DAT340 - Assignment 2

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This Notebook can be viewed online at this link: https://colab.research.google.com/drive/1sMNNrs7crcaSTpWAKS
KPbMg?usp=sharing

1 Programming Assignment 2: Random Forests

1.1 Task 0: Setup

[2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[3]:
```
import os

ASSIGNMENT_ID = 'assignment_2'

data_dir = os.path.join(os.path.abspath(''), 'drive', 'MyDrive')
data_dir = os.path.join(data_dir, 'Colab Notebooks', 'dat340', ASSIGNMENT_ID)
data_dir = os.path.join(data_dir, 'data')
data_dir
```

[3]:
```
'/content/drive/MyDrive/Colab Notebooks/dat340/assignment_2/data'
```

[4]:
```
from IPython.display import set_matplotlib_formats
set_matplotlib_formats('pdf', 'svg')
```

1.2 Task 1: Working with a dataset with categorical features

1.2.1 Step 1. Reading the data

[ ]:
```python
import pandas as pd
from sklearn.model_selection import train_test_split

def get_dataset(filename):
    # Read the CSV file of data.
    data = pd.read_csv(filename).dropna()
    # Shuffle the dataset.
    data_shuffled = data.sample(frac=1.0, random_state=0)
    # Split into input part X and output part Y.
    X = data_shuffled.drop('target', axis=1)
    Y = data_shuffled['target'].to_frame()
    return X, Y

filename = os.path.join(data_dir, 'adult_train.csv')
Xtrain, Ytrain = get_dataset(filename)

filename = os.path.join(data_dir, 'adult_test.csv')
Xtest, Ytest = get_dataset(filename)

Xtest
```

[ ]:
```
       age  workclass     education  education-num      marital-status  \
15729   44    Private  Some-college             10  Married-civ-spouse
7077    37    Private       HS-grad              9            Divorced
14946   35    Private     Bachelors             13       Never-married
9416    38  State-gov     Bachelors             13       Never-married
5739    41    Private       HS-grad              9  Married-civ-spouse

             occupation   relationship   race     sex  capital-gain  \
15729  Transport-moving        Husband  White    Male             0
7077    Exec-managerial      Unmarried  White  Female             0
14946   Exec-managerial  Not-in-family  White    Male             0
9416    Exec-managerial  Not-in-family  White  Female             0
5739       Adm-clerical           Wife  White  Female          5013

       capital-loss  hours-per-week native-country
15729             0              48  United-States
7077              0              50  United-States
14946             0              45  United-States
9416              0              45  United-States
5739              0              30  United-States
```

1.2.2 Step 2. Encoding the features as numbers.

The `to_dict()` method of a pandas data frame allows to generate a list of dictionaries, *i.e.* one dictionary per table entry.

```
[ ]: from sklearn.feature_extraction import DictVectorizer

     Xtrain.to_dict('records')[:2]
```

```
[ ]: [{'age': 49,
       'capital-gain': 0,
       'capital-loss': 0,
       'education': 'HS-grad',
       'education-num': 9,
       'hours-per-week': 40,
       'marital-status': 'Married-civ-spouse',
       'native-country': 'United-States',
       'occupation': 'Transport-moving',
       'race': 'White',
       'relationship': 'Husband',
       'sex': 'Male',
       'workclass': 'Local-gov'},
      {'age': 49,
       'capital-gain': 0,
       'capital-loss': 0,
       'education': 'HS-grad',
       'education-num': 9,
       'hours-per-week': 40,
       'marital-status': 'Divorced',
       'native-country': 'United-States',
       'occupation': 'Other-service',
       'race': 'Black',
       'relationship': 'Not-in-family',
       'sex': 'Female',
       'workclass': 'Private'}]
```

The `DictVectorizer` transforms the list of dictionaries into a "learned" matrix of features.

```
[ ]: dv = DictVectorizer(sparse=False)
     # Input training data
     Xtrain_encoded = dv.fit_transform(Xtrain.to_dict('records'))
     # Input test data
     Xtest_encoded = dv.transform(Xtest.to_dict('records'))
     Xtrain_encoded.shape
```

```
[ ]: (32561, 107)
```

Note that before the vetorization the dataset had 13 columns, *i.e.* each entry had 13 fields. After fitting the dataset via `DictVectorizer` instead, the resulting vectorized dataset now has 107 ”columns” (*i.e.* features).

