Proj_01 : Finding Donors for *CharityML*

- Source : UdaCity, Machine Learning Intro, Supervided Learning

Introduction

In this project, I will employ several supervised algorithms to accurately model indivisuals' income using data collected from the 1944 U.S. Census.
I will then chose the best candidate algorithm from preliminary results and further optimize this algorithm to best model the data.

Goal

The goal of this project is to construct a model that accurately predicts whether an individual makes more than $50,000.

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1. Exploring the Dataset

In [1]:

```
# Import libraries
import numpy as np
import pandas as pd
from time import time
from IPython.display import display # this allows the use of display() for DataFrames
# import visuals as vs #
import matplotlib.pyplot as plt
%matplotlib inline
```

1-1. Overview the data

- The dataset for this project originates from the UCI Machine Learning Repository.
- From the table below, I found that there are numerical and string features.

In [2]:

```
# Load the Census dataset
data = pd.read_csv("./Data/Proj_01/census.csv")

# Display the first 5 records
display(data.head(5))

# Display the unique income values
print("The unique values of INCOME")
display(data["income"].unique())
```

	age	workclass	education_level	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capita lo
0	39	State-gov	Bachelors	13.0	Never-married	Adm-clerical	Not-in-family	White	Male	2174.0	C
1	50	Self-emp-not-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male	0.0	C
2	38	Private	HS-grad	9.0	Divorced	Handlers-cleaners	Not-in-family	White	Male	0.0	C
3	53	Private	11th	7.0	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0.0	C
4	28	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0.0	C

```
The unique values of INCOME
array(['<=50K', '>50K'], dtype=object)
```

1-2. Check invalid and missing data

- There are no invalid data.

In [3]:

```
data.isnull().sum(axis=0)
```

Out[3]:

```
age                    0
```

```
workclass          0
education_level    0
education-num      0
marital-status     0
occupation         0
relationship       0
race               0
sex                0
capital-gain       0
capital-loss       0
hours-per-week     0
native-country     0
income             0
dtype: int64
```

1-3. Data exploration : income

A cursory investigation of the dataset will determine how many individuals fit into either group, and will tell us about the percentage of these individuals making more than $50,000.
In the code cell below, I will compute the following:

- The total number of records : `n_records`
- The number of individuals making more than $50,000 annually `n_greater_50k`
- The number of individuals making at most $50,000 annually : `n_at_most_50k`
- The percentage of individuals making more than $50,000 annually : `greater_percent`

In [4]:
```
n_records       = data.shape[0]
n_greater_50k   = (data["income"] == ">50K" ).sum()
n_at_most_50k   = (data["income"] == "<=50K").sum()
greater_percent = n_greater_50k / n_records * 100

# Print results
print("Total number of records                                  : {}".format(n_rec
print("The number of individuals making more than $50,000 annually    : {}".format(n_gre
print("The number of individuals making at most $50,000 annually      : {}".format(n_at_
print("The percentage of individuals making more than $50,000 annually: {0:5.1f} %".form
```

```
Total number of records                                        : 45222
The number of individuals making more than $50,000 annually    : 11208
The number of individuals making at most $50,000 annually      : 34014
The percentage of individuals making more than $50,000 annually:  24.8 %
```

1-4. Data exploration : numerical data

- From the table and the graph below, `capital-gain` and `capital-loss` are highly skewed.
- So, some transformation are needed for those features.

In [5]:
```
col_names_numerical = ["age", "education-num", "capital-gain", "capital-loss", "hours-pe
data_numerical      = data.loc[:, col_names_numerical]
data_numerical.describe()
```

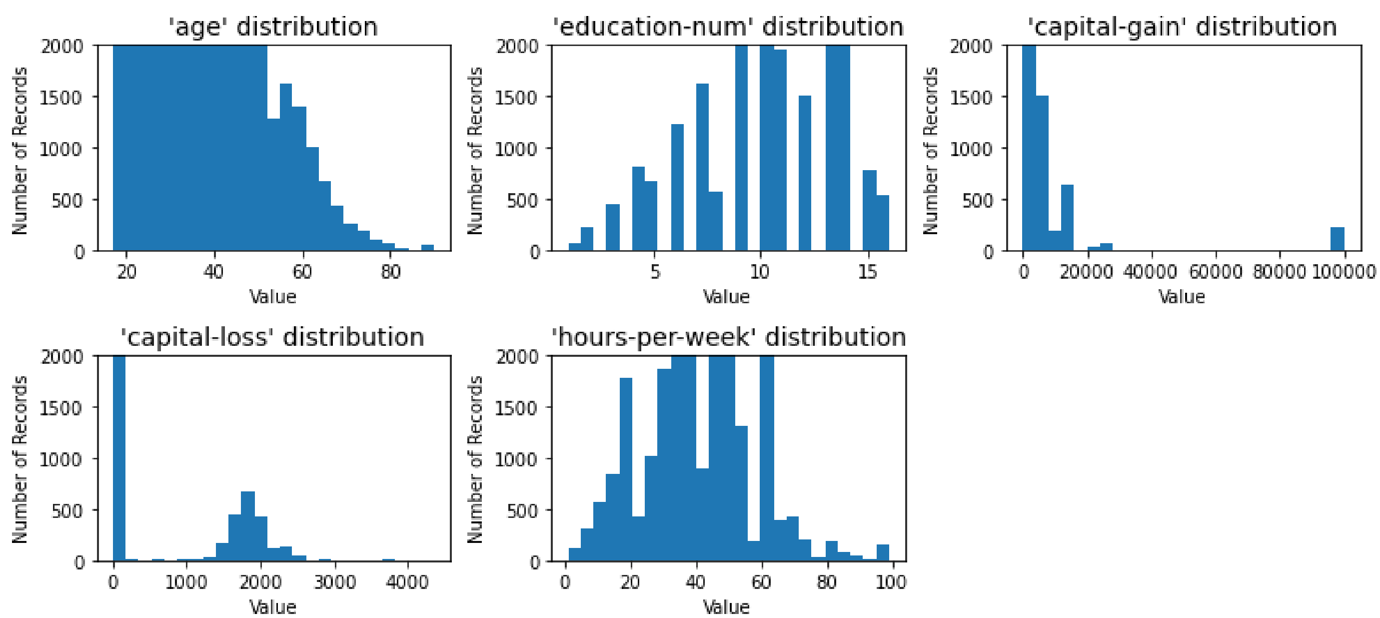
Out[5]:

	age	education-num	capital-gain	capital-loss	hours-per-week
count	45222.000000	45222.000000	45222.000000	45222.000000	45222.000000
mean	38.547941	10.118460	1101.430344	88.595418	40.938017
std	13.217870	2.552881	7506.430084	404.956092	12.007508
min	17.000000	1.000000	0.000000	0.000000	1.000000

