Supervised Learning

Project: Finding Donors for *CharityML*

Getting Started

In this project, you will employ several supervised algorithms of your choice to accurately model individuals' income using data collected from the 1994 U.S. Census. You will then choose the best candidate algorithm from preliminary results and further optimize this algorithm to best model the data. Your goal with this implementation is to construct a model that accurately predicts whether an individual makes more than $50,000.

Exploring the Data

In [1]:
```python
# Import libraries necessary for this project
import numpy as np
import pandas as pd
from time import time
from IPython.display import display # Allows the use of display() for DataFrames

# Import supplementary visualization code visuals.py
import visuals as vs

# Pretty display for notebooks
%matplotlib inline

# Load the Census dataset
data = pd.read_csv(r"C:\Users\Carnival\Downloads\census (1).csv")

# Success - Display the first record
display(data.head(n=1))
```

	age	workclass	education_level	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	nati coun
0	39	State-gov	Bachelors	13.0	Never-married	Adm-clerical	Not-in-family	White	Male	2174.0	0.0	40.0	Unit Sta

Implementation: Data Exploration

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, you will need to 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 [2]:
```python
data.describe()
```

Out[2]:

	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 [3]:
```python
data.income.value_counts()
```

Out[3]:
```
<=50K    34014
>50K     11208
Name: income, dtype: int64
```

In [4]:
```python
# TODO: Total number of records
n_records = data.shape[0]

# TODO: Number of records where individual's income is more than $50,000
n_greater_50k = data.query("income=='>50K'")['income'].count()

# TODO: Number of records where individual's income is at most $50,000
n_at_most_50k = data.query("income=='<=50K'")['income'].count()

# TODO: Percentage of individuals whose income is more than $50,000
greater_percent = (n_greater_50k / n_records)*100

# Print the results
print("Total number of records: {}".format(n_records))
print("Individuals making more than $50,000: {}".format(n_greater_50k))
print("Individuals making at most $50,000: {}".format(n_at_most_50k))
print("Percentage of individuals making more than $50,000: {:.3f}%".format(greater_percent))
```

```
Total number of records: 45222
Individuals making more than $50,000: 11208
Individuals making at most $50,000: 34014
Percentage of individuals making more than $50,000: 24.784%
```

Featureset Exploration

- **age**: continuous.
- **workclass**: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
- **education**: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
- **education-num**: continuous.
- **marital-status**: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
- **occupation**: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
- **relationship**: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
- **race**: Black, White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other.
- **sex**: Female, Male.
- **capital-gain**: continuous.
- **capital-loss**: continuous.
- **hours-per-week**: continuous.
- **native-country**: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

Preparing the Data

Before data can be used as input for machine learning algorithms, it often must be cleaned, formatted, and restructured — this is typically known as **preprocessing**. 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.