On the other hand, the output data are transformed into one-hot encoding data: since there are only two classes, the output shape is equal to `(N, 2)`.

```
[ ]: dv = DictVectorizer(sparse=False, separator='')
     # Output training data
     Ytrain_encoded = dv.fit_transform(Ytrain.to_dict('records'))
     # Output testing data
     Ytest_encoded = dv.transform(Ytest.to_dict('records'))
     print(dv.get_feature_names_out(['target']))
     print(type(Ytrain_encoded))
     print(Ytrain_encoded.shape)
     print(Ytrain_encoded)
```

```
['target<=50K' 'target>50K']
<class 'numpy.ndarray'>
(32561, 2)
[[1. 0.]
 [1. 0.]
 [1. 0.]
 …
 [1. 0.]
 [0. 1.]
 [1. 0.]]
```

Now that the datasets are cleaned, we can try some classifiers on it, *i.e.* apply cross-validation.

```
[ ]: # Baseline: Dummy Classifier
     from sklearn.dummy import DummyClassifier
     # Tree-based classifiers
     from sklearn.tree import DecisionTreeClassifier
     from sklearn.ensemble import RandomForestClassifier
     from sklearn.ensemble import GradientBoostingClassifier
     # Linear classifiers
     from sklearn.linear_model import Perceptron
     from sklearn.linear_model import LogisticRegression
     from sklearn.svm import LinearSVC
     # Neural network classifier (will take longer time to train)
     from sklearn.neural_network import MLPClassifier
```

```
[ ]: from sklearn.metrics import accuracy_score
     from sklearn.model_selection import cross_val_score

     def aggregate_scores(scores):
         return scores.mean()

     models = {
```

