In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from scipy.stats import chi2_contingency
import sklearn
from sklearn.tree import DecisionTreeClassifier
from sklearn import preprocessing
```

Data Preparation

In the cell below, column names for the dataset are based upon the metadata file and are saved in an array. They are used as the column names when the training and testing datasets are loaded into panda dataframes. Once, the data has been loaded into pandas, the target variable 'year' is coded to numeric.

In [2]:
```
#data is loaded into pandas
colnames = ["age","class of worker","detailed industry recode","detailed
train_set = pd.read_csv('census_income_learn.csv',names = colnames, head
test_set = pd.read_csv('census_income_test.csv',names = colnames, header

#target variable to numberic
train_set['year'].replace(to_replace = ' - 50000.',value = 0, inplace = 
train_set['year'].replace(to_replace = ' 50000+.',value = 1, inplace = T
test_set['year'].replace(to_replace = ' - 50000.',value = 0, inplace = T
test_set['year'].replace(to_replace = ' 50000+.',value = 1, inplace = Tr

#instance weight is dropped from the dataset since this field should not
train_set.drop('instance weight', 1, inplace = True)
test_set.drop('instance weight', 1, inplace = True)
```

Variable Analysis

I first start off my variable analysis by calculating the percentage of missing values for each variable.

In [3]:
```
null_col=train_set.columns[train_set.isnull().any()]
train_set[null_col].isnull().sum()
```

Out[3]:
```
Series([], dtype: float64)
```

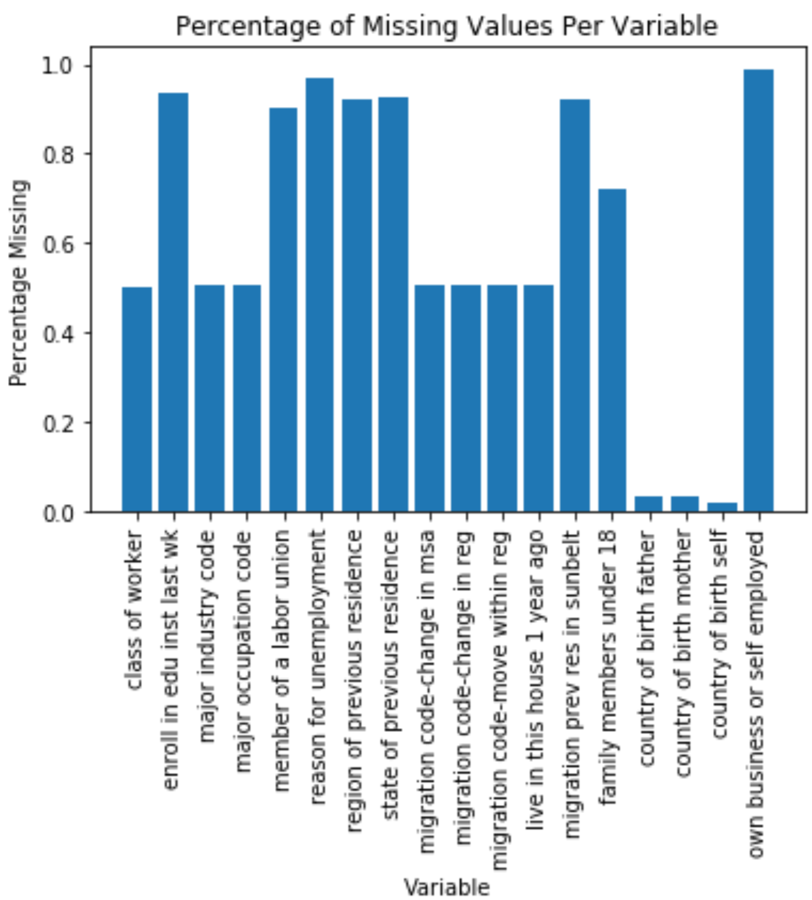
However, there does not appear to be any values that are explicitly "null" in the dataset. So I delved deeper into the dataset and found that there were some variables that had values "Not in universe" or "?". These missing value placeholders cannot really provide us with any real insights into what particular feature values may predict the target variable. The percentage of missing values for each variable is caclculated below.

In [4]:
```
missing_values = {}
for col in train_set.columns:
    num_missing = []
    num_missing = len(train_set[(train_set[col].astype(str).str.contains
    if num_missing != 0:
        missing_values[col] = num_missing
```