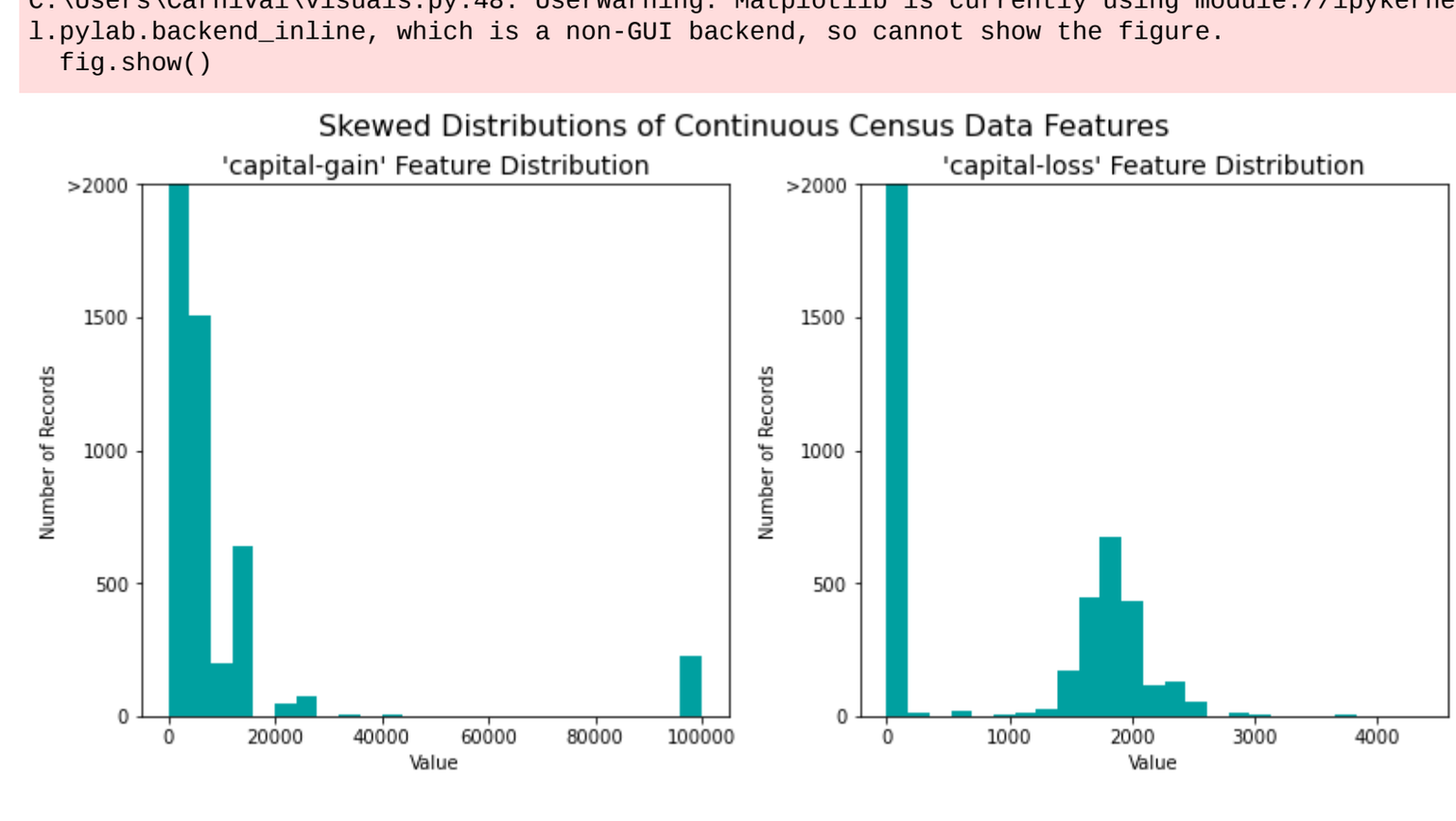
Transforming Skewed Continuous Features

A dataset may sometimes contain at least one feature whose values tend to lie near a single number, but will also have a non-trivial number of vastly larger or smaller values than that single number. Algorithms can be sensitive to such distributions of values and can underperform if the range is not properly normalized. With the census dataset two features fit this description: '`capital-gain'` and `'capital-loss'`.

In [5]:
```python
# Split the data into features and target label
income_raw = data['income']
features_raw = data.drop('income', axis = 1)

# Visualize skewed continuous features of original data
vs.distribution(data)
```