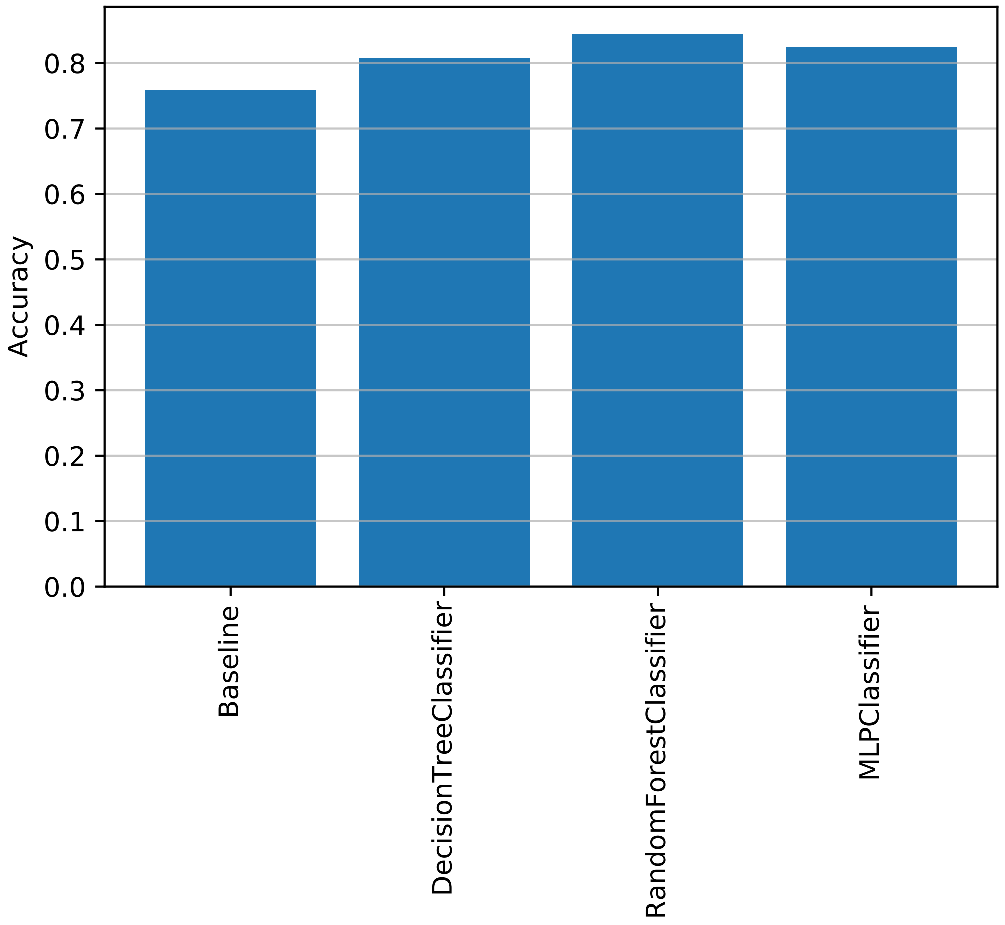
```
    'Baseline' : DummyClassifier(strategy='most_frequent'),
    'DecisionTreeClassifier' : DecisionTreeClassifier(max_depth=None), # None:␣
↪till necessary
    'RandomForestClassifier' : RandomForestClassifier(n_estimators=80), # 100
    # 'GradientBoostingClassifier' :␣
↪GradientBoostingClassifier(n_estimators=100),
    # 'LogisticRegression' : LogisticRegression(solver='saga', max_iter=2000,␣
↪tol=0.1, C=5.5),
    # 'Perceptron' : Perceptron(early_stopping=True, tol=0.01),
    # 'LinearSVC' : LinearSVC(dual=False, max_iter=2000, tol=0.0001, C=2.),
    'MLPClassifier' : MLPClassifier(hidden_layer_sizes=(32, 32, 32,),␣
↪learning_rate_init=0.01, batch_size=128, max_iter=100),
}

scores = {}

for model_type in models.keys():
    model = models[model_type]
    score = aggregate_scores(cross_val_score(model, Xtrain_encoded,␣
↪Ytrain_encoded))
    scores[model_type] = score
    print(f'INFO. Model {model_type} aggregated score: {score:.4f}')

best_model_type = max(scores, key=scores.get)
print('=' * 80)
print(f'INFO. Best Model is {best_model_type} with score:␣
↪{scores[best_model_type]:.4f}')
```

```
INFO. Model Baseline aggregated score: 0.7592
INFO. Model DecisionTreeClassifier aggregated score: 0.8069
INFO. Model RandomForestClassifier aggregated score: 0.8439
```

```
/usr/local/lib/python3.7/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:696:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (100) reached and
the optimization hasn't converged yet.
  ConvergenceWarning,
```

```
INFO. Model MLPClassifier aggregated score: 0.8238
================================================================================
INFO. Best Model is RandomForestClassifier with score: 0.8439
```

[ ]:
```
import matplotlib.pyplot as plt

linspace = [x for x in range(len(models.keys()))]
plt.bar(linspace, scores.values())
plt.xticks(linspace, [f'{m}' for m in models.keys()], rotation=90)
plt.grid(which='both', axis='y', alpha=0.7, zorder=1)
plt.ylabel('Accuracy')
plt.title('Accuracy score of different classifiers')
plt.show()
```



[ ]:
```
models[best_model_type].fit(Xtrain_encoded, Ytrain_encoded)
acc_orig = accuracy_score(Ytest_encoded, models[best_model_type].
 ↪predict(Xtest_encoded))
print(f'INFO. Original accuracy: {acc_orig:.4f}')
```

```
INFO. Original accuracy: 0.8418
```

1.2.3 Step 3. Combining the steps.

We can combine the vectorization and the model into a single pipeline object as follows:

[ ]:
```
from sklearn.pipeline import make_pipeline
from sklearn.base import clone
```

```
pipeline = make_pipeline(
  DictVectorizer(sparse=False),
  clone(models[best_model_type]) # Cloning effectively resets training
)
pipeline
```

```
[ ]: Pipeline(steps=[('dictvectorizer', DictVectorizer(sparse=False)),
                     ('randomforestclassifier',
                      RandomForestClassifier(n_estimators=80))])
```

We can then call `fit()` on the pipeline object and perform bothe cleaning and model training in one function call.

```
[ ]: pipeline.fit(Xtrain.to_dict('records'), Ytrain_encoded)
```

```
[ ]: Pipeline(steps=[('dictvectorizer', DictVectorizer(sparse=False)),
                     ('randomforestclassifier',
                      RandomForestClassifier(n_estimators=80))])
```

