accuracy_score baseline: {accuracy_score(y_pred_rf,
f_y_test)}, accuracy_score reconstructions:
{accuracy_score(y_pred_rf_recon, f_y_test)}")
```

```
accuracy_score baseline: 0.878, accuracy_score reconstructions: 0.82
```

```
k_rf_classifier = RandomForestClassifier()
k_rf_classifier.fit(k_x_train, k_y_train)
y_pred_rf = k_rf_classifier.predict(k_x_test)
```

```
y_pred_rf_recon = k_rf_classifier.predict(reconstructions_k_x_test)
print(f"accuracy_score baseline: {accuracy_score(y_pred_rf,
k_y_test)}, accuracy_score reconstructions:
{accuracy_score(y_pred_rf_recon, k_y_test)}")
```

```
accuracy_score baseline: 0.8553, accuracy_score reconstructions:
0.7156
```

Wnioski:

Klasyfikator random forest dla baseline-u zwracał lepsze wyniki niż logistic regression. Ale dla rekonstrukcji logistic regression ma lepsze wyniki. Porównując z podpunktem 5 to MNIST i F-MNIST miały lepszy wynik, a K-MNIST osiągnął słabszy. Porównując z podpunktem 6 to MNIST i K-MNIST miały słabszy wynik, a F-MNIST osiągnął lepszy. RBM i autoencoder poprawiły wyniki klasyfikacji. Ekstrakcja cech pomaga w wyszukiwaniu wzorców i klasyfikacji danych.

1. ⋆ Zaproponuj własną architekturę głębokiego Autoencodera wykorzystującego filtry konwolucyjne. Nowe podejście do ekstrakcji cech powinno poprawić dokładność klasyfikacji na wszystkich zbiorach danych.

Ten podpunkt został zrealizowany w oddzielnym notebooku o nazwie: task7_Adrian_Chrobot.ipynb