```
/anaconda3/lib/python3.6/site-packages/pandas/core/ops.py:1649: Future
Warning: elementwise comparison failed; returning scalar instead, but
in the future will perform elementwise comparison
  result = method(y)
```

In [5]:

```
percent_miss = {}
omit = []

for key,value in missing_values.items():
    percent_miss[key] = value / len(train_set)

for key, value in percent_miss.items():
    if value > .60:
        omit.append(key)

columns = percent_miss.keys()
x_pos = np.arange(len(columns))

plt.bar(columns,percent_miss.values())
plt.xticks(x_pos,columns,rotation = 90)
plt.ylabel('Percentage Missing')
plt.xlabel('Variable')
plt.title('Percentage of Missing Values Per Variable')
plt.show()
```



The graph above displays the percentage of missing values for each variable. Below I actually decided to omit variables whose missing percentage is greater than 60%. Any features with missing percentage values higher than that cannot really add any value when trying to predict the target variable.

In [6]:
```
train_set = train_set.loc[:,~train_set.columns.isin(omit)]
test_set = test_set.loc[:,~test_set.columns.isin(omit)]
```

In order to properly visualize and analyze different variable distributions and relationships to the target variable (whether someone makes more or less than $50,000 per year), I felt it was important to recognize that both nominal/categorical and continuous variables were present in the dataset. I decided to start my analysis by creating a dataframe with only the continuous variables according to the metadata file.

In [7]:
```
continuous_feats = train_set.loc[:,['age','wage per hour','capital gains
```

Below is simply a summary of minimum values, maximum values, and etc for the continuous variables.