Once trained, the model should perform similarly to the model trained *without* being in a pipeline.

```
[ ]: Ypred = pipeline.predict(Xtest.to_dict('records'))
pipeline_acc = accuracy_score(Ytest_encoded, Ypred)
print(f'INFO. Pipeline accuracy: {pipeline_acc:.4f}')
print(f'INFO. Original vs. Pipeline accuracy difference: {acc_orig -␣
 ↪pipeline_acc:.4f}')
```

```
INFO. Pipeline accuracy: 0.8436
INFO. Original vs. Pipeline accuracy difference: -0.0018
```

Note that the transformation is not applied to the output datasets, *i.e.* `Ytrain` and `Ytest`. (TODO: is there a way to do that through the Pipeline?).

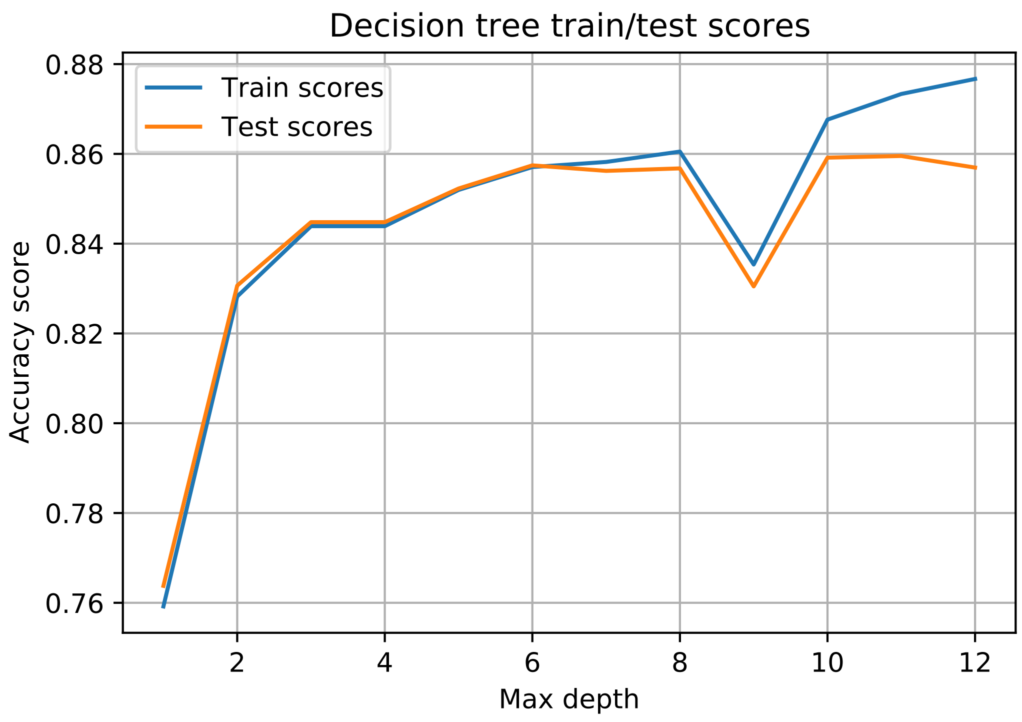
1.3 Task 2: Decision trees and random forests

