ML Classification Template

Feature Scaling are applied to improve the overall result even though some algorithms DO NOT need it.

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

In [2]:
```
df = pd.read_csv("Data.csv")
df.head()
```

Out[2]:

	Sample code number	Clump Thickness	Uniformity of Cell Size	Uniformity of Cell Shape	Marginal Adhesion	Single Epithelial Cell Size	Bare Nuclei	Bland Chromatin	Normal Nucleoli	Mitoses	Class
0	1000025	5	1	1	1	2	1	3	1	1	2
1	1002945	5	4	4	5	7	10	3	2	1	2
2	1015425	3	1	1	1	2	2	3	1	1	2
3	1016277	6	8	8	1	3	4	3	7	1	2
4	1017023	4	1	1	3	2	1	3	1	1	2

In [3]:
```
df.isnull().sum()
```

Out[3]:
```
Sample code number            0
Clump Thickness               0
Uniformity of Cell Size       0
Uniformity of Cell Shape      0
Marginal Adhesion             0
Single Epithelial Cell Size   0
Bare Nuclei                   0
Bland Chromatin               0
Normal Nucleoli               0
Mitoses                       0
Class                         0
dtype: int64
```

In [4]:
```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

Decision Trees

In [5]:
```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

In [6]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)
classifier.fit(X_train, y_train)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           2       0.97      0.96      0.97       107
           4       0.94      0.95      0.95        64

    accuracy                           0.96       171
   macro avg       0.96      0.96      0.96       171
weighted avg       0.96      0.96      0.96       171

[[103   4]
 [  3  61]]
0.9590643274853801
```

K Nearst Neighbors

In [7]:
```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

In [8]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
```

```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
classifier.fit(X_train, y_train)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           2       0.95      0.96      0.96       107
           4       0.94      0.92      0.93        64

    accuracy                           0.95       171
   macro avg       0.95      0.94      0.94       171
weighted avg       0.95      0.95      0.95       171

[[103   4]
 [  5  59]]
0.9473684210526315
```

Support Vector Machine (kernel='linear')

In [9]:
```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

In [10]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from sklearn.svm import SVC
classifier = SVC(kernel = 'linear', random_state = 0)
classifier.fit(X_train, y_train)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           2       0.95      0.95      0.95       107
           4       0.92      0.92      0.92        64

    accuracy                           0.94       171
   macro avg       0.94      0.94      0.94       171
weighted avg       0.94      0.94      0.94       171

[[102   5]
 [  5  59]]
0.9415204678362573
```

Support Vector Machine (Kernel="rbf")

In [11]:
```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

In [12]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from sklearn.svm import SVC
classifier = SVC(kernel = 'rbf', random_state = 0)
classifier.fit(X_train, y_train)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           2       0.97      0.95      0.96       107
           4       0.92      0.95      0.94        64

    accuracy                           0.95       171
   macro avg       0.95      0.95      0.95       171
weighted avg       0.95      0.95      0.95       171

[[102   5]
```

```
[  3  61]]
0.9532163742690059
```

Logistic Regression

In [13]:
```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

In [14]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           2       0.95      0.96      0.96       107
           4       0.94      0.92      0.93        64

    accuracy                           0.95       171
   macro avg       0.95      0.94      0.94       171
weighted avg       0.95      0.95      0.95       171

[[103   4]
 [  5  59]]
0.9473684210526315
```

Naive Bayes (GaussianNB)

In [15]:
```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

In [16]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           2       0.98      0.93      0.95       107
           4       0.89      0.97      0.93        64

    accuracy                           0.94       171
   macro avg       0.93      0.95      0.94       171
weighted avg       0.94      0.94      0.94       171

[[99  8]
 [ 2 62]]
0.9415204678362573
```

Navie Bayes (MultinomialNB)

In [17]:
```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

In [18]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from sklearn.naive_bayes import MultinomialNB
classifier = MultinomialNB()
classifier.fit(X_train, y_train)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
y_pred = classifier.predict(X_test)
```