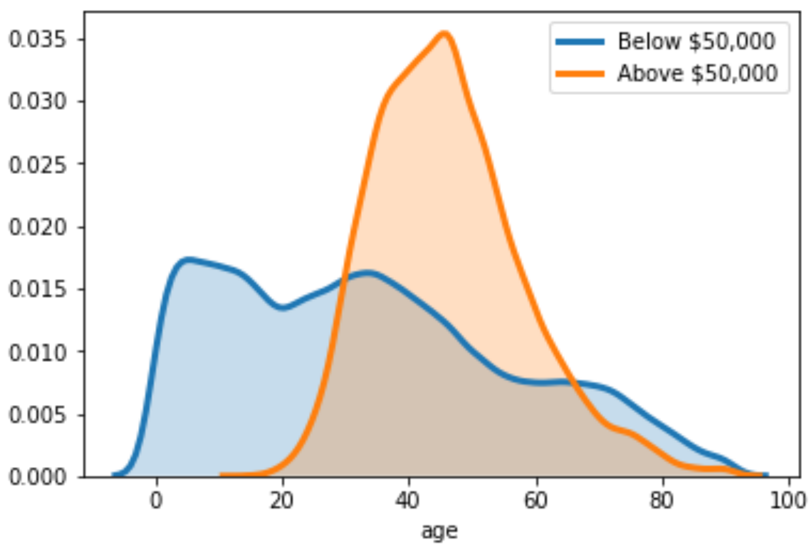
In [8]:
```
continuous_feats.loc[:,~continuous_feats.columns.isin(['year'])].describ
```

Out[8]:

	age	wage per hour	capital gains	capital losses	dividends from stocks	num persons worked fo employe
count	199523.000000	199523.000000	199523.00000	199523.000000	199523.000000	199523.00000(
mean	34.494199	55.426908	434.71899	37.313788	197.529533	1.95618(
std	22.310895	274.896454	4697.53128	271.896428	1984.163658	2.36512(
min	0.000000	0.000000	0.00000	0.000000	0.000000	0.00000(
25%	15.000000	0.000000	0.00000	0.000000	0.000000	0.00000(
50%	33.000000	0.000000	0.00000	0.000000	0.000000	1.00000(
75%	50.000000	0.000000	0.00000	0.000000	0.000000	4.00000(
max	90.000000	9999.000000	99999.00000	4608.000000	99999.000000	6.00000(

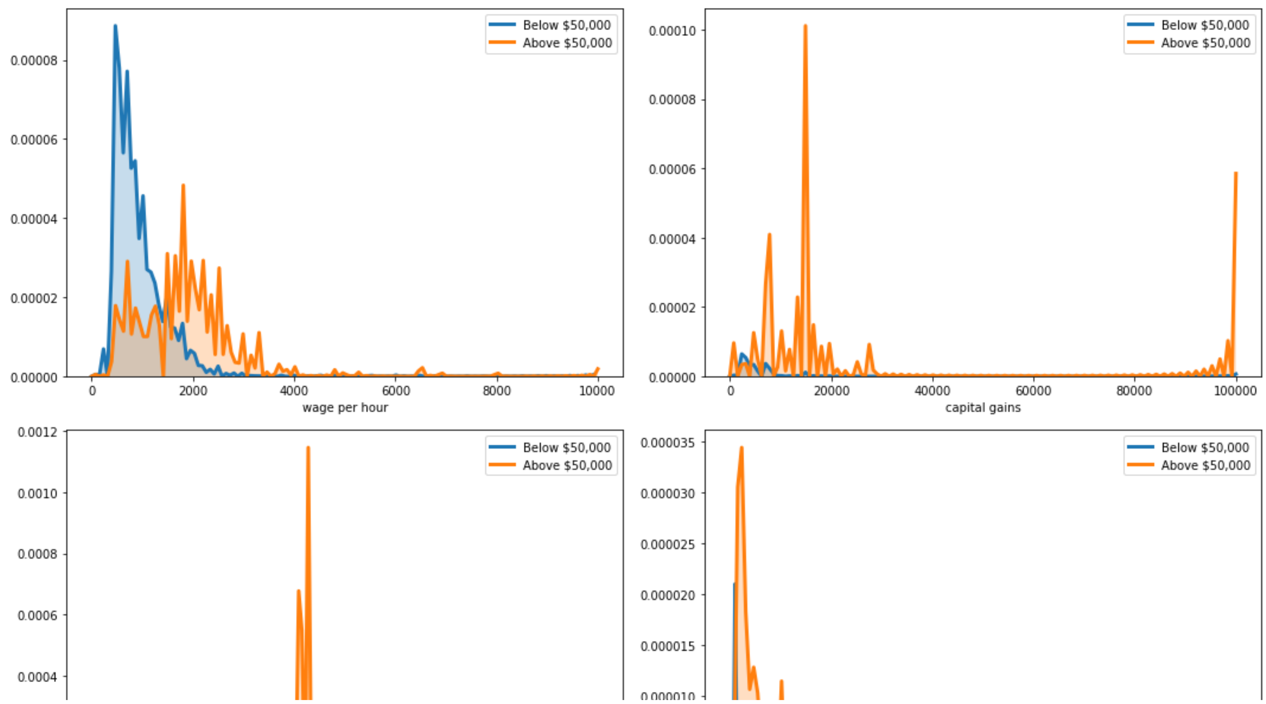
With a dataframe of just continuous variables, I decided to plot density distributions of each variable. The variables were seperated out by their target variable outcome (whether the person made above or below $50,000 per year). The goal here was to visualize and find data points that could offer the most seperability between classes for each variable. For example, for the variable "age" directly below, it appears that age 20 is a decent point of sepearation between the two classes.

In [9]:
```
classification = ['Below $50,000', 'Above $50,000']
for i in range(0,2):
    sns.distplot(continuous_feats['age'].loc[continuous_feats['year'] ==
                     kde_kws = {'shade': True, 'linewidth': 3},
                    label = classification[i])
```



Here are density plots for the other continuous variables seperated out by class.

In [10]:
```
f, axes = plt.subplots(nrows= 3, ncols= 2,figsize=(15,15))
classification = ['Below $50,000', 'Above $50,000']