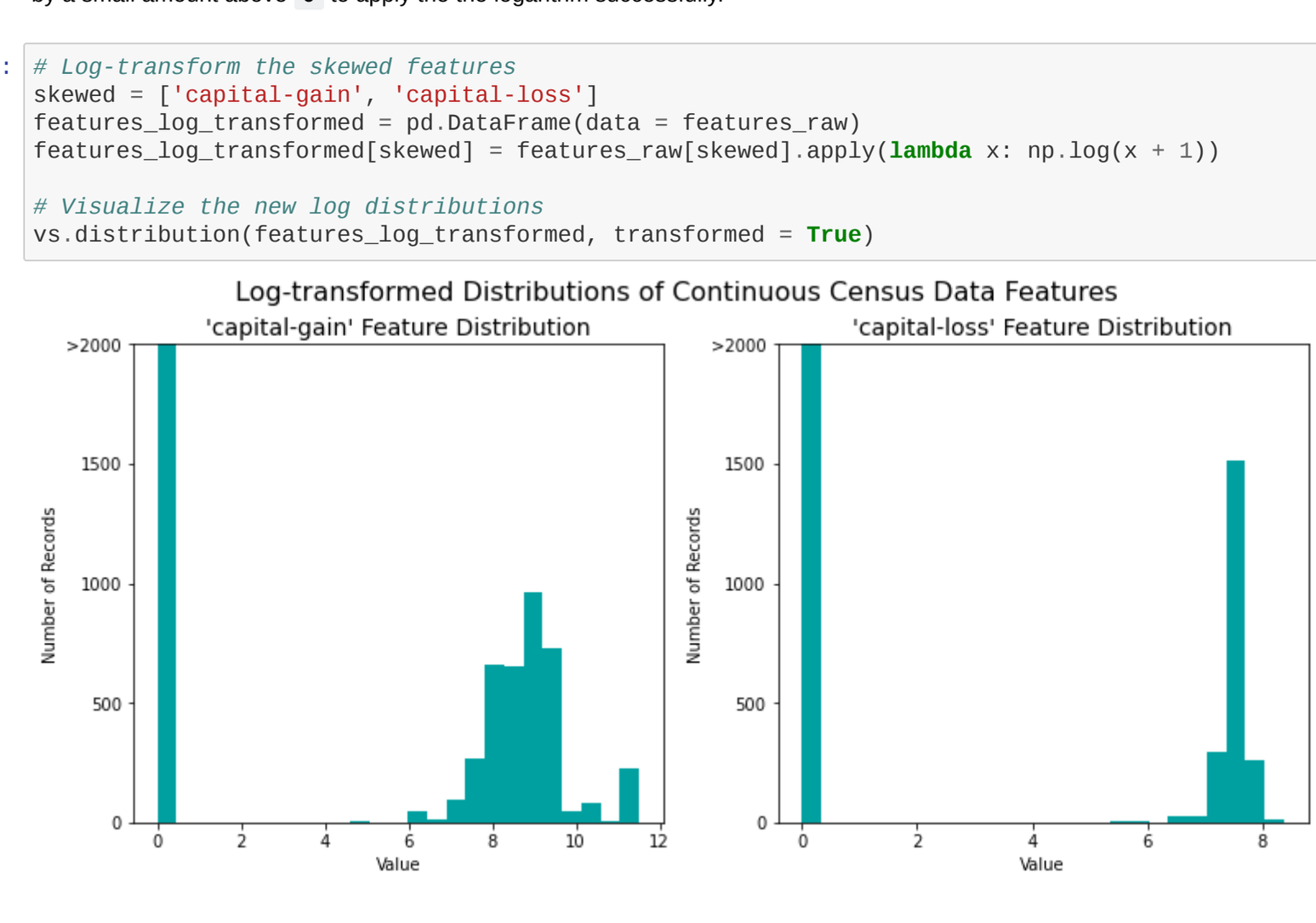
```
C:\Users\Carnival\visuals.py:48: UserWarning: Matplotlib is currently using module://ipykerne
l.pylab.backend_inline, which is a non-GUI backend, so cannot show the figure.
  fig.show()
```



For highly-skewed feature distributions such as `'capital-gain'` and `'capital-loss'`, it is common practice to apply a logarithmic transformation on the data so that the very large and very small values do not negatively affect the performance of a learning algorithm. Using a logarithmic transformation significantly reduces the range of values caused by outliers. Care must be taken when applying this transformation however: The logarithm of `0` is undefined, so we must translate the values by a small amount above `0` to apply the the logarithm successfully.

In [6]:
```python
# Log-transform the skewed features
skewed = ['capital-gain', 'capital-loss']
features_log_transformed = pd.DataFrame(data = features_raw)
features_log_transformed[skewed] = features_raw[skewed].apply(lambda x: np.log(x + 1))

# Visualize the new log distributions
vs.distribution(features_log_transformed, transformed = True)
```



Normalizing Numerical Features

In addition to performing transformations on features that are highly skewed, it is often good practice to perform some type of scaling on numerical features. Applying a scaling to the data does not change the shape of each feature's distribution (such as `'capital-gain'` or `'capital-loss'` above).