25%	28.000000	9.000000	0.000000	0.000000	40.000000
50%	37.000000	10.000000	0.000000	0.000000	40.000000
75%	47.000000	13.000000	0.000000	0.000000	45.000000
max	90.000000	16.000000	99999.000000	4356.000000	99.000000

In [6]:
```
def plot_hist(df, col_names, plot_row_num=2, plot_col_num=3, y_limit=(0,2000)):
    # create figure
    fig = plt.figure(figsize = (11,5));

    # plot in bin
    for i, feature in enumerate(col_names):
        ax = fig.add_subplot(plot_row_num, plot_col_num, i+1)
        ax.hist(df[feature], bins=25)
        ax.set_title("'%s' distribution"%(feature), fontsize=14)
        ax.set_xlabel("Value")
        ax.set_ylabel("Number of Records")
        ax.set_ylim(y_limit)
    #
    fig.tight_layout()
```

In [7]:
```
#plot_hist(data, ["capital-gain", "capital-loss"])
plot_hist(data, col_names_numerical)
```



1-5. Data exploration : string data(other than `income`)

- I show the unique values of string data.
- A conversion from string to numerical data is needed.

In [8]:
```
pd.set_option("display.max_columns", 100)
pd.set_option('display.max_rows', 150)
col_names_string = set(data.columns) ^ set(col_names_numerical) ^ set(["income"])

for i, col_name in enumerate(col_names_string):
    print("--------------------------")
    unique_names = data[col_name].unique()
    output_name  = ""
    print("{}. [{}] : unique value num = {}".format(i, col_name, len(unique_names)))
    #
```

```
    for j, unique_name in enumerate(unique_names):
        if j == 0:
            output_name = unique_name
        else:
            output_name = output_name + ", " + unique_name

    print(output_name)
```

```
--------------------------
0. [sex] : unique value num = 2
 Male,  Female
--------------------------
1. [education_level] : unique value num = 16
 Bachelors,  HS-grad,  11th,  Masters,  9th,  Some-college,  Assoc-acdm,  7th-8th,  Doct
orate,  Assoc-voc,  Prof-school,  5th-6th,  10th,  Preschool,  12th,  1st-4th
--------------------------
2. [workclass] : unique value num = 7
 State-gov,  Self-emp-not-inc,  Private,  Federal-gov,  Local-gov,  Self-emp-inc,  Witho
ut-pay
--------------------------
3. [relationship] : unique value num = 6
 Not-in-family,  Husband,  Wife,  Own-child,  Unmarried,  Other-relative
--------------------------
4. [occupation] : unique value num = 14
 Adm-clerical,  Exec-managerial,  Handlers-cleaners,  Prof-specialty,  Other-service,  S
ales,  Transport-moving,  Farming-fishing,  Machine-op-inspct,  Tech-support,  Craft-rep
air,  Protective-serv,  Armed-Forces,  Priv-house-serv
--------------------------
5. [marital-status] : unique value num = 7
 Never-married,  Married-civ-spouse,  Divorced,  Married-spouse-absent,  Separated,  Mar
ried-AF-spouse,  Widowed
--------------------------
6. [race] : unique value num = 5
 White,  Black,  Asian-Pac-Islander,  Amer-Indian-Eskimo,  Other
--------------------------
7. [native-country] : unique value num = 41
 United-States,  Cuba,  Jamaica,  India,  Mexico,  Puerto-Rico,  Honduras,  England,  Ca
nada,  Germany,  Iran,  Philippines,  Poland,  Columbia,  Cambodia,  Thailand,  Ecuador,
  Laos,  Taiwan,  Haiti,  Portugal,  Dominican-Republic,  El-Salvador,  France,  Guatema
la,  Italy,  China,  South,  Japan,  Yugoslavia,  Peru,  Outlying-US(Guam-USVI-etc),  Sc
otland,  Trinadad&Tobago,  Greece,  Nicaragua,  Vietnam,  Hong,  Ireland,  Hungary,  Hol
and-Netherlands
```

2. Preprocessing the Dataset

- Fortunately, for this dataset, there are no invalid or missing entries we must deal with.
- However, there are some qualities about certain features that must be adjusted.
- This preprocessing can help tremendously with the outcome and predictive power of nearly all learning algorithms.

In [9]:
```
# Split the dataset into "target label" and "features"
income_raw  = data["income"]
features_raw = data.drop("income", axis=1)
```

2-1. Transformation : skewed continuous data

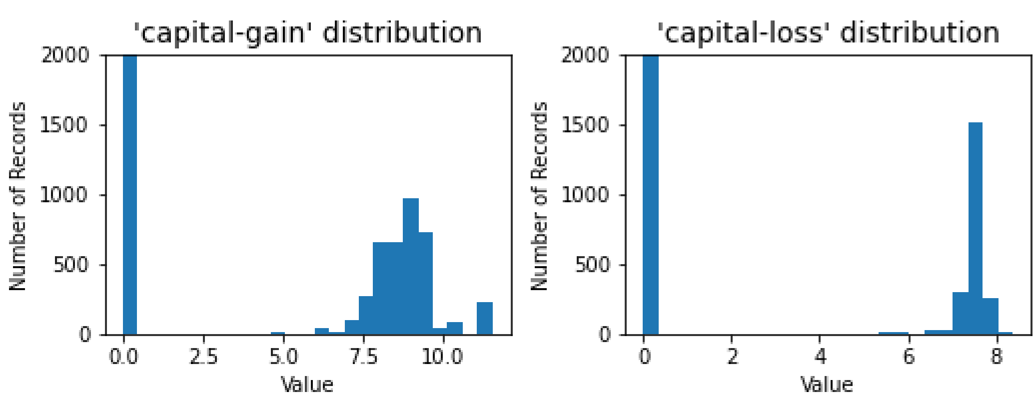
- Algorithms can be sensitive hightly skewed feature distribution such as `capital-gain` and `capital-loss`, and underperform if the range is not properly normalized.