```
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-18-6c27a474db04> in <module>
      9 from sklearn.naive_bayes import MultinomialNB
     10 classifier = MultinomialNB()
---> 11 classifier.fit(X_train, y_train)
     12
     13 from sklearn.metrics import confusion_matrix, accuracy_score, classification_report

~\anaconda3\lib\site-packages\sklearn\naive_bayes.py in fit(self, X, y, sample_weight)
    636
    637         self._init_counters(n_effective_classes, n_features)
--> 638         self._count(X, Y)
    639         alpha = self._check_alpha()
    640         self._update_feature_log_prob(alpha)

~\anaconda3\lib\site-packages\sklearn\naive_bayes.py in _count(self, X, Y)
    769     def _count(self, X, Y):
    770         """Count and smooth feature occurrences."""
--> 771         check_non_negative(X, "MultinomialNB (input X)")
    772         self.feature_count_ += safe_sparse_dot(Y.T, X)
    773         self.class_count_ += Y.sum(axis=0)

~\anaconda3\lib\site-packages\sklearn\utils\validation.py in check_non_negative(X, whom)
   1123
   1124     if X_min < 0:
-> 1125         raise ValueError("Negative values in data passed to %s" % whom)
   1126
   1127

ValueError: Negative values in data passed to MultinomialNB (input X)
```

Stochastic Gradient Descent

In [19]:

```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

In [20]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from sklearn.linear_model import SGDClassifier
# classifier = SGDClassifier(loss="hinge", penalty="l2", max_iter=5)
classifier = SGDClassifier()
classifier.fit(X_train, y_train)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           2       0.95      0.97      0.96       107
           4       0.95      0.91      0.93        64

    accuracy                           0.95       171
   macro avg       0.95      0.94      0.94       171
weighted avg       0.95      0.95      0.95       171

[[104   3]
 [  6  58]]
0.9473684210526315
```

XGBoost

In [21]:

```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

In [22]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from xgboost import XGBClassifier
classifier = XGBClassifier()
classifier.fit(X_train, y_train)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
[12:32:31] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/src/learner.cc:1095: Starting in XGBoost 1.
3.0, the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'logloss'. Explicit
ly set eval_metric if you'd like to restore the old behavior.
              precision    recall  f1-score   support

           2       0.95      0.96      0.96       107
           4       0.94      0.92      0.93        64

    accuracy                           0.95       171
   macro avg       0.95      0.94      0.94       171
weighted avg       0.95      0.95      0.95       171

[[103   4]
 [  5  59]]
0.9473684210526315
```

```
C:\Users\Perry\anaconda3\lib\site-packages\xgboost\sklearn.py:1146: UserWarning: The use of label encoder in XGBClassifier i
s deprecated and will be removed in a future release. To remove this warning, do the following: 1) Pass option use_label_enc
oder=False when constructing XGBClassifier object; and 2) Encode your labels (y) as integers starting with 0, i.e. 0, 1, 2,
..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
```

Catboost (Tune by itself and no need to parameter tuning, good results when having multiple categorical variables)

In [23]:
```
# pip install catboost
```

In [24]:
```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

In [25]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from catboost import CatBoostClassifier
classifier = CatBoostClassifier()
classifier.fit(X_train, y_train)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
992:    learn: 0.0097515        total: 1.84s    remaining: 12.9ms
993:    learn: 0.0097357        total: 1.84s    remaining: 11.1ms
994:    learn: 0.0097215        total: 1.84s    remaining: 9.24ms
995:    learn: 0.0096939        total: 1.84s    remaining: 7.39ms
996:    learn: 0.0096689        total: 1.84s    remaining: 5.54ms
997:    learn: 0.0096557        total: 1.84s    remaining: 3.69ms
998:    learn: 0.0096378        total: 1.84s    remaining: 1.85ms
999:    learn: 0.0096212        total: 1.85s    remaining: 0us
              precision    recall  f1-score   support