In [7]:
```python
# Import sklearn.preprocessing.StandardScaler
from sklearn.preprocessing import MinMaxScaler

# Initialize a scaler, then apply it to the features
scaler = MinMaxScaler() # default=(0, 1)
numerical = ['age', 'education-num', 'capital-gain', 'capital-loss', 'hours-per-week']

features_log_minmax_transform = pd.DataFrame(data = features_log_transformed)
features_log_minmax_transform[numerical] = scaler.fit_transform(features_log_transformed[num
erical])

# Show an example of a record with scaling applied
display(features_log_minmax_transform.head(n = 5))
```

	age	workclass	education_level	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	h
0	0.301370	State-gov	Bachelors	0.800000	Never-married	Adm-clerical	Not-in-family	White	Male	0.667492	0.0	0.39
1	0.452055	Self-emp-not-inc	Bachelors	0.800000	Married-civ-spouse	Exec-managerial	Husband	White	Male	0.000000	0.0	0.12
2	0.287671	Private	HS-grad	0.533333	Divorced	Handlers-cleaners	Not-in-family	White	Male	0.000000	0.0	0.39
3	0.493151	Private	11th	0.400000	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0.000000	0.0	0.39
4	0.150685	Private	Bachelors	0.800000	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0.000000	0.0	0.39

Implementation: Data Preprocessing

From the table in **Exploring the Data** above, we can see there are several features for each record that are non-numeric. Typically, learning algorithms expect input to be numeric, which requires that non-numeric features (called *categorical variables*) be converted. One popular way to convert categorical variables is by using the **one-hot encoding** scheme. One-hot encoding creates a *"dummy"* variable for each possible category of each non-numeric feature. For example, assume `someFeature` has three possible entries: `A`, `B`, or `C`. We then encode this feature into `someFeature_A`, `someFeature_B` and `someFeature_C`.

	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, as with the non-numeric features, we need to convert the non-numeric target label, `'income'` to numerical values for the learning algorithm to work. 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`, respectively. In code cell below, you will need to implement the following:

- Use `pandas.get_dummies()` to perform one-hot encoding on the `'features_log_minmax_transform'` data.
- Convert the target label `'income_raw'` to numerical entries.
  - Set records with "<=50K" to `0` and records with ">50K" to `1`.

In [8]:
```python
# TODO: One-hot encode the 'features_log_minmax_transform' data using pandas.get_dummies()
features_final = pd.get_dummies(data=features_log_minmax_transform, columns=['workclass','ed
ucation_level','marital-status','occupation','relationship','race','sex','native-country'])

# TODO: Encode the 'income_raw' data to numerical values
income = income_raw.replace({'<=50K':0, '>50K':1})

# Print the number of features after one-hot encoding
encoded = list(features_final.columns)
print("{} total features after one-hot encoding.".format(len(encoded)))

# Uncomment the following line to see the encoded feature names
print (encoded)
```

```
103 total features after one-hot encoding.
['age', 'education-num', 'capital-gain', 'capital-loss', 'hours-per-week', 'workclass_ Federa
l-gov', 'workclass_ Local-gov', 'workclass_ Private', 'workclass_ Self-emp-inc', 'workclass_
Self-emp-not-inc', 'workclass_ State-gov', 'workclass_ Without-pay', 'education_level_ 10th',
'education_level_ 11th', 'education_level_ 12th', 'education_level_ 1st-4th', 'education_leve
l_ 5th-6th', 'education_level_ 7th-8th', 'education_level_ 9th', 'education_level_ Assoc-acd
m', 'education_level_ Assoc-voc', 'education_level_ Bachelors', 'education_level_ Doctorate',
'education_level_ HS-grad', 'education_level_ Masters', 'education_level_ Preschool', 'educat
ion_level_ Prof-school', 'education_level_ Some-college', 'marital-status_ Divorced', 'marita
l-status_ Married-AF-spouse', 'marital-status_ Married-civ-spouse', 'marital-status_ Married-
spouse-absent', 'marital-status_ Never-married', 'marital-status_ Separated', 'marital-status
_ Widowed', 'occupation_ Adm-clerical', 'occupation_ Armed-Forces', 'occupation_ Craft-repai
r', 'occupation_ Exec-managerial', 'occupation_ Farming-fishing', 'occupation_ Handlers-clean
ers', 'occupation_ Machine-op-inspct', 'occupation_ Other-service', 'occupation_ Priv-house-s
erv', 'occupation_ Prof-specialty', 'occupation_ Protective-serv', 'occupation_ Sales', 'occu
pation_ Tech-support', 'occupation_ Transport-moving', 'relationship_ Husband', 'relationship
_ Not-in-family', 'relationship_ Other-relative', 'relationship_ Own-child', 'relationship_ U
nmarried', 'relationship_ Wife', 'race_ Amer-Indian-Eskimo', 'race_ Asian-Pac-Islander', 'rac
e_ Black', 'race_ Other', 'race_ White', 'sex_ Female', 'sex_ Male', 'native-country_ Cambodi
a', 'native-country_ Canada', 'native-country_ China', 'native-country_ Columbia', 'native-co
untry_ Cuba', 'native-country_ Dominican-Republic', 'native-country_ Ecuador', 'native-countr
y_ El-Salvador', 'native-country_ England', 'native-country_ France', 'native-country_ German
y', 'native-country_ Greece', 'native-country_ Guatemala', 'native-country_ Haiti', 'native-c
ountry_ Holand-Netherlands', 'native-country_ Honduras', 'native-country_ Hong', 'native-coun
try_ Hungary', 'native-country_ India', 'native-country_ Iran', 'native-country_ Ireland', 'n
ative-country_ Italy', 'native-country_ Jamaica', 'native-country_ Japan', 'native-country_ L
aos', 'native-country_ Mexico', 'native-country_ Nicaragua', 'native-country_ Outlying-US(Gua
m-USVI-etc)', 'native-country_ Peru', 'native-country_ Philippines', 'native-country_ Polan
d', 'native-country_ Portugal', 'native-country_ Puerto-Rico', 'native-country_ Scotland', 'n
ative-country_ South', 'native-country_ Taiwan', 'native-country_ Thailand', 'native-country_
Trinadad&Tobago', 'native-country_ United-States', 'native-country_ Vietnam', 'native-country
_ Yugoslavia']
```