- I will apply logarithmic transformation) on the data, so that the very large and very small values do not genatively affect the performance of a learning algorithm.
- Using a logarithmic transformation significantly reduces the range of values caused by outliers.
  - The logarighm of `0` is undefined, so we must translate the values by a small amount above `0` to apply the logarithm successfully.

In [10]:
```
col_names_skewed = ["capital-gain", "capital-loss"]
features_log_transformed = pd.DataFrame(data=features_raw)
features_log_transformed[col_names_skewed] = features_raw[col_names_skewed].apply(lambda
```

In [11]:
```
# Visualize the transformed features
display(features_log_transformed[col_names_skewed].describe())
plot_hist(features_log_transformed, col_names_skewed)
```

	capital-gain	capital-loss
count	45222.000000	45222.000000
mean	0.740759	0.355489
std	2.466527	1.595914
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	11.512925	8.379539



- From the table above, the data range becomes smaller.
  - `capital-gain` : **99999.0** --> **11.5**
  - `capital-loss` : **4356.0** --> **8.3**

2-2. Normalization : numerical data

- Normalization enusures that each feature is treated equally when applying supervised learners.
- I will use `sklearn.preprocessing.MinMaxScaler` for this.

In [12]:
```
# Import sklearn.preprocessing.MinMaxScaler
from sklearn.preprocessing import MinMaxScaler

# Initialize scaler, then apply it to the features
scaler = MinMaxScaler((0, 1))
```

```
features_log_minmax_transform = pd.DataFrame(data=features_log_transformed)
features_log_minmax_transform[col_names_numerical] = scaler.fit_transform(features_log_t

# Show results
display(features_log_minmax_transform[col_names_numerical].describe())
```

	age	education-num	capital-gain	capital-loss	hours-per-week
count	45222.000000	45222.000000	45222.000000	45222.000000	45222.000000
mean	0.295177	0.607897	0.064342	0.042423	0.407531
std	0.181067	0.170192	0.214240	0.190454	0.122526
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.150685	0.533333	0.000000	0.000000	0.397959
50%	0.273973	0.600000	0.000000	0.000000	0.397959
75%	0.410959	0.800000	0.000000	0.000000	0.448980
max	1.000000	1.000000	1.000000	1.000000	1.000000

2-3. Normalization : non-numerical data

- There are several features for each record that are non-numeric.
- Typically, learning algorithms expect input to be numeric.
- I will use `one-hot encoding` to convert categorical features.
  - `One-hot encoding` creates a **dummy** cariable for each possible category of each non-numerical feature.
  - For exapmle, assume `someFeature` has three possible entiries: `A` , `B` or `C` .
  - We then endode this feature into `someFeatureA` , `someFeatureB` and `someFeatureC` .
- I will use `pandas.get_dummies()` to perform `one-hot encoding` on the `feature_log_minmax_transform` data.

	someFeature		someFeature_A	someFeature_B	someFeature_C
0	B		0	1	0
1	C	----> one-hot encode ---->	0	0	1
2	A		1	0	0

- Additionally, I will convert the non-numerical target label `income` to numerical values.
- Since there are only two possible categories for this label(`<=50K` and `>50K`), we can avoid using `one-hot encoding` and simply encode these two categories as `0` and `1` .
  - I set records with `<=50K` to `0` and record with `>50K` to `1` .

In [13]:
```
# One-hot encoding : features
features_final = pd.get_dummies(features_log_minmax_transform)
display(features_final.describe())
```

	age	education-num	capital-gain	capital-loss	hours-per-week	workclass_ Federal-gov	workclass_ Local-gov	work P

count	45222.000000	45222.000000	45222.000000	45222.000000	45222.000000	45222.000000	45222.000000	45222.0
mean	0.295177	0.607897	0.064342	0.042423	0.407531	0.031091	0.068551	0.7
std	0.181067	0.170192	0.214240	0.190454	0.122526	0.173566	0.252691	0.4
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0
25%	0.150685	0.533333	0.000000	0.000000	0.397959	0.000000	0.000000	0.0
50%	0.273973	0.600000	0.000000	0.000000	0.397959	0.000000	0.000000	1.0
75%	0.410959	0.800000	0.000000	0.000000	0.448980	0.000000	0.000000	1.0
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.0

8 rows × 103 columns

In [14]:

```
# One-hot encoding : target label
income = income_raw.map({"<=50K":0, ">50K":1})
display(income.describe())
```

```
count    45222.000000
mean         0.247844
std          0.431766
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          1.000000
Name: income, dtype: float64
```

2-4. Shuffle and Split Data

Now all *categorical features* have been converted into numerical features, and all numerical features have been normalized. As always, I will now split the data into `training` and `test` sets.
80% of the data will be used for trainging and 20% for testing.

In [15]:

```
# Import train_test_split
from sklearn.model_selection import train_test_split

# Spline the features and the label into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(features_final, income, test_size =

# Show resutls
print("Training set has {} samples.".format(x_train.shape[0]))
print("Testing  set has {} samples.".format(x_test.shape[0]))
```

```
Training set has 36177 samples.
Testing  set has 9045 samples.
```

3. Modeling

In this section, I will investigate four different algorithms and determine which is best at modeling the data. Three of these algorithms will be supervised learners, and the fourth algorithm is known as a `naive predictor`.

