In [8]:

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

import numpy as np
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier
from sklearn.model_selection import train_test_split

import matplotlib.pyplot as plt
from sklearn.model_selection import RandomizedSearchCV
```

Introduction

For today's tutorial, I will show the demos of tree-base methods. 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.

Decision Tree

In this section, I will show the demo of Decision Tree (DT) to classify the hand-written digits.

Table of Contents

References

- Decision Trees
- Bagging Classifier
- Random Forest

Data Preparation

In this demo, I will use the same dataset as the previous tutorial, MNIST. This includes the hand-written digits and mostly used for classification.

In [24]:
```
mnist = fetch_openml("mnist_784", data_home="mnist/")
data_num = 3000
X = mnist.data.values[:data_num]/255
y = np.array(mnist.target.values[:data_num], dtype=np.int)
```

In [25]:
```
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 : 2400
# of test data     : 600
```

Data Visualization

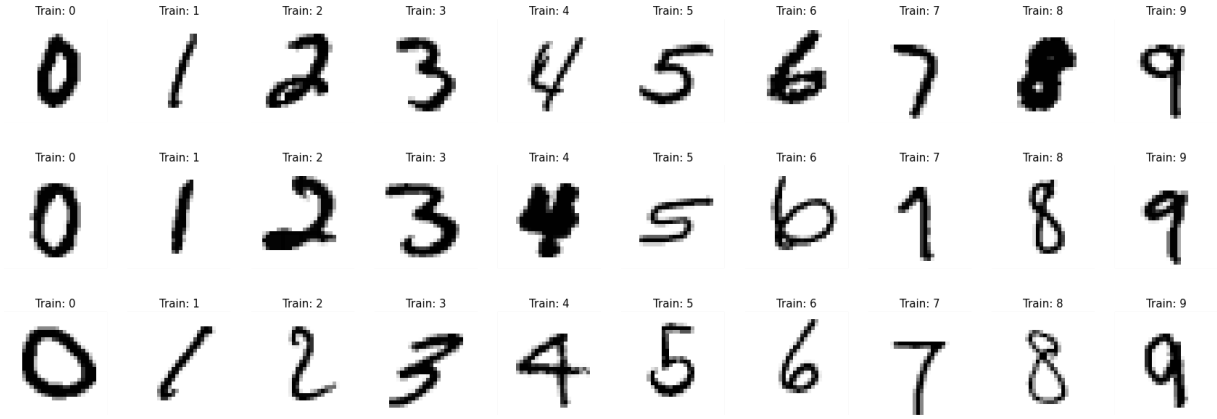
Since data is originally represented as 2d image, we can visualize it with the reshaping function. Since some codes are unique to python (numpy) programming, you do not need to obsess with this cell.

In [26]:
```
# --- 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]
    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)
```



Coding Samples

Let's train your own tree models to classify hand-written digits. Among the models explained in the lesson (please check *DDA3020 Lecture 08 Tree-based methods.pdf*), I will introduce the demos of Single Tree, Bagging Classifier, and Random Forest. And, since they have tree-related hyperparameters to set, I will conduct a hyper-parameter tuning later in this tutorial.

Single Tree

Among hyper-parameters, I will focus on two hyper-parameters: `max_depth` and `min_samples_split` (ppg.52 in the slide).

- Functions
  - `DecisionTreeClassifier` : Define Single Tree.
- Hyper-Parameters
  - `max_depth` : The maximum depth of the tree
  - `min_samples_split` : The minimum number of samples required to split an internal node

---

In [29…

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

max_depth = 8
min_samples_split = 2

# ---------------------------- #
clf = DecisionTreeClassifier(random_state=0,
                             min_samples_split=min_samples_split,
                             max_depth=max_depth
                            )
clf.fit(X_train, y_train)
print(f"Train Accuracy : {clf.score(X_train, y_train)}")
print(f"Test  Accuracy : {clf.score(X_test, y_test)}")
```

```
Train Accuracy : 0.8866666666666667
Test  Accuracy : 0.7466666666666667
```

Bagging Classifier

As explained in the lecture, Bagging Classifier includes multiple classifiers with different sub-training dataset. We have `n_estimators` to set the # of classifiers (decision trees).