Shuffle and Split Data

Now all *categorical variables* have been converted into numerical features, and all numerical features have been normalized. As always, we will now split the data (both features and their labels) into training and test sets. 80% of the data will be used for training and 20% for testing.

Run the code cell below to perform this split.

In [9]:
```python
# Import train_test_split
from sklearn.model_selection import train_test_split

# Split the 'features' and 'income' data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features_final, income, test_size = 0.2,
random_state = 2)

# Show the results of the split
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.
```

Evaluating Model Performance

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

Metrics and the Naive Predictor

CharityML, equipped with their 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 performace 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. We can use **F-beta score** as a metric that considers both precision and recall:

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

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).

Looking at the distribution of classes (those who make at most \$50,000, and those who make more), it's clear most individuals do not make more than \$50,000. This can greatly affect **accuracy**, since we could simply say *"this person does not make more than \$50,000"* and generally be right, without ever looking at the data! Making such a statement would be called **naive**, since we have not considered any information to substantiate the claim. It is always important to consider the *naive prediction* for your data, to help establish a benchmark for whether a model is performing well. That been said, using that prediction would be pointless: If we predicted all people made less than \$50,000, *CharityML* would identify no one as donors.

Accuracy measures how often the classifier makes 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 tells us what proportion of messages we classified as spam, actually were spam. It is a ratio of true positives(words classified as spam, and which are actually spam) to all positives(all words classified as spam, irrespective of whether that was the correct classificatio), in other words it is the ratio of

`[True Positives/(True Positives + False Positives)]`

Recall(sensitivity) tells us what proportion of messages that actually were spam were classified by us as spam. It is a ratio of true positives(words classified as spam, and which are actually spam) to all the words that were actually spam, in other words it is the ratio of

`[True Positives/(True Positives + False Negatives)]`

For classification problems that are skewed in their classification distributions like in our case, for example if we had a 100 text messages and only 2 were spam and the rest 98 weren't, accuracy by itself is not a very good metric. We could classify 90 messages as not spam(including the 2 that were spam but we classify them as not spam, hence they would be false negatives) and 10 as spam(all 10 false positives) and still get a reasonably good accuracy score. For such cases, precision and recall come in very handy. These two metrics can be combined to get the F1 score, which is weighted average(harmonic mean) of the precision and recall scores. This score can range from 0 to 1, with 1 being the best possible F1 score(we take the harmonic mean as we are dealing with ratios).

Naive Predictor Performace

- If we chose a model that always predicted an individual made more than $50,000, what would that model's accuracy and F-score be on this dataset? You must use the code cell below and assign your results to `'accuracy'` and `'fscore'` to be used later.