3-1. Metrics

CharityML, equipped with theire research, knows individuals that make more than $50,000 are most likely to donate to their charity. Because of this, *CharityML* is particularly interested in predicting who makes more than $50,000 accurately.
It would seem that using **accuracy** as a metric for evaluating a particular model's performance would be appropriate.
Additionally, identifying someone that does not make more than $50,000 as someone who does would be detrimental to *CharityML*, since they are looking to find individuals willing to donate.
 Therefore, a model's ability to precisely predict those that make more than $50,000 is *more important* than the model's ability to recall those individuals.
I can use **F-beta score** as a metric that considers both precision and recall:

$$F_\beta = (1+\beta^2) \cdot \frac{precision \cdot recall}{(\beta^2 \cdot precision) + recall}$$

In particular, when $\beta = 0.5$, more emphasis is placed on precision. This is called the $F_{0.5} score$ or (F-score for simplicity).

$$F_1 = (1+1^2) \cdot \frac{precision \cdot recall}{(1^2 \cdot precision) + recall} = \frac{2 \cdot precision \cdot recall}{precision + recall}$$

$$F_0 = (1+0^2) \cdot \frac{precision \cdot recall}{(0^2 \cdot precision) + recall} = precision$$

3-2. Recap of Metrics

		Prediction Value	
		Yes	**No**
Answer Value	**Yes**	TP: True Positive	FN: False Negative
	No	FP: False Positive	TN: True Negative

Accuracy

- Accurach = TP / (TP + FP + TN + FN)
- Accracy mesures how often the classifier make the correct prediction.
- It's the ratio of the number of correct predictions to the total number of predictions (the number of test data points).

Precision

- Precision = TP / (TP + FP)
- Precision tells us what proportion of messages we classified as spam , actually were spam.
- It is a ratio of true positives to all positives.
- If we want to reduce the ration of FP, we ues precision.
- e.g.
    - true positives : words classified as spam, and which are accually spam

- all positives : all words classified as spam, irrespective of whether that was the correct classification

Recall (sensitivity)

- Recall = TP / (TP + FN)
- Recall tells us what proportion of messages that actually were spam were classified by us as spam.
- It is a ration of true positives to all the words that were actually spam.
- If we want to reduce the ration of FN, we use recall. (e.g. cancer detection)

3-3. Naive Predictor Performace

- I create a naive predictor which always predicts `1` (i.e. the individuals makes more than 50k).
- I will evaluate this model's accuracy and F-score.
- The purpose of generating a native predictor is simply to show what a base model without any intelligence would look like.
- This model will have no TN(true negative) or FN(false negative).

In [16]:

```
TP = np.sum(income)
FP = income.shape[0] - TP
TN = 0
FN = 0
#
accuracy  = TP / (TP+FP+TN+FN)
precision = TP / (TP+FP)
recall    = TP / (TP+FN)
beta      = 0.5
fscore    = (1+beta**2)*(precision*recall)/(beta**2*precision+recall)

# Show Results
print("Naive Predictor Performance")
print("   Accuracy = {:.4f}".format(accuracy))
print("   F-score  = {:.4f}".format(fscore))
```

```
Naive Predictor Performance
   Accuracy = 0.2478
   F-score  = 0.2917
```

3-4. Select Supervised Learning Models

I choose three models which are appropriate for this model. I will explain the reasons about the four points below.

1. Describe one real-world application in industry where the model can be applied.
2. What are the strengths of the model; when does it perform well?
3. What are the weaknesses of the model; when does it perform poorly?
4. What makes this model a good candidate for the problem, given what you know about the data?

1:Gaussian Naive Bayes

1. Real time forecast of stock prices
2. Training time and prediction time are small. We use it when features are independent.

3. When features are not independent, accuracy will become bad.
4. For 1st trial, I use this. I want to find quickly whether features are independent.

2:Decision Tree

1. Optimization of the arrangement of workers according to the weather forecast
2. By using this, we can easily visualize the result.
3. This tends to overfit the data.
4. To get good understanding of the data visually.

3:AdaBoost

1. classification of image data
2. To get better accuracy, this method can select the features which mostly contribute to the true prediction.
3. This tends to overfit the data.
4. To use this, we can find the necessary features, so we will be able to do better preprocessings.

3-5. Create a Training and Predicting Pipeline

To properly evaluate the performance of each model you've chosen, it's important that I create a training and predicting pipeline that allows me to quickly and effectively train models using various sizes of training data and perform predictions on the testing data.

I will implement the following:

- Import `fbeta_score` and `accuracy_score` from `sklearn.metrics`
- Fit the learner to the sampled training data and record the training time.
- Perform predictions on the test data `X_test`, and also on the first 300 training points `X_train[:300]`
  - Record the total prediction time.
- Calculate the accuracy score for both the training subset and testing subset
- Calculate the F-score for both the training subset and testing subset

In [17]:
```python
from sklearn.metrics import fbeta_score, accuracy_score

def train_and_predict(learner, sample_size, x_train, y_train, x_test, y_test):
    '''
    inputs:
      - learner     : the learning algorithm to be trained and predicted on
      - sample_size : the size of samples (number) to be drawn from training set
      - x_train     : features training set
      - y_train     : income training set
      - x_test      : features testing set
      - y_test      : income testing set
    '''

    results = {}

    # Training
    t_start = time()
    learner = learner.fit(x_train.iloc[:sample_size, :], y_train.iloc[:sample_size])
    t_end   = time()
```

```
    results['train_time'] = t_end - t_start

    # Prediction
    t_start = time()
    predictions_train = learner.predict(x_train.iloc[:300])
    predictions_test  = learner.predict(x_test)
    t_end   = time()
    results['pred_time'] = t_end - t_start
    beta = 0.5

    # Evaluation : train
    results['train_acc'] = accuracy_score(y_train[:300], predictions_train[:300])
    results['train_f']   = fbeta_score(   y_train[:300], predictions_train[:300], beta=b

    # Evaluation : test
    results['test_acc'] = accuracy_score(y_test, predictions_test)
    results['test_f']   = fbeta_score(   y_test, predictions_test, beta=beta)

    return results
```

I implement a plot function to evaluate.