1.3.1 Underfitting and overfitting in decision tree classifiers.

```
[ ]: eval_scores_train = {}
eval_scores_test = {}
table_data = []

for depth in range(1, 13):
    model_id = f'd={depth}'
    model = DecisionTreeClassifier(max_depth=depth)
    # Training
    model.fit(Xtrain_encoded, Ytrain_encoded)
    # Evaluation
    train_acc = accuracy_score(Ytrain_encoded, model.predict(Xtrain_encoded))
    test_acc = accuracy_score(Ytest_encoded, model.predict(Xtest_encoded))
    # Logging
    eval_scores_train[model_id] = train_acc
    eval_scores_test[model_id] = test_acc
    table_data.append([depth, train_acc, test_acc])
    # print(f'INFO. Model with depth={depth} achieved test accuracy of:␣
 ↪{test_acc:.4f}')
table_columns = ['Max Depth', 'Train Accuracy', 'Test Accuracy']
decision_tree_df = pd.DataFrame(table_data, columns=table_columns)
decision_tree_df
```

```
[ ]:     Max Depth  Train Accuracy  Test Accuracy
    0           1        0.759190       0.763774
    1           2        0.828230       0.830662
    2           3        0.843893       0.844788
    3           4        0.843893       0.844788
    4           5        0.851970       0.852220
    5           6        0.857068       0.857380
    6           7        0.858205       0.856458
    7           8        0.860569       0.856888
    8           9        0.835355       0.830170
    9          10        0.867633       0.858977
    10         11        0.873468       0.859222
    11         12        0.876509       0.856704
```

```
[ ]: x = range(1, 13)
     plt.plot(x, list(eval_scores_train.values()), label='Train scores')
     plt.plot(x, list(eval_scores_test.values()), label='Test scores')
     plt.legend()
     plt.xlabel('Max depth')
     plt.ylabel('Accuracy score')
     # plt.ylim([0, 1])
     plt.title('Decision tree train/test scores')
     plt.grid()
     plt.show()
```



As the maximum depth increases, we see an improvement on the model performance. Moreover, we do not observe a significant difference in the train/test score curves, meaning that the model is not overfitted.

1.3.2 Underfitting and overfitting in random forest classifiers.

[ ]:
```python
import time

eval_scores_train = {}
eval_scores_test = {}
table_data = []

for estimators in [1] + list(range(0, 300, 50))[1:]:
    model_id = f'{estimators}'
    eval_scores_train[model_id] = []
    eval_scores_test[model_id] = []
    # print('=' * 80)
    # print(f'N. Estimators: ')
    # print('=' * 80)
    for depth in range(1, 13):
        model = RandomForestClassifier(max_depth=depth, n_estimators=estimators,
                                       n_jobs=8)
        # Training
        start_time = time.time()
        model.fit(Xtrain_encoded, Ytrain_encoded)
        stop_time = time.time()
        train_time = stop_time - start_time
        # Evaluation
        train_acc = accuracy_score(Ytrain_encoded, model.
 ↪predict(Xtrain_encoded))
        test_acc = accuracy_score(Ytest_encoded, model.predict(Xtest_encoded))
        # Logging
        eval_scores_train[model_id].append(train_acc)
        eval_scores_test[model_id].append(test_acc)
        table_data.append([estimators, depth, train_acc, test_acc, train_time])
        # print(f'INFO. Model with depth={depth} and estimators={estimators},␣
 ↪achieved test accuracy of: {test_acc:.4f}')
table_columns = [
                 'N. Estimators', 'Max Depth', 'Train Accuracy',
                 'Test Accuracy', 'Training Time [s]'
                ]
random_forest_df = pd.DataFrame(table_data, columns=table_columns)
random_forest_df
```

[ ]:

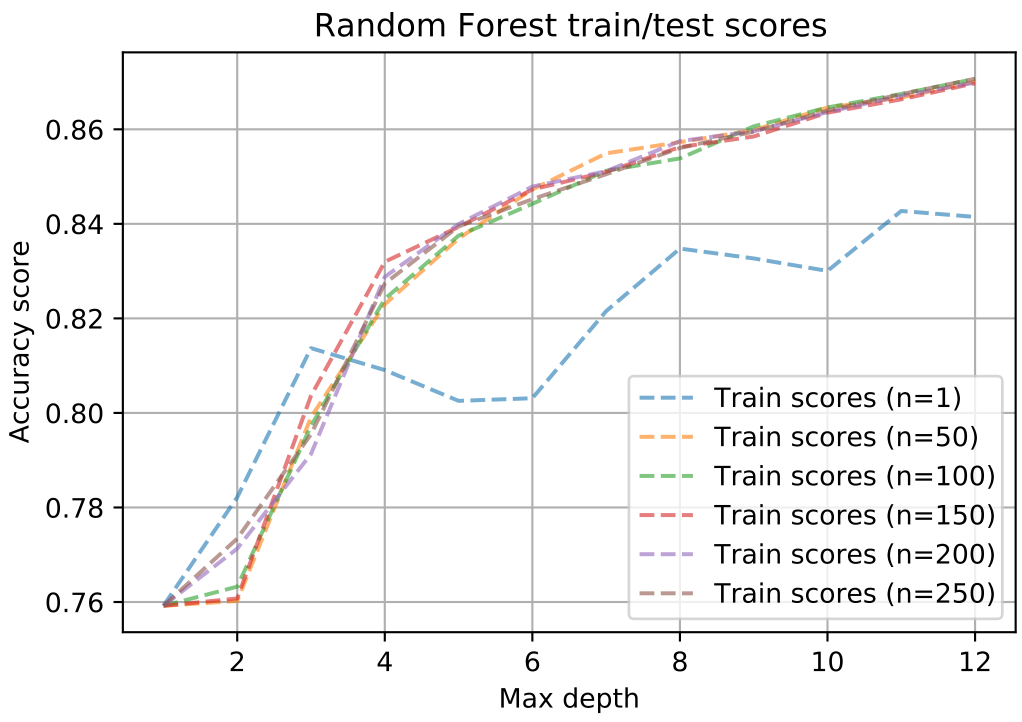
```
    N. Estimators  Max Depth  Train Accuracy  Test Accuracy  Training Time [s]
0               1          1        0.759190       0.763774           0.120895
1               1          2        0.771966       0.774522           0.120489
2               1          3        0.817850       0.819176           0.120203
3               1          4        0.799699       0.802039           0.120718
4               1          5        0.763122       0.767705           0.120125
..            …         …            …             …                 …
67            250          8        0.856700       0.853203           5.386783
68            250          9        0.859003       0.855291           5.681913
69            250         10        0.864593       0.859652           6.011736
70            250         11        0.867387       0.859775           6.374560
71            250         12        0.872025       0.860758           6.805789

[72 rows x 5 columns]
```

Let us now plot the training and testing score curves for difference ensemble sizes and increasing the maximum depth of the estimators.

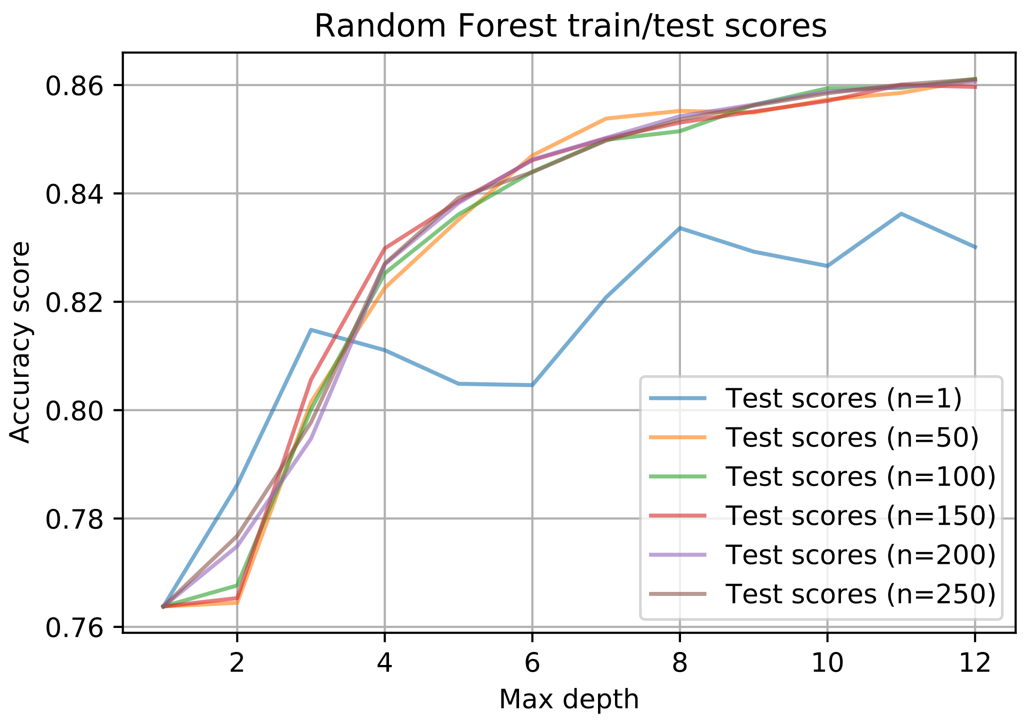
[ ]:

```
for n in eval_scores_train.keys():
    plt.plot(range(1, 13), eval_scores_train[n], '--', label=f'Train scores␣
 ↪(n={n})', alpha=0.6)

# for n in eval_scores_test.keys():
#     plt.plot(range(1, 13), eval_scores_test[n], label=f'Test scores (n={n})',␣
 ↪alpha=0.6)
```

```
plt.legend()
plt.xlabel('Max depth')
plt.ylabel('Accuracy score')
plt.title('Random Forest train/test scores')
# plt.xlim([0, 1])
plt.grid()
plt.show()
```