In [10]:
```python
'''
TP = np.sum(income) # Counting the ones as this is the naive case. Note that 'income' is the
'income_raw' data
encoded to numerical values done in the data preprocessing step.
FP = income.count() - TP # Specific to the naive case

TN = 0 # No predicted negatives in the naive case
FN = 0 # No predicted negatives in the naive case
'''
# TODO: Calculate accuracy, precision and recall
accuracy = (np.sum(income)+0)/ (np.sum(income)+income.count() - np.sum(income)+0+0)
recall = (np.sum(income))/ (np.sum(income)+0)
precision = (np.sum(income))/ (np.sum(income)+income.count() - np.sum(income))

# TODO: Calculate F-score using the formula above for beta = 0.5 and correct values for prec
ision and recall.
fscore = (1+0.5**2) * ( (precision * recall) / ((0.5**2*precision) + recall) )


# Print the results
print("Naive Predictor: [Accuracy score: {:.4f}, F-score: {:.4f}]".format(accuracy, fscore))
```

```
Naive Predictor: [Accuracy score: 0.2478, F-score: 0.2917]
```

Supervised Learning Models

The following are some of the supervised learning models that are currently available in `scikit-learn` that you may choose from:

- Gaussian Naive Bayes (GaussianNB)
- Decision Trees
- Ensemble Methods (Bagging, AdaBoost, Random Forest, Gradient Boosting)
- K-Nearest Neighbors (KNeighbors)
- Stochastic Gradient Descent Classifier (SGDC)
- Support Vector Machines (SVM)
- Logistic Regression

Implementation - Creating a Training and Predicting Pipeline

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

In [11]:
```python
# TODO: Import two metrics from sklearn - fbeta_score and accuracy_score
from sklearn.metrics import fbeta_score
from sklearn.metrics import accuracy_score
from sklearn import svm
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression

def train_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 = {}

    # TODO: Fit the learner to the training data using slicing with 'sample_size' using .fit
(training_features[:], training_labels[:])
    start = time() # Get start time
    learner = learner.fit( X_train[:sample_size], y_train[:sample_size] )
    end = time() # Get end time


    # TODO: Calculate the training time
    results['train_time'] = end-start

    # TODO: Get the predictions on the test set(X_test),
    #       then get predictions on the first 300 training samples(X_train) using .predict()
    start = time() # Get start time
    predictions_test = learner.predict(X_test)
    predictions_train = learner.predict(X_train[:300])
    end = time() # Get end time

    # TODO: Calculate the total prediction time
    results['pred_time'] = end-start

    # TODO: Compute accuracy on the first 300 training samples which is y_train[:300]
    results['acc_train'] = accuracy_score(y_train[:300], predictions_train[:300])

    # TODO: Compute accuracy on test set using accuracy_score()
    results['acc_test'] = accuracy_score(y_test, predictions_test)

    # TODO: Compute F-score on the the first 300 training samples using fbeta_score()
    results['f_train'] = fbeta_score(y_train[:300], predictions_train[:300], average=None, b
eta=0.5)

    # TODO: Compute F-score on the test set which is y_test
    results['f_test'] = fbeta_score(y_test, predictions_test, average=None, beta=0.5)

    # Success
    print("{} trained on {} samples.".format(learner.__class__.__name__, sample_size))

    # Return the results
    return results
```

Implementation: Initial Model Evaluation

In [12]:
```python
# TODO: Import the three supervised learning models from sklearn
from sklearn.neighbors import KNeighborsClassifier

# TODO: Initialize the three models
clf_A = LogisticRegression(random_state=1)
clf_B = svm.SVC(random_state=1)
clf_C = KNeighborsClassifier()

# TODO: Calculate the number of samples for 1%, 10%, and 100% of the training data
# HINT: samples_100 is the entire training set i.e. len(y_train)
# HINT: samples_10 is 10% of samples_100 (ensure to set the count of the values to be `int`
 and not `float`)
# HINT: samples_1 is 1% of samples_100 (ensure to set the count of the values to be `int` an
d not `float`)
samples_100 = int(len(y_train))
samples_10 = int(len(y_train)*0.1)
samples_1 = int(len(y_train)*0.01)

# Collect results on the learners
results = {}
for clf in [clf_A, clf_B, clf_C]:
    clf_name = clf.__class__.__name__
    results[clf_name] = {}
    for i, samples in enumerate([samples_1, samples_10, samples_100]):
        results[clf_name][i] = \
        train_predict(clf, samples, X_train, y_train, X_test, y_test)

# Run metrics visualization for the three supervised learning models chosen
vs.evaluate(results, accuracy, fscore)
```

```
LogisticRegression trained on 361 samples.
LogisticRegression trained on 3617 samples.
```

```
C:\Users\Carnival\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:762: Converge
nceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
C:\Users\Carnival\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:762: Converge
nceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
LogisticRegression trained on 36177 samples.
SVC trained on 361 samples.
SVC trained on 3617 samples.
SVC trained on 36177 samples.
KNeighborsClassifier trained on 361 samples.
KNeighborsClassifier trained on 3617 samples.
KNeighborsClassifier trained on 36177 samples.
```

```
C:\Users\Carnival\visuals.py:118: UserWarning: Tight layout not applied. tight_layout cannot
make axes width small enough to accommodate all axes decorations
  pl.tight_layout()
```