In [18]:
```
import matplotlib.patches as mpatches

def plot_evaluate(results, bar_width=0.3, figsize=(11,7)):
    """
    Visualization code to display results of learners.

    inputs:
      - results: a map. results[model_name][sample_num_id][metric]
    """

    # Create a figure
    fig, ax = plt.subplots(2,3,figsize=figsize)

    # Parameters
    model_colors = ["tab:blue", "tab:orange", "tab:green", "tab:red", "tab:purple", \
                    "tab:brown","tab:pink","tab:gray","tab:olive","tab:cyan"]
    metric_names = ["train_time", "train_acc", "train_f", "pred_time", "test_acc", "test
    ylabels      = ["Time[s]",    "Accuracy",  "F-score", "Time[s]",   "Accuracy", "F-sc
    titles       = ["Training:Time", "Training:Accuracy", "Training:F-score", "Pred:Time
    model_names  = results.keys()
    num_sampling_type = 3;
    #
    # Loops for bar plot
    for model_id, model_name in enumerate(model_names):
        model_color = model_colors[model_id]
        #
        for metric_id, metric_name in enumerate(metric_names):
            plot_row = metric_id // 3 #//len(model_names); # shou
            plot_col = metric_id %  3 #len(model_names); # amari
            tmp_ax   = ax[plot_row, plot_col]
            #
            for sample_id in range(num_sampling_type):
                x = sample_id + model_id * bar_width;
                y = results[model_name][sample_id][metric_name]
                #
                tmp_ax.bar(x,y, width=bar_width, color=model_color)
                #
                tmp_ax.set_xticks([0.45, 1.45, 2.45])
                tmp_ax.set_xticklabels(["1%", "10%", "100%"])
                tmp_ax.set_xlabel("Training Set Size")
                tmp_ax.set_xlim((-0.1, 3.0))
                tmp_ax.set_title(titles[metric_id])
                tmp_ax.set_ylabel(ylabels[metric_id])
```

```
                #
            # end of [for sample_id]
        # end of [for metric_id]
    # end of [for model_id]

    # Create patches for the legend
    patches = []
    for model_id, model_name in enumerate(model_names):
        patches.append(mpatches.Patch(color=model_colors[model_id], label=model_name))
    #
    plt.legend(handles=patches, bbox_to_anchor=(1.05, 2.0), loc='upper left', \
               borderaxespad = 0.0, ncol = 1, fontsize = 'x-large')

    # To avoid overlapping xlabel and title
    fig.subplots_adjust(wspace=0.5, hspace=0.3)
```

3-6. Initial Model Evaluation

I will implement the following:

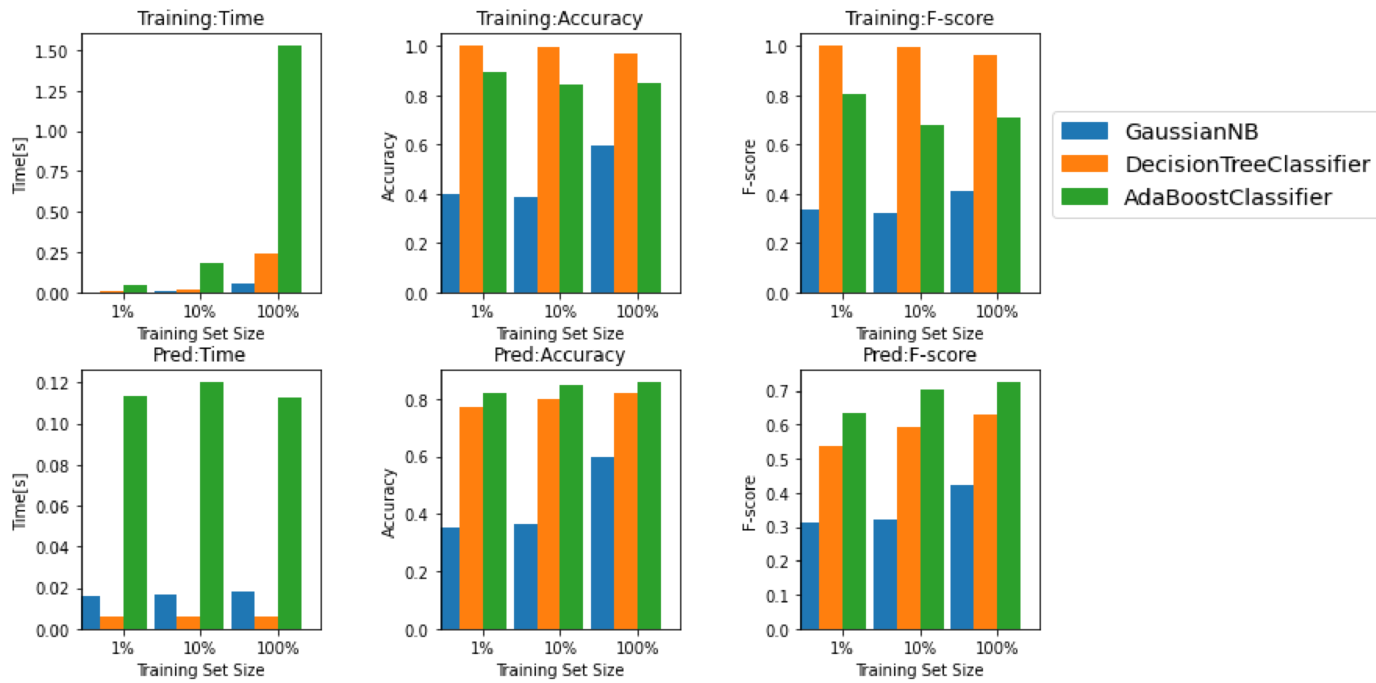
- Import the three supervised learning models which I have discussed in the previous section.
- Initialize the three models
    - I will use the default settings for each model. I will tune one specific model in a later section.
- Calculate the number of records equal to 1%, 10% and 100% of the training data.