           2       0.95      0.96      0.96       107
           4       0.94      0.92      0.93        64

    accuracy                           0.95       171
   macro avg       0.95      0.94      0.94       171
weighted avg       0.95      0.95      0.95       171

[[103   4]
 [  5  59]]
0.9473684210526315
```

LightGBM (Light Gradient Boosting Machine)

In [26]:
```
# pip install lightgbm
```

In [27]:
```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

In [28]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from lightgbm import LGBMClassifier
classifier = LGBMClassifier()
classifier.fit(X_train, y_train)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
              precision    recall  f1-score   support
```

```
           2       0.96      0.96      0.96       107
           4       0.94      0.94      0.94        64

    accuracy                           0.95       171
   macro avg       0.95      0.95      0.95       171
weighted avg       0.95      0.95      0.95       171

[[103   4]
 [  4  60]]
0.9532163742690059
```

In [29]:

```
#!/usr/bin/python
# -*- coding: utf-8 -*-

"""
====================
Classifier comparison
====================

A comparison of a several classifiers in scikit-learn on synthetic datasets.
The point of this example is to illustrate the nature of decision boundaries
of different classifiers.
This should be taken with a grain of salt, as the intuition conveyed by
these examples does not necessarily carry over to real datasets.

Particularly in high-dimensional spaces, data can more easily be separated
linearly and the simplicity of classifiers such as naive Bayes and linear SVMs
might lead to better generalization than is achieved by other classifiers.

The plots show training points in solid colors and testing points
semi-transparent. The lower right shows the classification accuracy on the test
set.
"""
print(__doc__)


# Code source: Gaël Varoquaux
#              Andreas Müller
# Modified for documentation by Jaques Grobler
# License: BSD 3 clause

import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import make_moons, make_circles, make_classification
from sklearn.neural_network import MLPClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.gaussian_process.kernels import RBF
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from tqdm.notebook import tqdm

h = .02  # step size in the mesh

names = ["Nearest Neighbors", "Linear SVM", "RBF SVM", "Gaussian Process",
         "Decision Tree", "Random Forest", "Neural Net", "AdaBoost",
         "Naive Bayes", "QDA"]

classifiers = [
    KNeighborsClassifier(3),
    SVC(kernel="linear", C=0.025),
    SVC(gamma=2, C=1),
    GaussianProcessClassifier(1.0 * RBF(1.0)),
    DecisionTreeClassifier(max_depth=5),
    RandomForestClassifier(max_depth=5, n_estimators=10, max_features=1),
    MLPClassifier(alpha=1, max_iter=1000),
    AdaBoostClassifier(),
    GaussianNB(),
    QuadraticDiscriminantAnalysis()]

X, y = make_classification(n_features=2, n_redundant=0, n_informative=2,
                           random_state=1, n_clusters_per_class=1)
rng = np.random.RandomState(2)
X += 2 * rng.uniform(size=X.shape)
linearly_separable = (X, y)

datasets = [make_moons(noise=0.3, random_state=0),
            make_circles(noise=0.2, factor=0.5, random_state=1),
            linearly_separable
            ]

figure = plt.figure(figsize=(27, 9))
i = 1
# iterate over datasets
for ds_cnt, ds in tqdm(enumerate(datasets)):
    # preprocess dataset, split into training and test part
    X, y = ds
    X = StandardScaler().fit_transform(X)
    X_train, X_test, y_train, y_test = \
        train_test_split(X, y, test_size=.4, random_state=42)

    x_min, x_max = X[:, 0].min() - .5, X[:, 0].max() + .5
    y_min, y_max = X[:, 1].min() - .5, X[:, 1].max() + .5
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
```

```
                         np.arange(y_min, y_max, h))

    # just plot the dataset first
    cm = plt.cm.RdBu
    cm_bright = ListedColormap(['#FF0000', '#0000FF'])
    ax = plt.subplot(len(datasets), len(classifiers) + 1, i)
    if ds_cnt == 0:
        ax.set_title("Input data")
    # Plot the training points
    ax.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap=cm_bright,
               edgecolors='k')
    # Plot the testing points
    ax.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap=cm_bright, alpha=0.6,
               edgecolors='k')
    ax.set_xlim(xx.min(), xx.max())
    ax.set_ylim(yy.min(), yy.max())
    ax.set_xticks(())
    ax.set_yticks(())
    i += 1

    # iterate over classifiers
    for name, clf in zip(names, classifiers):
        ax = plt.subplot(len(datasets), len(classifiers) + 1, i)
        clf.fit(X_train, y_train)
        score = clf.score(X_test, y_test)

        # Plot the decision boundary. For that, we will assign a color to each
        # point in the mesh [x_min, x_max]x[y_min, y_max].
        if hasattr(clf, "decision_function"):
            Z = clf.decision_function(np.c_[xx.ravel(), yy.ravel()])
        else:
            Z = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]

        # Put the result into a color plot
        Z = Z.reshape(xx.shape)
        ax.contourf(xx, yy, Z, cmap=cm, alpha=.8)

        # Plot the training points
        ax.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap=cm_bright,
                   edgecolors='k')
        # Plot the testing points
        ax.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap=cm_bright,
                   edgecolors='k', alpha=0.6)

        ax.set_xlim(xx.min(), xx.max())
        ax.set_ylim(yy.min(), yy.max())
        ax.set_xticks(())
        ax.set_yticks(())
        if ds_cnt == 0:
            ax.set_title(name)
        ax.text(xx.max() - .3, yy.min() + .3, ('%.2f' % score).lstrip('0'),
                size=15, horizontalalignment='right')
        i += 1

plt.tight_layout()
# plt.show()

```

```
=====================
Classifier comparison
=====================

A comparison of a several classifiers in scikit-learn on synthetic datasets.
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of different classifiers.
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these examples does not necessarily carry over to real datasets.

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linearly and the simplicity of classifiers such as naive Bayes and linear SVMs
might lead to better generalization than is achieved by other classifiers.

The plots show training points in solid colors and testing points
semi-transparent. The lower right shows the classification accuracy on the test
set.
```
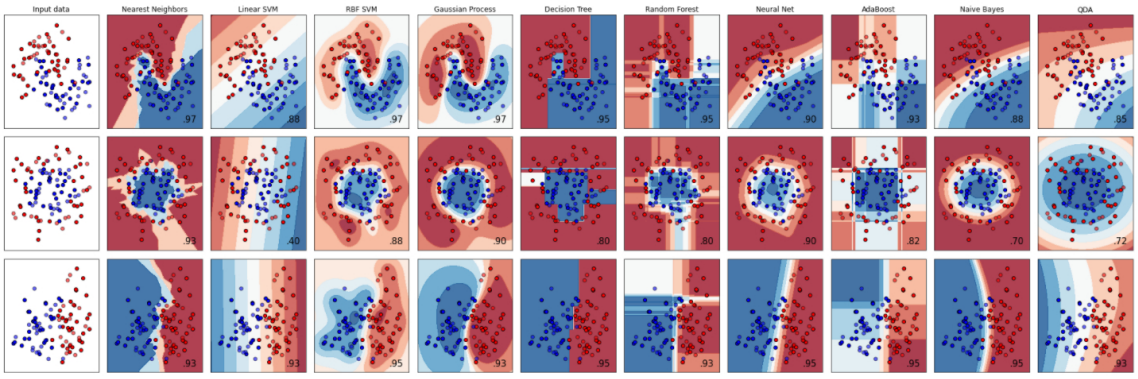

3/? [00:05<00:00, 1.78s/it]



In [30]:

```
%%time
```

```
import time
from tqdm import tqdm, trange

for i in tqdm(range(3)):
        time.sleep(1)

for i in trange(3):
        time.sleep(1)
```

```
100%|██████████| 3/3 [00:03<00:00,  1.01s/it]
100%|██████████| 3/3 [00:03<00:00,  1.01s/it]
```

```
Wall time: 6.08 s
```