Note: We can use any classifier for Bagging Classifier (ex. SVC)

- Functions
  - `BaggingClassifier` : Define Bagging Classifier
- Hyper-Parameters
  - `n_estimators` : # of classifiers

In [27…

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

max_depth = 8
min_samples_split = 2
n_estimators = 10

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

dt = DecisionTreeClassifier(random_state=0,
                            min_samples_split=min_samples_split,
                            max_depth=max_depth)

clf = BaggingClassifier(base_estimator=dt,
                        n_estimators=n_estimators,
                        random_state=0,
                       )

clf.fit(X_train, y_train)
print(f"Train Accuracy : {clf.score(X_train, y_train)}")
print(f"Test  Accuracy : {clf.score(X_test, y_test)}")
```

```
Train Accuracy : 0.9654166666666667
Test  Accuracy : 0.8533333333333334
```

Random Forest

For Random Forest, it has the same hyper-parameters as Bagging Classifier but expected to be better than that.

- Functions
  - `RandomForestClassifier` : Define Random Forest

In [27…

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

max_depth = 8
min_samples_split = 2
n_estimators = 10

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

clf = RandomForestClassifier(random_state=0,
                             n_estimators=n_estimators,
                             min_samples_split=min_samples_split,
                             max_depth=max_depth,
                            )
```

```
clf.fit(X_train, y_train)
print(f"Train Accuracy : {clf.score(X_train, y_train)}")
print(f"Test  Accuracy : {clf.score(X_test, y_test)}")
```

```
Train Accuracy : 0.96125
Test  Accuracy : 0.8766666666666667
```

Hyper-Parameters Tuning

As explained in the lesson, tree-based models are vulnerable to overfitting. So, we need to find better hyperparameters (high accuracy and weaker overfitting) via hyper-parameters tuning. Since the grid search requires much time to process, I will use Randomized Search used in the last tutorial.

`cv` in arguments of `RandomizedSearchCV` indicates the k in Cross Validation.

- Hyper-Parameters
  - `max_depth` : The maximum depth of the tree
  - `min_samples_split` : The minimum number of samples required to split an internal node

---

Single Tree

In [30…

```
models = {}
dt = DecisionTreeClassifier(random_state=0)
distributions = dict(
    max_depth=np.arange(5, 31),
    min_samples_split=2**np.arange(0, 4),
)

# Random Search

clf = RandomizedSearchCV(dt, distributions, random_state=0, n_iter=20, 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]}")

# Classification with Best Parameters

st = DecisionTreeClassifier(random_state=0,
                            min_samples_split=best_params["min_samples_split"],
                            max_depth=best_params["max_depth"]
                           )
st.fit(X_train, y_train)
models["single tree"] = st

print()
print(f"Train Accuracy : {st.score(X_train, y_train)}")
print(f"Test  Accuracy : {st.score(X_test, y_test)}")
```

```
Best Parameters:
    min_samples_split: 4
```

```
    max_depth: 20

Train Accuracy : 0.9729166666666667
Test  Accuracy : 0.7583333333333333
```

Bagging Classifier

In [30…

```
dt = DecisionTreeClassifier(random_state=0)
bc = BaggingClassifier(base_estimator=dt,
                       n_estimators=10,
                       random_state=0)

distributions = dict(
    base_estimator__max_depth=np.arange(5, 31),
    base_estimator__min_samples_split=2**np.arange(0, 4),
)

# Random Search

clf = RandomizedSearchCV(bc, distributions, random_state=0, n_iter=20, 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]}")

# Classification with Best Parameters

dt = DecisionTreeClassifier(random_state=0,
                            min_samples_split=best_params["base_estimator__min_sample
                            max_depth=best_params["base_estimator__max_depth"])

bc = BaggingClassifier(base_estimator=dt,
                       n_estimators=10,
                       random_state=0)

bc.fit(X_train, y_train)
models["bagging"] = bc

print()
print(f"Train Accuracy : {bc.score(X_train, y_train)}")
print(f"Test  Accuracy : {bc.score(X_test, y_test)}")
```

```
Best Parameters:
    base_estimator__min_samples_split: 4
    base_estimator__max_depth: 11

Train Accuracy : 0.9925
Test  Accuracy : 0.875
```