In [19]:

```
# Import models
from sklearn.naive_bayes import GaussianNB
from sklearn.tree        import DecisionTreeClassifier
from sklearn.ensemble    import AdaBoostClassifier

# Initialize the three models
models = [GaussianNB(), DecisionTreeClassifier(random_state=0), AdaBoostClassifier(rando

# list of number of sample
sample_list = [int(len(y_train)/100), int(len(y_train)/10), int(len(y_train))]

# Train models and Predict results
results = {}
#
for model in models:
    model_name = model.__class__.__name__
    results[model_name] = {}
    #
    for i, sample_size in enumerate(sample_list):
        t_start = time()
        results[model_name][i] = train_and_predict(model, sample_size, x_train, y_train,
        t_end   = time()
        print("{}[{}] : {:.3f}[s]".format(model_name, i, (t_end-t_start)))
print("Finish !")
```

```
GaussianNB[0] : 0.021[s]
GaussianNB[1] : 0.026[s]
GaussianNB[2] : 0.072[s]
DecisionTreeClassifier[0] : 0.012[s]
DecisionTreeClassifier[1] : 0.027[s]
DecisionTreeClassifier[2] : 0.246[s]
AdaBoostClassifier[0] : 0.165[s]
AdaBoostClassifier[1] : 0.306[s]
AdaBoostClassifier[2] : 1.642[s]
Finish !
```

In [20]:
```
plot_evaluate(results)
```



In [21]:
```
def show_results_table(results):
    df_results = []
    model_names = results.keys()
    for i, model_name in enumerate(model_names):
        df_results.append( pd.DataFrame(results[model_name]) )
        df_results[i].columns = [ model_name[:5]+"_1", model_name[:5]+"_10", model_name[
        #
        print("----------------------------------------------------")
        print(df_results[i])
    #
    return df_results
```

In [22]:
```
show_results_table(results);
```

```
----------------------------------------------------
             Gauss_1  Gauss_10  Gauss_100
train_time  0.001966  0.005980   0.051188
pred_time   0.015855  0.016969   0.017952
train_acc   0.400000  0.383333   0.593333
train_f     0.333333  0.325092   0.412500
test_acc    0.351797  0.366059   0.597678
test_f      0.310134  0.320258   0.420899
----------------------------------------------------
             Decis_1  Decis_10  Decis_100
train_time  0.002992  0.018694   0.237493
pred_time   0.005765  0.005985   0.005847
train_acc   1.000000  0.996667   0.970000
train_f     1.000000  0.997191   0.963855
test_acc    0.771918  0.801658   0.818242
test_f      0.535978  0.593875   0.627250
----------------------------------------------------
             AdaBo_1  AdaBo_10  AdaBo_100
train_time  0.047863  0.182667   1.526668
pred_time   0.113699  0.120073   0.112408
train_acc   0.893333  0.840000   0.850000
train_f     0.801282  0.680147   0.711538
test_acc    0.820674  0.849862   0.857601
test_f      0.632757  0.701882   0.724551
```

3-7. Chose the Best Model

From the table above, I select the `Adaboost` mode.

- F-score using 100% of traning data(colum= `AdaBo_100` , row= `test_f`) is the best.
- Both of the training and prediction time are small enough.
- From the value of F-score(train_f and test_f), the result of `AdaBoost` did not overfit.

3-8. Model Tuning

I will fine tune the chosen model using gird search(`GridSearchCV`).
I will implement the following:

- Import `sklearn.grid_search.GridSearchCV` and `sklearn.metrics.make_scorer` .
- Initialize the classifier which I've chosen and store it in `base_model` .
- Create a dictionary of parameters I wich to tune for the chosen model.
- Use `make_scorer` to create an `fbeta_score` scoring object(with β=0.5)
- Perform grid search on the classifier `base_model` using the `scorer` and store it in `grid_obj` .
- Fit the grid search object to the training data(`x_train` , `y_train`), and store it in `grid_fit`

In [23]:

```python
import os
import pickle
from sklearn.model_selection import GridSearchCV
from sklearn.metrics         import make_scorer, f1_score, fbeta_score

# Initialize my model
base_model = AdaBoostClassifier(random_state=0)

file_name_best_model = './Data/Proj_01/best_model.sav'

if os.path.isfile(file_name_best_model):
    print("Load the best model from a file")
    # If there is already a file which contains the best model, load it.
    best_model = pickle.load(open(file_name_best_model, 'rb'))

else:
    print("Train the model with grid search to get the best model")
    # Paremter settings
    params = {}
    params['base_estimator'] = [DecisionTreeClassifier(random_state=0, max_depth=x) for
    params['n_estimators']   = [50, 100, 200, 400] # default = 50
    params['learning_rate']  = [0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1] # default = 1.0

    # Grid search and Cross Validation
    scorer     = make_scorer(fbeta_score, beta=0.5)
    grid_obj   = GridSearchCV(base_model, params, scoring=scorer)
    grid_fit   = grid_obj.fit(x_train, y_train)
    best_model = grid_fit.best_estimator_

    # save the model to a file
    pickle.dump(best_model, open(file_name_best_model, 'wb'))
```

```
Load the best model from a file
```

- I show the score

In [24]:
```
pred_base = (base_model.fit(x_train, y_train)).predict(x_test)
pred_best = best_model.predict(x_test)
#
# Report the before-and-afterscores
print("------ Unoptimized model ------")
print("Accuracy score on testing data: {:.4f}".format(accuracy_score(y_test, pred_base)))
print("F-score on testing data:         {:.4f}".format(fbeta_score(y_test, pred_base, bet
#
print("------ Optimized model ------")
print("Final accuracy score on the testing data: {:.4f}".format(accuracy_score(y_test, p
print("Final F-score on the testing data:        {:.4f}".format(fbeta_score(y_test, pred
```

```
------ Unoptimized model ------
Accuracy score on testing data: 0.8576
F-score on testing data:        0.7246
------ Optimized model ------
Final accuracy score on the testing data: 0.8690
Final F-score on the testing data:        0.7489
```

- These are parameter of the `best_model`.