Improving Results

In this final section, you will choose from the three supervised learning models the *best* model to use on the student data. You will then perform a grid search optimization for the model over the entire training set (`X_train` and `y_train`) by tuning at least one parameter to improve upon the untuned model's F-score.

Implementation: Model Tuning

In [13]:
```python
# TODO: Import 'GridSearchCV', 'make_scorer', and any other necessary libraries
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer

# TODO: Initialize the classifier
clfc = LogisticRegression(random_state=1)

# TODO: Create the parameters list you wish to tune, using a dictionary if needed.
# HINT: parameters = {'parameter_1': [value1, value2], 'parameter_2': [value1, value2]}
parameters = {'penalty':['l1','l2'], 'C':[1,2,3,4,5,6]}

# TODO: Make an fbeta_score scoring object using make_scorer()
scorer = make_scorer(fbeta_score, beta = 0.5)

# TODO: Perform grid search on the classifier using 'scorer' as the scoring method using Gri
dSearchCV()
grid_obj = GridSearchCV(estimator=clfc, param_grid=parameters, scoring=scorer, n_jobs = -1)

# TODO: Fit the grid search object to the training data and find the optimal parameters usin
g fit()
grid_fit = grid_obj.fit(X_train, y_train)

# Get the estimator
best_clf = grid_fit.best_estimator_

# Make predictions using the unoptimized and model
predictions = (clf.fit(X_train, y_train)).predict(X_test)
best_predictions = best_clf.predict(X_test)

# Report the before-and-afterscores
print("Unoptimized model\n------")
print("Accuracy score on testing data: {:.4f}".format(accuracy_score(y_test, predictions)))
print("F-score on testing data: {:.4f}".format(fbeta_score(y_test, predictions, beta = 0.5
)))
print("\nOptimized Model\n------")
print("Final accuracy score on the testing data: {:.4f}".format(accuracy_score(y_test, best_
predictions)))
print("Final F-score on the testing data: {:.4f}".format(fbeta_score(y_test, best_prediction
s, beta = 0.5)))
```

```
C:\Users\Carnival\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:762: Converge
nceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
Unoptimized model
------
Accuracy score on testing data: 0.8188
F-score on testing data: 0.6344

Optimized Model
------
Final accuracy score on the testing data: 0.8422
Final F-score on the testing data: 0.6902
```

Final Model Evaluation

Results:

Metric	Unoptimized Model	Optimized Model
Accuracy Score	0.8188	0.8423
F-score	0.6344	0.6907