Random Forest

In [30…

```
rf = RandomForestClassifier(random_state=0,
                            n_estimators=10)
distributions = dict(
    max_depth=np.arange(5, 31),
    min_samples_split=2**np.arange(0, 4),
)

# Random Search

clf = RandomizedSearchCV(rf, distributions, random_state=0, n_iter=20, 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]}")

# Classification with Best Parameters

rf = RandomForestClassifier(random_state=0,
                            n_estimators=10,
                             min_samples_split=best_params["min_samples_split"],
                             max_depth=best_params["max_depth"]
                            )
rf.fit(X_train, y_train)
models["random forest"] = rf

print()
print(f"Train Accuracy : {rf.score(X_train, y_train)}")
print(f"Test  Accuracy : {rf.score(X_test, y_test)}")
```

```
Best Parameters:
    min_samples_split: 4
    max_depth: 12

Train Accuracy : 0.9945833333333334
Test  Accuracy : 0.9016666666666666
```

Feature Importance

One of other advantages of using tree-based models is its interpretability. In other words, We can easily understand how the models process data. Among them, I will introduce feature importance, which shows how each feature (in our case, pixels of images) affects the result.

- New Attributes
  - `feature_importances_` : feature importance of each feature

Single Tree

In [31…

```
model = models["single tree"]

fi = model.feature_importances_
fi_df = pd.DataFrame([np.array([f"pixel-({i//28}, {i%28})" for i in range(784)]), fi
fi_df["importance"] = fi_df["importance"].values.astype("float")

fi_df.sort_values(by="importance", ascending=False)
```

Out[317]:

	name	importance
455	pixel-(16, 7)	0.054454
101	pixel-(3, 17)	0.049829
433	pixel-(15, 13)	0.048679
401	pixel-(14, 9)	0.046974
319	pixel-(11, 11)	0.037186
…	…	…

	name	importance
275	pixel-(9, 23)	0.000000
277	pixel-(9, 25)	0.000000
278	pixel-(9, 26)	0.000000
279	pixel-(9, 27)	0.000000
783	pixel-(27, 27)	0.000000

784 rows × 2 columns

Bagging Classifier

In [27…

```
model = models["bagging"]

fi = np.zeros((784))
for tree in model.estimators_:
    fi += tree.feature_importances_
fi = fi/len(model.estimators_)
fi_df = pd.DataFrame([np.array([f"pixel-({i//28}, {i%28})" for i in range(784)]), fi
fi_df["importance"] = fi_df["importance"].values.astype("float")

fi_df.sort_values(by="importance", ascending=False)
```

Out[270]:

	name	importance
101	pixel-(3, 17)	0.044064
211	pixel-(7, 15)	0.038646
377	pixel-(13, 13)	0.032051
271	pixel-(9, 19)	0.026425
455	pixel-(16, 7)	0.025969
…	…	…
252	pixel-(9, 0)	0.000000
251	pixel-(8, 27)	0.000000
250	pixel-(8, 26)	0.000000
244	pixel-(8, 20)	0.000000
783	pixel-(27, 27)	0.000000

784 rows × 2 columns

Random Forest

In [27…

```
model = models["random forest"]

fi = model.feature_importances_
fi_df = pd.DataFrame([np.array([f"pixel-({i//28}, {i%28})" for i in range(784)]), fi
fi_df["importance"] = fi_df["importance"].values.astype("float")

fi_df.sort_values(by="importance", ascending=False)
```