In [25]:
```
best_model.get_params()
```

Out[25]:
```
{'algorithm': 'SAMME.R',
 'base_estimator__ccp_alpha': 0.0,
 'base_estimator__class_weight': None,
 'base_estimator__criterion': 'gini',
 'base_estimator__max_depth': 2,
 'base_estimator__max_features': None,
 'base_estimator__max_leaf_nodes': None,
 'base_estimator__min_impurity_decrease': 0.0,
 'base_estimator__min_samples_leaf': 1,
 'base_estimator__min_samples_split': 2,
 'base_estimator__min_weight_fraction_leaf': 0.0,
 'base_estimator__random_state': 0,
 'base_estimator__splitter': 'best',
 'base_estimator': DecisionTreeClassifier(max_depth=2, random_state=0),
 'learning_rate': 0.5,
 'n_estimators': 100,
 'random_state': 0}
```

4. Evaluation

4-1. Final Model Evaluation

I show the results.

Metric	Naive Predictor	Unoptimized AdaBoost	Optimized AdaBoost
Accuracy Score	0.2478	0.8576	0.8690
F-score	0.2917	0.7246	0.7489

Compaired to the `Navive Predictor`, the performance of the `Optimized Model` is improved by 62.1%.
Compaired to the `Unoptimized Model`, the performance of the `Optimized Model` is improved by 2.4%.

4-2. Feature Importance

An important task when performing supervised learning on a dataset like the census data is determining which features provide the most predictive power.

By focusing on the relationship between only a few crucial features and the target label, I can simplify our understanding of the phenomenon, which is most always a useful thing to do.

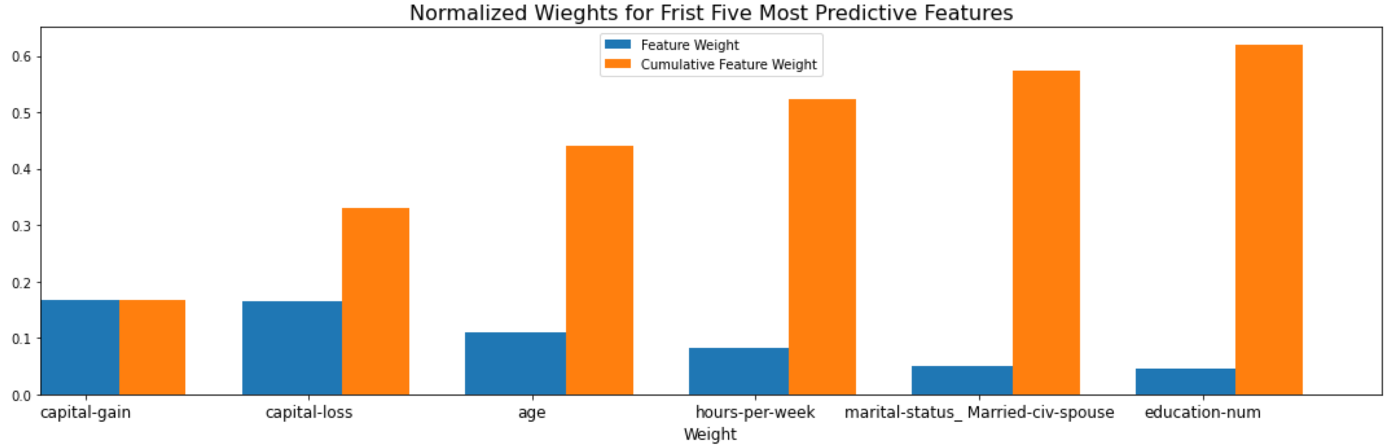
In the case of this project, that means I wish to identify a small number of features that most strongly predict whether an indivisual makes at most or more than $50,000.

Some scikit-learn classifiers(e.g., adaboost, random forests) have a `feature_importance_` attributee, which is a function that ranks the importance of features. In the code cell below, I will use this attribute to determin the top X most important features for the census dataset.

In [26]:
```
# This is a plot function which display the top X most important features
def plot_features(importances, x_train, y_train, top_x, figsize=(15,5)):
    # Get Top X most important features
    indices = np.argsort(importances)[::-1]
    columns = x_train.columns.values[indices[:top_x]]
    weights = importances[indices][:top_x]

    # Create Figure
    bar_x1 = np.arange(top_x) - 0.3
    bar_x2 = np.arange(top_x)
    bar_y1 = weights
    bar_y2 = np.cumsum(weights)
    #
    colors = ["tab:blue", "tab:orange", "tab:green", "tab:red", "tab:purple"]
    labels = ["Feature Weight", "Cumulative Feature Weight"]
    fig    = plt.figure(figsize=figsize)
    plt.title("Normalized Wieghts for Frist Five Most Predictive Features", fontsize=16)

    # Plot Bar
    plt.bar(bar_x1, bar_y1, width=0.6, align="center", color=colors[0], label=labels[0])
    plt.bar(bar_x2, bar_y2, width=0.3, align="center", color=colors[1], label=labels[1])
    #
    plt.xticks(bar_x1, columns, fontsize=12)
    plt.xlim((-0.5, top_x-0.5))
    plt.xlabel("Feature", fontsize=12)
    plt.xlabel("Weight",  fontsize=12)
    plt.legend(loc="upper center")
    plt.tight_layout()
    #
    return columns
```

In [27]:
```
# Extranct feature importances
importances = best_model.feature_importances_

# plot
top_x = 6
important_columns = plot_features(importances, x_train, y_train, top_x)
display(important_columns)
```

```
array(['capital-gain', 'capital-loss', 'age', 'hours-per-week',
       'marital-status_ Married-civ-spouse', 'education-num'],
      dtype=object)
```



Observation about the top 5 features extraction

1. capital-gain
2. capital-loss
    - I guess that those who can afford to invest can donate a lot.
3. age
    - I guess that experience of how to earn relates with investing.
4. hours-per-week
    - I guess that who can use more time to invest makes more money.
5. marital-status_ Married-civ-spouse
    - I geuss that a lot of citizens with spouse can afford to pay attention not only to themselves but also to their surrounding.