Feature Importance

Feature Relevance Observation

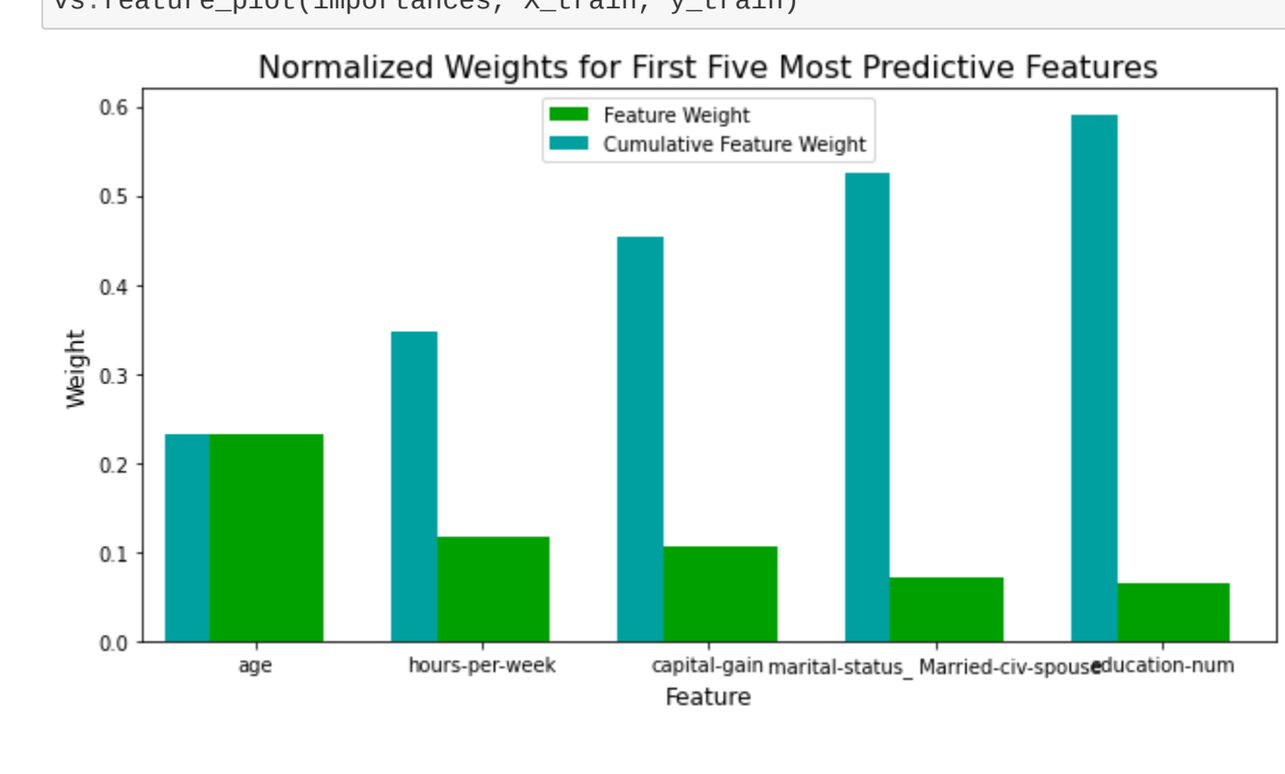
Implementation - Extracting Feature Importance

In [14]:
```python
# TODO: Import a supervised learning model that has 'feature_importances_'
from sklearn.ensemble import RandomForestClassifier

# TODO: Train the supervised model on the training set using .fit(X_train, y_train)
model = RandomForestClassifier().fit(X_train,y_train)

# TODO: Extract the feature importances using .feature_importances_
importances = model.feature_importances_

# Plot
vs.feature_plot(importances, X_train, y_train)
```



Extracting Feature Importance

Feature Selection

In [15]:
```python
# Import functionality for cloning a model
from sklearn.base import clone

# Reduce the feature space
X_train_reduced = X_train[X_train.columns.values[(np.argsort(importances)[::-1])[:5]]]
X_test_reduced = X_test[X_test.columns.values[(np.argsort(importances)[::-1])[:5]]]

# Train on the "best" model found from grid search earlier
clf = (clone(best_clf)).fit(X_train_reduced, y_train)

# Make new predictions
reduced_predictions = clf.predict(X_test_reduced)

# Report scores from the final model using both versions of data
print("Final Model trained on full data\n------")
print("Accuracy on testing data: {:.4f}".format(accuracy_score(y_test, best_predictions)))
print("F-score on testing data: {:.4f}".format(fbeta_score(y_test, best_predictions, beta =
0.5)))
print("\nFinal Model trained on reduced data\n------")
print("Accuracy on testing data: {:.4f}".format(accuracy_score(y_test, reduced_predictions
)))
print("F-score on testing data: {:.4f}".format(fbeta_score(y_test, reduced_predictions, beta
= 0.5)))
```

```
Final Model trained on full data
------
Accuracy on testing data: 0.8422
F-score on testing data: 0.6902

Final Model trained on reduced data
------
Accuracy on testing data: 0.8265
F-score on testing data: 0.6542
```