Out[271]:

	name	importance
409	pixel-(14, 17)	0.011869
541	pixel-(19, 9)	0.011469
430	pixel-(15, 10)	0.010728
350	pixel-(12, 14)	0.010294
373	pixel-(13, 9)	0.009845
...	...	...
255	pixel-(9, 3)	0.000000
254	pixel-(9, 2)	0.000000
253	pixel-(9, 1)	0.000000
252	pixel-(9, 0)	0.000000
783	pixel-(27, 27)	0.000000

784 rows × 2 columns

2d Representation of Feature Importance

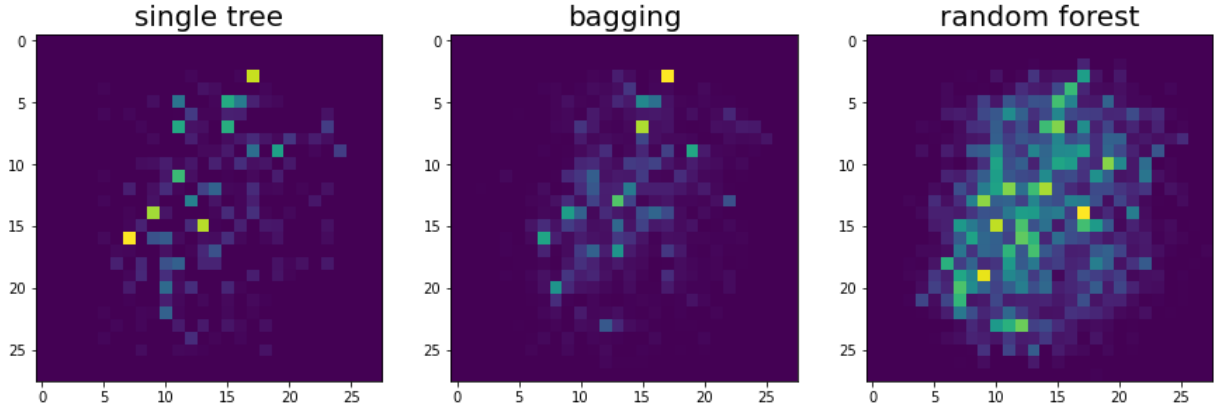
Of course, the feature name of MNIST is not intuitive, so let's visualize it in 2d-representation.

In [15...

```
width = len(models)
length = 1

fig = plt.figure(figsize=(width*5, length*5.5))

for i, name in enumerate(models):
    if name in ["bagging"]:
        fi = np.zeros((784))
        for tree in models[name].estimators_:
            fi += tree.feature_importances_
        fi = fi/len(models[name].estimators_)
    else:
        fi = models[name].feature_importances_
    ax = fig.add_subplot(length, width, i+1)
    ax.imshow(fi.reshape(28, 28))
    ax.set_title(name, fontsize=20)
```



Let's Observe the Validity of Feature Importance

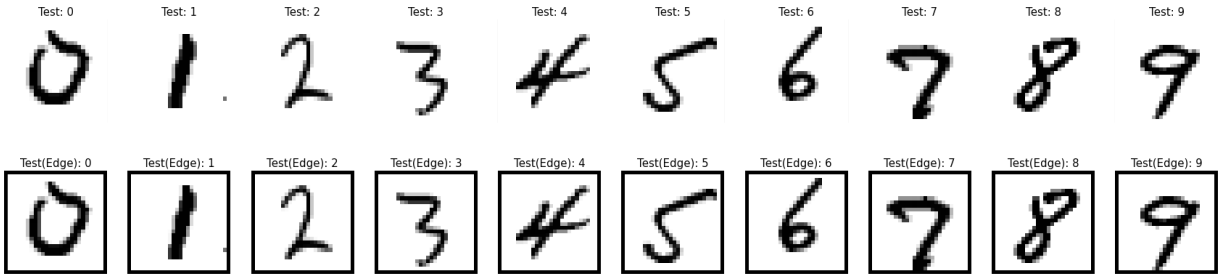
Let's modify the values of the *un-important* features and the *important* features; and see the result.

In [22…

```
frame = np.zeros((28, 28))
frame[[0,-1],:] = 1
frame[:, [0,-1]] = 1
X_test_edge = X_test + frame.reshape(1, 784)
X_test_edge[X_test_edge>1] = 1

width = len(classes)
length = 2
fig = plt.figure(figsize=(width*3, length*3.5))
for i in classes:
    images = X_test[y_test==i][:1]
    ax = fig.add_subplot(length, width, i+1)
    ax.set_axis_off()
    image = images[0].reshape(28, 28)
    ax.imshow(image, cmap=plt.cm.gray_r)
    ax.set_title(f"Test: {i}", fontsize=15)

    images = X_test_edge[y_test==i][:1]
    ax = fig.add_subplot(length, width, width+i+1)
    ax.set_axis_off()
    image = images[0].reshape(28, 28)
    ax.imshow(image, cmap=plt.cm.gray_r)
    ax.set_title(f"Test(Edge): {i}", fontsize=15)
```



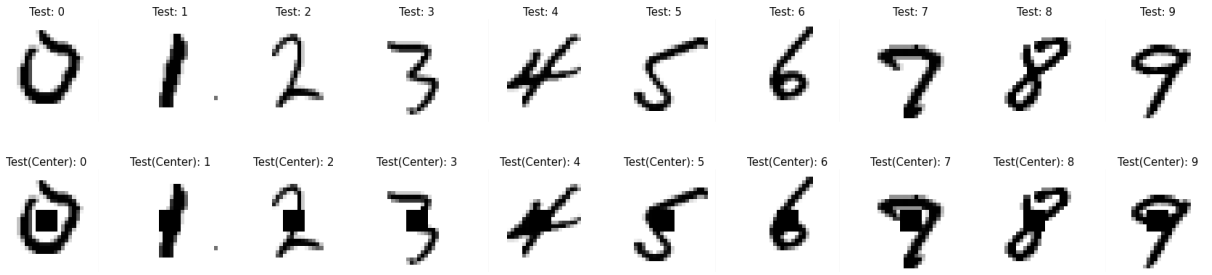
In [22…

```
frame = np.zeros((28, 28))
frame = np.zeros((28, 28))
frame[11:17,11:17] = 1
X_test_center = X_test + frame.reshape(1, 784)
X_test_center[X_test_center>1] = 1

width = len(classes)
length = 2
fig = plt.figure(figsize=(width*3, length*3.5))
for i in classes:
    images = X_test[y_test==i][:1]
    ax = fig.add_subplot(length, width, i+1)
    ax.set_axis_off()
    image = images[0].reshape(28, 28)
    ax.imshow(image, cmap=plt.cm.gray_r)
    ax.set_title(f"Test: {i}", fontsize=15)

    images = X_test_center[y_test==i][:1]
    ax = fig.add_subplot(length, width, width+i+1)
    ax.set_axis_off()
    image = images[0].reshape(28, 28)
```

```
    ax.imshow(image, cmap=plt.cm.gray_r)
    ax.set_title(f"Test(Center): {i}", fontsize=15)
```



In [30…

```
for i, name in enumerate(models):
    print(f"Classifier: {name}")
    print(f"    Original Test Accuracy: {models[name].score(X_test, y_test)}")
    print(f"    Edge     Test Accuracy: {models[name].score(X_test_edge, y_test)}")
    print(f"    Center   Test Accuracy: {models[name].score(X_test_center, y_test)}")
    print()
```

```
Classifier: single tree
    Original Test Accuracy: 0.7583333333333333
    Edge     Test Accuracy: 0.7583333333333333
    Center   Test Accuracy: 0.32

Classifier: bagging
    Original Test Accuracy: 0.875
    Edge     Test Accuracy: 0.875
    Center   Test Accuracy: 0.5566666666666666

Classifier: random forest
    Original Test Accuracy: 0.9016666666666666
    Edge     Test Accuracy: 0.9016666666666666
    Center   Test Accuracy: 0.6916666666666667
```