Features Selection

I will train the model with less features. The expectation is that training and prediction time is much lower. From the visualization above, I see that the top 6 most important features contributes more than half of the importance of all features present in the data.
This hins that I can attempt to reduce the feature space and simplify the information required to the model to learn.

In [28]:
```
from sklearn.base import clone

# create reduced features ant target
x_train_reduced = x_train[important_columns]
x_test_reduced  = x_test[important_columns]

# calculate the training time of best_model
t_start = time()
best_model = best_model.fit(x_train, y_train)
training_time_best_model = time() - t_start

# clone the best model and train
light_model = clone(best_model)
t_start = time()
light_model = light_model.fit(x_train_reduced, y_train)
training_time_light_model = time() - t_start

# predict
pred_reduced = light_model.predict(x_test_reduced)

# Report the before-and-afterscores
```

```
print("------ Optimized model ------")
print("Accuracy score on testing data: {:.4f}".format(accuracy_score(y_test, pred_best))
print("F-score on testing data:        {:.4f}".format(fbeta_score(y_test, pred_best, bet
print("Training Time[s]:               {:.4f}".format(training_time_best_model))
#
print("------ Optimized model on reduced data ------")
print("Accuracy score on the testing data: {:.4f}".format(accuracy_score(y_test, pred_re
print("F-score on the testing data:        {:.4f}".format(fbeta_score(y_test, pred_reduc
print("Training Time[s]:                   {:.4f}".format(training_time_light_model))
```

```
------ Optimized model ------
Accuracy score on testing data: 0.8690
F-score on testing data:        0.7489
Training Time[s]:               4.3591
------ Optimized model on reduced data ------
Accuracy score on the testing data: 0.8601
F-score on the testing data:        0.7318
Training Time[s]:                   0.9891
```

`Optimized model` used 103 features, and `optimized model on reduced data` used only 6 features.
With reduced features, the F-score reduced only 1.7% and training time is about 4 time faster.

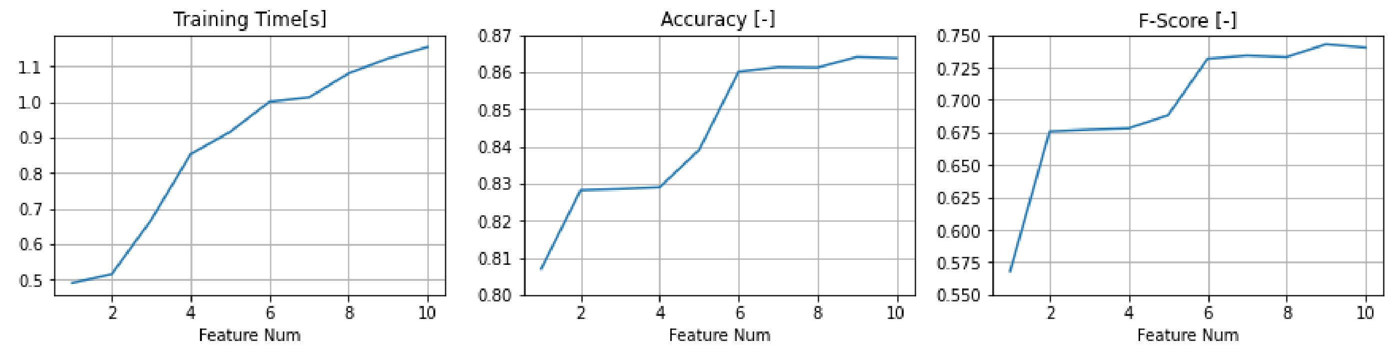
For more information about Features Selection

I will research the detail effect of the number of features which are used on training.
I will show the training time, accuracy and f-score chaging the number of features from 1 to 10.

In [29]:
```
indices = np.argsort(importances)[::-1]
all_columns_sorted = x_train.columns.values[indices]

train_time_list = []
accuracy_list   = []
fscore_list     = []

for cnt in range(10):
    top_x = cnt + 1
    important_columns = all_columns_sorted[:top_x]
    #---------------------------#
    # create reduced features ant target
    x_train_reduced = x_train[important_columns]
    x_test_reduced  = x_test[important_columns]

    # clone the best model and train
    light_model = clone(best_model)
    t_start     = time()
    light_model = light_model.fit(x_train_reduced, y_train)
    t_end       = time()

    # predict
    pred_reduced = light_model.predict(x_test_reduced)

    # output
    train_time_list.append(t_end-t_start)
    accuracy_list.append(accuracy_score(y_test, pred_reduced))
    fscore_list.append(fbeta_score(y_test, pred_reduced, beta = 0.5))
```

In [30]:
```
fig = plt.figure(figsize=(15,3))
x_data = np.arange(10) + 1

ax = fig.add_subplot(1,3,1)
plt.plot(x_data, train_time_list)
plt.grid(1)
plt.title('Training Time[s]')
```

```
plt.xlabel('Feature Num')

ax = fig.add_subplot(1,3,2)
plt.plot(x_data, accuracy_list)
plt.grid(1)
plt.title('Accuracy [-]')
plt.xlabel('Feature Num')
plt.ylim((0.8, 0.87));

ax = fig.add_subplot(1,3,3)
plt.plot(x_data, fscore_list)
plt.grid(1)
plt.title('F-Score [-]')
plt.xlabel('Feature Num')
plt.ylim((0.55, 0.75));
```



In [31]:

```
# Save to .html
!!jupyter nbconvert --to html Proj_01_Finding_Donors.ipynb
```

Out[31]:

```
['[NbConvertApp] Converting notebook Proj_01_Finding_Donors.ipynb to html',
 '[NbConvertApp] Writing 888081 bytes to Proj_01_Finding_Donors.html']
```

In [ ]: