In [1]:

```
import warnings
warnings.filterwarnings("ignore")

import numpy as np
import pandas as pd
from sklearn.datasets import load_breast_cancer
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix

from sklearn.datasets import fetch_openml
from sklearn.svm import SVC
import matplotlib.pyplot as plt
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import loguniform

from util import plot_confusion_matrix
```

Introduction

For today's tutorial, I will show the demos of Logistic Regression and SVC (Support Vector Classification). While taking this tutorial, you can run this notebook step by step. I will use the python package called *scikit-learn* for models and *pandas* for feature visualization.

Logistic Regression

In this section, I will show the demo of Logistic Regression to predict whether the tumor is malignant or benign (you do not need to worry about these words). More specifically, it conducts binary classification.

Table of Contents

References

- Confusion Matrix
- train_test_split
- Logistic Regression

Data Preparation (Visualization)

I will use Breast Cancer Wisconsin (Diagnostic) Data Set), which is used for binary classification. It includes 30 features (attributes) of tumors and we need to judge whether the tumor is malignant or benign from these features. This dataset is available on *scikit-learn*, so we can call it by their loading function.

- Functions
  - `load_breast_cancer` : call dataset.
  - `train_test_split` : split dataset into the train and the test datasets.

In [2]:

```
data = load_breast_cancer()
X = data.data
y = data.target
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state

print(f"# of training data : {len(y_train)}")
print(f"# of test data     : {len(y_test)}")

df = pd.DataFrame(X_train, columns=data.feature_names)
df.describe()
```

```
# of training data : 455
# of test data     : 114
```

Out[2]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	c
count	455.000000	455.000000	455.000000	455.000000	455.000000	455.000000	455.000000	455.
mean	14.117635	19.185033	91.882242	654.377582	0.095744	0.103619	0.088898	0.
std	3.535815	4.266005	24.322027	354.943187	0.013923	0.052470	0.079468	0.
min	7.691000	9.710000	47.920000	170.400000	0.052630	0.019380	0.000000	0.
25%	11.705000	16.170000	75.100000	420.300000	0.085825	0.062890	0.029320	0.
50%	13.300000	18.680000	85.980000	551.700000	0.094620	0.090970	0.061540	0.
75%	15.740000	21.585000	103.750000	767.600000	0.104550	0.131300	0.132350	0.
max	28.110000	39.280000	188.500000	2501.000000	0.163400	0.311400	0.426800	0.

8 rows × 30 columns

Training

Let's train your own logistic regression model. We have two hyper-parameters for the model. You can change these parameters to define different models.

- Functions
  - `LogisticRegression` : Define Logistic Regression Models.
  - `fit` : Train the model.
  - `predict_proba` : Compute the probability

- `predict` : Predict from the probability
- `score` : Compute accuracy

- Hyper-Parameters

  - `penalty` : the norm of the penalty: 'none' or 'l2'
  - `C` : Inverse of regularization strength

In [3]:

```
# --- Adjustable Parameters --- #

penalty = "none"
C = 1

# ----------------------------- #

clf = LogisticRegression(penalty=penalty, C=C)
clf.fit(X_train, y_train);

y_train_pred = clf.predict_proba(X_train) # We can use "clf.predict()" to directly ge
y_train_pred = np.argmax(y_train_pred, axis=1)
print(f"Train Accuracy : {clf.score(X_train, y_train)}")
```

```
Train Accuracy : 0.9538461538461539
```

Evaluation

You can compute the test accuracy.

In [4]:

```
y_test_pred = clf.predict_proba(X_test) # We can use "clf.predict()" to directly get
y_test_pred = np.argmax(y_test_pred, axis=1)
print(f"Test  Accuracy : {clf.score(X_test, y_test)}")
```

```
Test  Accuracy : 0.956140350877193
```

When you analyze your model, observing accuracy is not enough and you can not validate your model with only accuracy. I will show you the more detailed analysis later in the SVC section.

Support Vector Classification

In this section, I will show the demo of Support Vector Classification (SVC) to classify the hand-written digits.

Table of Contents

- Evaluation

References

- Randomized Search
- MNIST dataset for SVC

Data Preparation

In this demo, I will use one of the most popular datasets named MNIST. This includes the hand-written digits and mostly used for classification.

- Functions
  - `fetch_openml` : Call machine learning datasets (it takes time to download).

In [5]:

```
mnist = fetch_openml("mnist_784", data_home="mnist/")
data_num = 1000
X = mnist.data.values[:data_num]/255
y = np.array(mnist.target.values[:data_num], dtype=np.int)
```

In [6]:

```
classes = np.sort(pd.unique(y))
n_samples = X.shape[0]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

print(f"# of training data : {len(y_train)}")
print(f"# of test data     : {len(y_test)}")
```

```
# of training data : 800
# of test data     : 200
```

Data Visualization

Since data is originally represented as 2d image, we can visualize it with the reshaping function. Since some codes are unique to python (numpy) programming, you do not need to obsess with this cell.

In [7]:

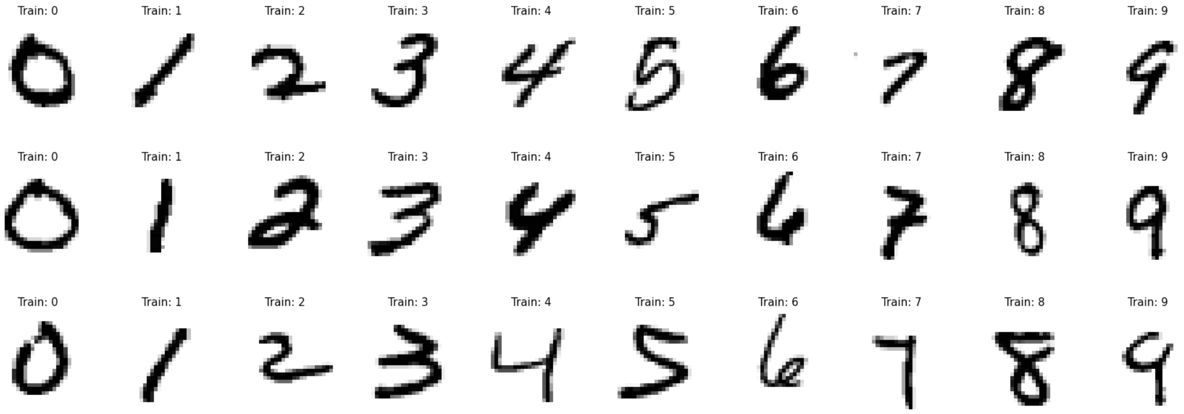
```
# --- Adjustable Parameters ---

display_num = 3

# -----------------------------

width = len(classes)
length = display_num
fig = plt.figure(figsize=(width*3, length*3.5))
for i in classes:
    images = X_train[y_train==i][:display_num]
```

```python
    for j in range(display_num):
        ax = fig.add_subplot(length, width, j*width+i+1)
        ax.set_axis_off()
        image = images[j].reshape(28, 28)
        ax.imshow(image, cmap=plt.cm.gray_r)
        ax.set_title(f"Train: {i}", fontsize=15)
```



Training

Let's train your own SVC to classify hand-written digits. As explained in the lesson (please check *DDA3020_SVM-II.pdf*), in SVM (SVC), *kernels* can add complexity (capability) to models. In this demo, I will use two kernels: linear and rbf; we can set it using a hyper-parameter `kernel` .

Linear

We can set a hyper-parameter `C` for linear.

- Functions
    - `SVC` : Define Support Vector Classification.
- Hyper-Parameters
    - `C` : Inverse of regularization strength

In [23]:

```python
# --- Adjustable Parameters ---

C = 1.0
kernel = "linear"

# ----------------------------

clf = SVC(C=C, kernel=kernel)
clf.fit(X_train, y_train)

y_train_pred = clf.predict(X_train)
print(f"Train Accuracy : {clf.score(X_train, y_train)}")

y_test_pred = clf.predict(X_test)
print(f"Test  Accuracy : {clf.score(X_test, y_test)}")
```

```
Train Accuracy : 1.0
Test  Accuracy : 0.875
```

Radial Basis Function (RBF)

We can set two hyper-parameters for rbf.

- Hyper-Parameters
  - `C` : Inverse of regularization strength
  - `gamma` : Kernel coefficient. We can add complexity to models with larger `gamma` .
    - Recall $K(x, x') = \exp(-\gamma \|x - x'\|^2)$

In [24]:

```
# --- Adjustable Parameters ---

C = 1.0
kernel = "rbf"
gamma = 0.1

# ----------------------------

clf = SVC(C=C, kernel=kernel, gamma=gamma)
clf.fit(X_train, y_train)

y_train_pred = clf.predict(X_train)
print(f"Train Accuracy : {clf.score(X_train, y_train)}")

y_test_pred = clf.predict(X_test)
print(f"Test  Accuracy : {clf.score(X_test, y_test)}")
```

```
Train Accuracy : 1.0
Test  Accuracy : 0.74
```

Hyper-Parameters Tuning for RBF

Hyper-parameters are the parameters we set, so we are not sure if the chosen parameters are good or bad. Hyper-parameter tuning is an essential concept to machine learning to be confident with your hyper-parameters. The most-known tuning method is Grid Search. It generates candidates from a grid of parameter values you specify and find the hyper-parameters with the best result. I put the sample code of Grid Search at the end of this notebook, so If you are interested, please check them. In this demo, I will use the more efficient one which is called Randomized Search. It randomly generates candidates from the chosen range.

`cv` in arguments of `RandomizedSearchCV` indicates the k in Cross Validation, this is also important concept for hyper-parameter tuning. Please refer to the website if necessary (I will explain this if I have time).

- Hyper-Parameters
  - `C` : Inverse of regularization strength
  - `gamma` : Kernel coefficient. We can add complexity to models with larger `gamma` .
    - Recall $K(x, x') = \exp(-\gamma \|x - x'\|^2)$

In [28]:

```
svc = SVC(kernel="rbf", random_state=42)
```

```
distributions = dict(
    C=loguniform(1e-2, 1e2),
    gamma=loguniform(1e-4, 1)
)
clf = RandomizedSearchCV(svc, distributions, random_state=42, n_iter=10, cv=3, n_jobs
search = clf.fit(X_train, y_train)
best_params = search.best_params_
print("Best Parameters:")
for key in best_params:
    print(f"    {key}: {best_params[key]}")
```

```
Best Parameters:
    C: 8.471801418819974
    gamma: 0.024810409748678097
```

In [29]:

```
clf = SVC(C=best_params["C"], kernel="rbf", gamma=best_params["gamma"])
clf.fit(X_train, y_train)

y_train_pred = clf.predict(X_train)
print(f"Train Accuracy : {clf.score(X_train, y_train)}")

y_test_pred = clf.predict(X_test)
print(f"Test  Accuracy : {clf.score(X_test, y_test)}")
```

```
Train Accuracy : 1.0
Test  Accuracy : 0.905
```

Evaluation

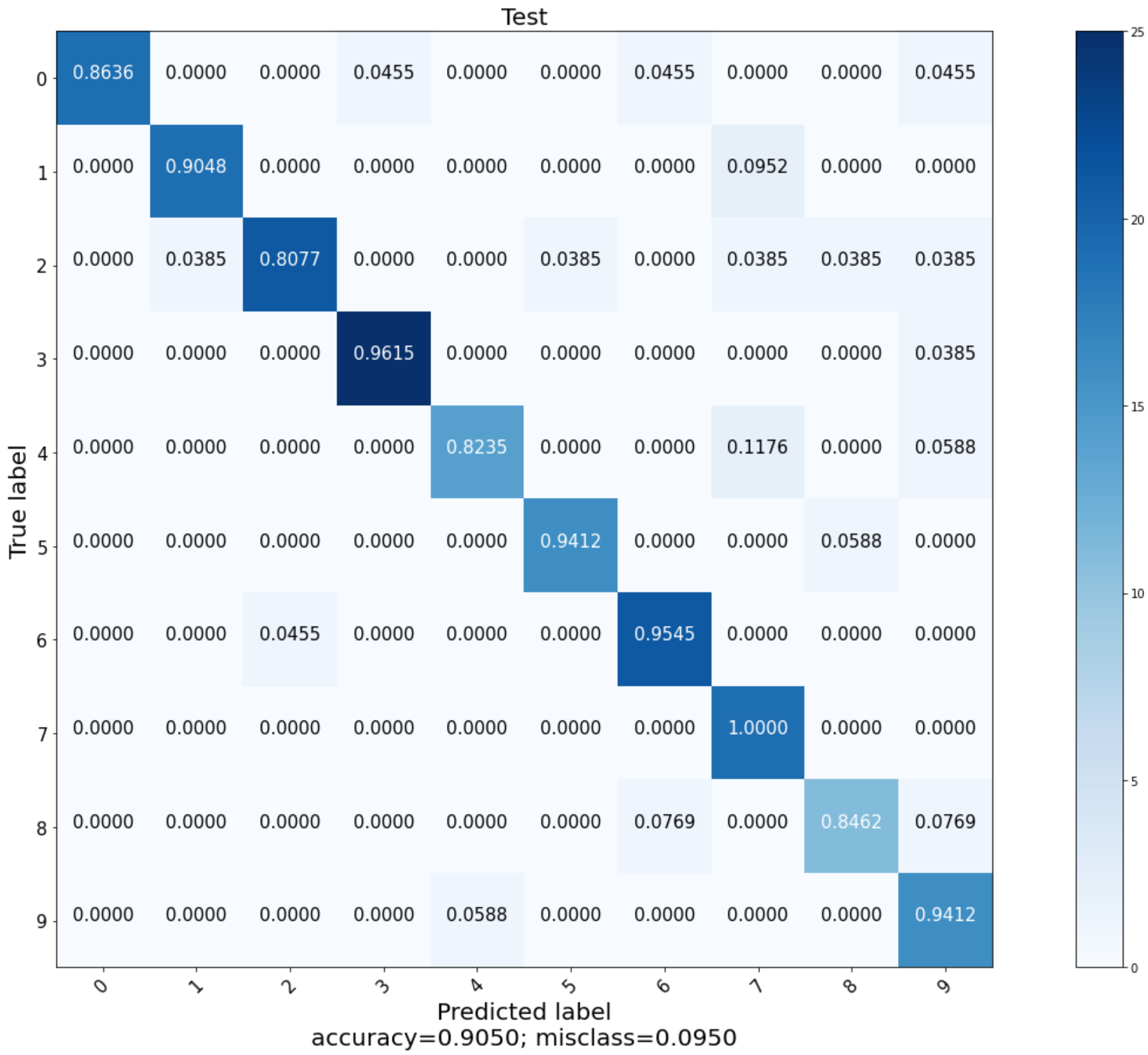
As I said, if you want to analyze your model, accuracy is not enough. So, I will show some ways to interpret your models.

Confusion Matrix

You can visualize Confusion Matrix to check more detailed errors.

In [15]:

```
cm = confusion_matrix(y_test_pred, y_test)
plot_confusion_matrix(cm, classes, title="Test", fontsize=15, figsize=(20,12))
```



Samples of Correct Prediction

It is nice to visualize the samples that the model correctly predict.

In [16]:

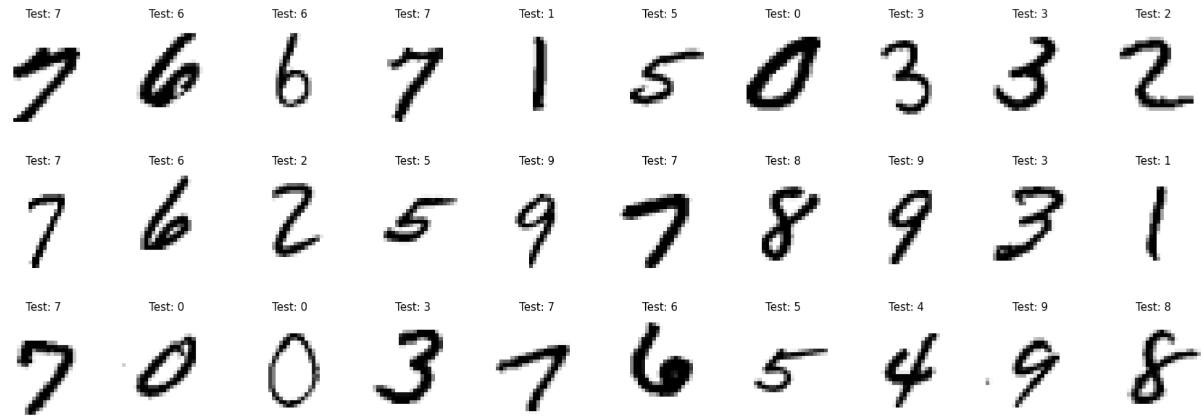
```
# --- Adjustable Parameters ---

width = 10
length = 3

# ----------------------------

index = y_test==y_test_pred
display_num = min(index.sum(), width*length)
images = X_test[index][:display_num]
true_labels = y_test[index][:display_num]

fig = plt.figure(figsize=(width*3, length*3.5))
for i in range(display_num):
    ax = fig.add_subplot(length, width, i+1)
    ax.set_axis_off()
    image = images[i].reshape(28, 28)
    ax.imshow(image, cmap=plt.cm.gray_r)
    ax.set_title(f"Test: {true_labels[i]}", fontsize=15)
```



Samples of Wrong Prediction

It is also nice to visualize the samples that the model failed to predict.

In [17]:

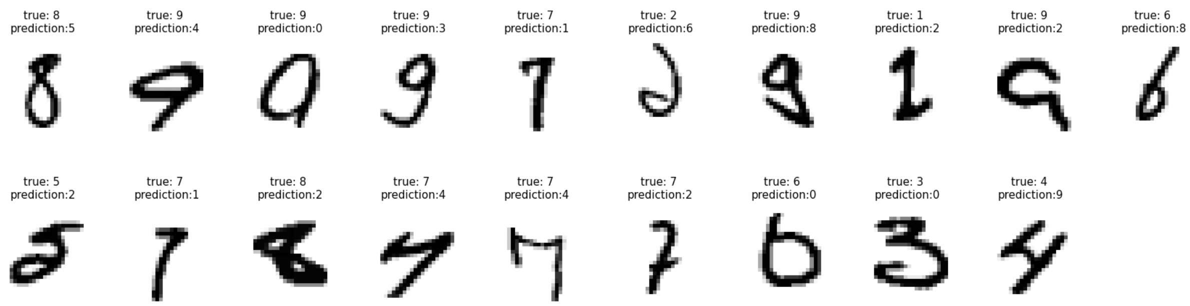
```
# --- Adjustable Parameters ---

width = 10
length = 3

# ----------------------------

index = y_test!=y_test_pred
display_num = min(index.sum(), width*length)
images = X_test[index][:display_num]
true_labels = y_test[index][:display_num]
predicted_labels = y_test_pred[index][:display_num]

fig = plt.figure(figsize=(width*3, length*4))
for i in range(display_num):
    ax = fig.add_subplot(length, width, i+1)
    ax.set_axis_off()
    image = images[i].reshape(28, 28)
    ax.imshow(image, cmap=plt.cm.gray_r)
#     ax.set_title(f"true: {true_labels[i]}, misclassified as {predicted_labels[i]}",
    ax.set_title(f"true: {true_labels[i]} \nprediction:{predicted_labels[i]}", fontsiz
```



Appendix

Grid Search

The cell below illustrates the example codes of Grid Search.

In [41]:

```
from sklearn.model_selection import GridSearchCV

gamma_grid = np.logspace(-3, 3, 5) # set the grid search parameter number for RBF SVM
C_grid = np.logspace(-3, 3, 5) # set the grid search parameter number for RBF SVM

svc = SVC(kernel="rbf")
parameters = [
    {'C': C_grid,
     'gamma': gamma_grid,
    }
]

clf = GridSearchCV(svc, param_grid=parameters, return_train_score=True, n_jobs=-1)
search = clf.fit(X_train, y_train)
best_params  = search.best_params_

print("Best Parameters:")
for key in best_params:
    print(f"    {key}: {best_params[key]}")

print()

clf = SVC(C=best_params["C"], kernel="rbf", gamma=best_params["gamma"])
clf.fit(X_train, y_train)

y_train_pred = clf.predict(X_train)
print(f"Train Accuracy : {clf.score(X_train, y_train)}")

y_test_pred = clf.predict(X_test)
print(f"Test  Accuracy : {clf.score(X_test, y_test)}")
```

```
Best Parameters:
    C: 31.622776601683793
    gamma: 0.03162277660168379
Train Accuracy : 1.0
Test  Accuracy : 0.905
```