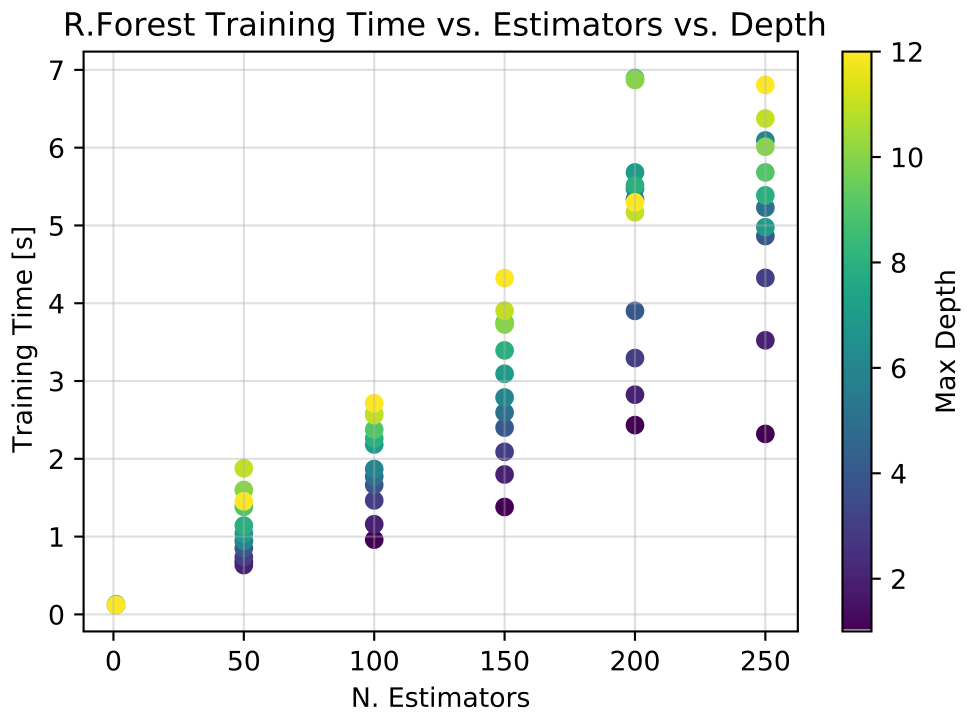
[ ]:
```
for n in eval_scores_test.keys():
    plt.plot(range(1, 13), eval_scores_test[n], label=f'Test scores (n={n})',␣
 ↪alpha=0.6)

plt.legend()
plt.xlabel('Max depth')
plt.ylabel('Accuracy score')
plt.title('Random Forest train/test scores')
# plt.xlim([0, 1])
plt.grid()
plt.show()
```



Some conclusions regarding the comparison between DTC and RFC:

- As for DTC, the RFC train/test curves suggest that the tested models are not overfitting.
- For ensemble size of 1, the Random Forest Classifier (RFC) and the Decision Tree Classifier (DTC) behave similarly, *i.e.* as the maximum depth increases so does the accuracy. In general, increasing the depth of the trees reduces the bias of the model, *i.e.* it helps with regularization. However, the RFC curve appear to be more ”oscillating”, not really monotonically increasing. This difference in the curves lies in the fact that each tree in the RFC is built *incorporating randomness*, whereas a DTC is not. Hence the single tree in a RFC with `n_estimators=1` won’t be equal to the tree of a DTC.
- As the number of ensembles increases, the curve seems to become ”smoother”, converging to a monotonically increasing function. In practice it seems that increasing the number of estimators makes the RFC converge to a cer
- According to the graph show below, the training time both depends on max depth and the ensemble size. If we consider the max depth fixed, however, we can see that the training time is linearly increasing as the number of ensembles grows.

```
[ ]: plt.scatter(random_forest_df['N. Estimators'],
                 random_forest_df['Training Time [s]'],
                 c=random_forest_df['Max Depth'])
     # plt.legend()
     plt.xlabel('N. Estimators')
     plt.ylabel('Training Time [s]')
     plt.title('R.Forest Training Time vs. Estimators vs. Depth')
     plt.colorbar(label='Max Depth')
     # plt.xlim([0, 1])
     plt.grid(alpha=0.4)
     plt.show()
```



1.4 Task 3: Feature importances in random forest classifiers

Let us extract the most important features from the RFC and the Vectorizer.

```
[ ]: vectorizer = pipeline.steps[0][1]
     randforest = pipeline.steps[1][1]
     # Get indeces of sorted importance values, then the sorted feature names
     sorted_idx = (-randforest.feature_importances_).argsort()
     features_names = vectorizer.get_feature_names_out()[sorted_idx]
     features_vals = randforest.feature_importances_[sorted_idx]
     # Logging
     table_data = []
     for elem in zip(features_names, features_vals):
         table_data.append(elem)
     pd.DataFrame(table_data, columns=['Feature Name', 'Importance'])
```

[ ]:
```
                                  Feature Name    Importance
0                                          age  2.295775e-01
1                               hours-per-week  1.146271e-01
2                                 capital-gain  1.040436e-01
3                                education-num  7.263606e-02
4              marital-status=Married-civ-spouse  6.366235e-02
..                                         …             …
102  native-country=Outlying-US(Guam-USVI-etc)  2.521825e-05
103                    occupation=Armed-Forces  1.086699e-05
104                    native-country=Honduras  4.569113e-06
105                     workclass=Never-worked  2.252197e-06
106            native-country=Holand-Netherlands  2.087596e-07

[107 rows x 2 columns]
```

It seems that the *age* is the feature that best divides the data set.

Sklearn default way of computing the feature importance is to measure, at training time, how well each feature decreases the impurity of the split. The measurement is then averaged across the training steps and averaged again across the ensembles, such that a single importance score per feature is obtained [1].

Another possible method for estimating features importance is to utilize *permutations of features* [2]: intuitively, given a fitted model with a known performance score, each feature, *i.e.* column, is randomly swapped and the score of the classifier is computed. The average drop in perfomance can then be used as a score for feature importance. In fact, the idea is that features with the highest performance drop will account the most and therefore have the highest importance score.

References:

- [1] Random Forest Feature Importance Computed in 3 Ways with Python, link: https://mljar.com/blog/feature-importance-in-random-forest/
- [2] Permutation feature importance, link: https://scikit-learn.org/stable/modules/permutation_importance.html#permutation-importance

1.5 Converting Notebook to PDF

The following two cells can be ignored for grading, as they just convert this notebook into a PDF file.

[1]:
```
%%capture
!apt-get update
!apt-get install -y texlive-xetex texlive-fonts-recommended␣
 ↪texlive-plain-generic
!apt-get install -y inkscape
!add-apt-repository -y universe
!add-apt-repository -y ppa:inkscape.dev/stable
!apt-get update -y
```

```
!apt install -y inkscape
```

[7]:
```
%%capture
import re

ASSIGNMENT_NAME = 'DAT340 - Assignment ' + ASSIGNMENT_ID.split('_')[1]
pdf_dir = os.path.join(os.path.abspath(''), 'drive', 'MyDrive')
pdf_dir = os.path.join(pdf_dir, 'Colab Notebooks', 'dat340', ASSIGNMENT_ID)
pdf_filename = re.escape(os.path.join(pdf_dir, ASSIGNMENT_NAME)) + '.ipynb'

!jupyter nbconvert --to pdf --TemplateExporter.exclude_input=False $pdf_filename
```

[ ]:
```

```