row = 0
column = 0

for col in ['wage per hour','capital gains', 'capital losses', 'dividend
    for i in range(0,2):
        sns.distplot(continuous_feats[col].loc[continuous_feats['year'] 
            kde_kws = {'shade': True, 'linewidth': 3}, label = classific

    column += 1
    if column == 2:
        column = 0
        row += 1

plt.tight_layout()
```



Leveraging the insights provided by these visualizations, I chose points along each continuous variable that seemed to offer the most seperability between classes when creating bins to categorize these continuous variables below.

In [11]:
```
train_set['age - binned'] = pd.cut(continuous_feats['age'],[-1,20,contin
train_set['wage per hour - binned'] = pd.cut(continuous_feats['wage per 
train_set['capital gains - binned'] = pd.cut(continuous_feats['capital g
train_set['capital losses - binned'] = pd.cut(continuous_feats['capital 
train_set['dividends from stocks - binned'] = pd.cut(continuous_feats['d
train_set['num persons worked for employer - binned'] = pd.cut(continuou
train_set['weeks worked in year - binned'] = pd.cut(continuous_feats['we
```

In [12]:
```
#testing set is also binned so the schema is the equivalent for model te
test_set['age - binned'] = pd.cut(continuous_feats['age'],[-1,20,continu
test_set['wage per hour - binned'] = pd.cut(continuous_feats['wage per h
test_set['capital gains - binned'] = pd.cut(continuous_feats['capital ga
test_set['capital losses - binned'] = pd.cut(continuous_feats['capital l
test_set['dividends from stocks - binned'] = pd.cut(continuous_feats['di
test_set['num persons worked for employer - binned'] = pd.cut(continuous
test_set['weeks worked in year - binned'] = pd.cut(continuous_feats['wee
```

These categorical/nominal features were created and added to the training set, because I wanted to make sure all variable comparison in terms of feature importance to the target variable were of the same standard. I chose a chi square contigency table to determine which features were most correlated with whether someone made above or below $50,000. I felt that this was an appropriate test to use, because it would give me an idea about what kind of impact feature values had on the target depending on how the data distribution compared to the data distribution if the variables values were totally independent of the target.

In [13]:
```
#creating new dataframe without the original continuous features (binned
categorical_feats = train_set.loc[:,~train_set.columns.isin(['age','wage
```

In [14]:
```
p_values = {}

#for each variable/feature a contingency table is created
for col in categorical_feats.columns:
    univariate_cnt = {}

    for i in train_set[col].unique():
        #each varable value is assigned its corresponding count for each
        univariate_cnt[i] = (len(train_set[(train_set[col] == i) & (trai
                             len(train_set[(train_set[col] == i) & (tra

    #empty table observations contingency table of the appropriate dimen
    obs = np.zeros((2,len(train_set[col].unique())))

    value_num = 0

    #contingency table for a feature/variable is created and populated w
    for key, value in univariate_cnt.items():
        obs[0,value_num] = value[0]
        obs[1,value_num] = value[1]
        value_num += 1

    #p-value for each variable based on chi square contingency table (va
    results = chi2_contingency(obs)
    p_values[col] = [results[1]]
```

In [15]:
```
#dataframe of p-value for features is created
p_val = pd.DataFrame.from_dict(p_values)
p_val = p_val.T.rename(index=str,columns={0:"p-value"})
p_val.sort_values("p-value", inplace=True)
```

In [16]:
```
p_val
```

Out[16]:

	p-value
class of worker	0.000000e+00
age - binned	0.000000e+00
veterans benefits	0.000000e+00
fill inc questionnaire for veteran's admin	0.000000e+00
num persons worked for employer	0.000000e+00
capital losses - binned	0.000000e+00
dividends from stocks - binned	0.000000e+00
num persons worked for employer - binned	0.000000e+00

detailed household and family stat	0.000000e+00
tax filer stat	0.000000e+00
detailed household summary in household	0.000000e+00
sex	0.000000e+00
detailed industry recode	0.000000e+00
detailed occupation recode	0.000000e+00
education	0.000000e+00
full or part time employment stat	0.000000e+00
marital stat	0.000000e+00
capital gains - binned	0.000000e+00
major occupation code	0.000000e+00
major industry code	0.000000e+00
wage per hour - binned	2.494526e-206
hispanic origin	2.231967e-196
country of birth father	1.865696e-186
country of birth mother	9.615471e-181
race	1.152407e-147
country of birth self	2.841975e-128
citizenship	4.392603e-71
migration code-change in msa	5.364861e-59
migration code-change in reg	1.340181e-57
migration code-move within reg	8.644038e-57
live in this house 1 year ago	1.706694e-34
weeks worked in year - binned	4.144781e-11

In [17]:
```
feats = list(p_val.loc[p_val['p-value'] == 0].index)
```

All of the features actually had p-values lower than standard levels of significance such as .01. So in order to choose the lowest amongst the low, I chose those variables whose p-value was equal to 0. A low p-value indicates statistical significance and strong feature correlation to the target, so these variables with values equal to zero could be the ones most closely correlated to the target variable.

In [18]:
```
feats
```

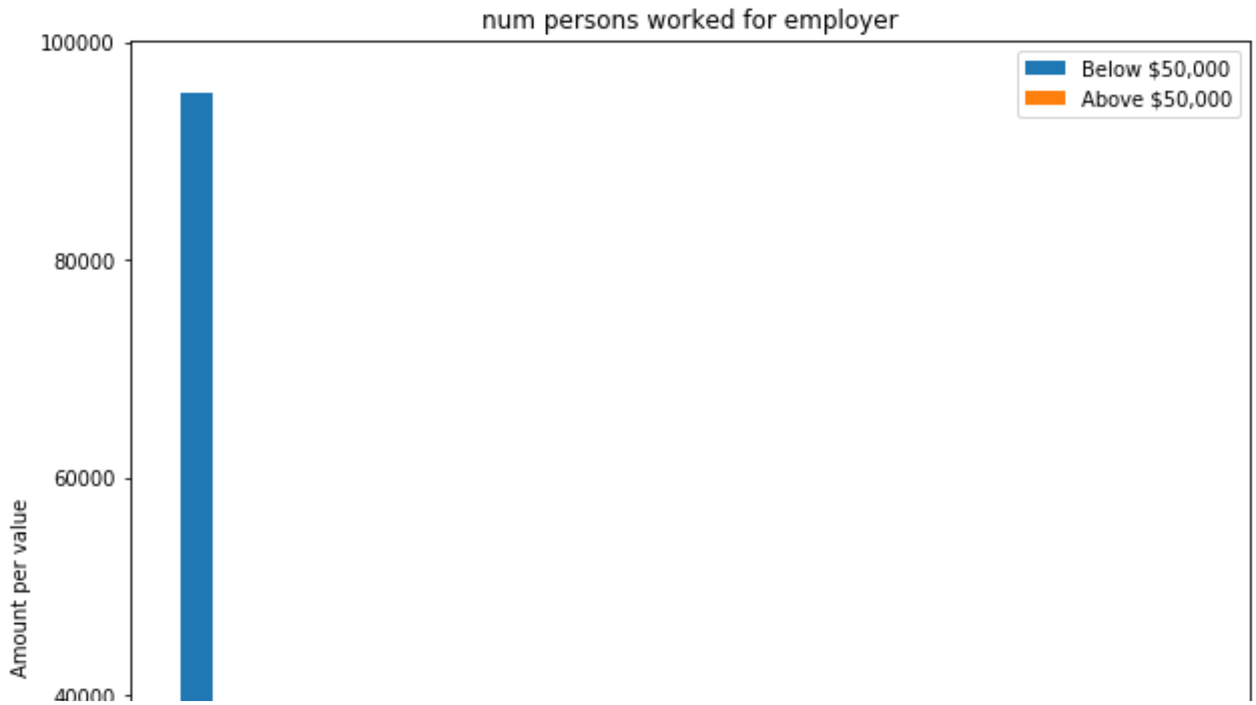
Out[18]:
```
['class of worker',
 'age - binned',
 'veterans benefits',
 "fill inc questionnaire for veteran's admin",
 'num persons worked for employer',
 'capital losses - binned',
 'dividends from stocks - binned',
 'num persons worked for employer - binned',
 'detailed household and family stat',
 'tax filer stat',
 'detailed household summary in household',
 'sex',
 'detailed industry recode',
 'detailed occupation recode',
 'education',
 'full or part time employment stat',
 'marital stat',
 'capital gains - binned',
 'major occupation code',
 'major industry code']
```

In [19]:
```
cat_feats_examples = [
 'num persons worked for employer',
 'detailed household summary in household',
 'tax filer stat',
 'full or part time employment stat',
 'sex']
```

Below plots visualizations for some of the original categorical variables that seem to be most important according to the chi square test.

In [20]:
```
%matplotlib inline

for col in cat_feats_examples:

    fig, ax = plt.subplots()
    ind = np.arange(len(list(train_set[col].unique())))     # the x locat
    width = 0.20         # the width of the bars

    above50 = []
    below50 = []

    for i in train_set[col].unique():
        above50.append(len(train_set[(train_set[col] == i) & (train_set[
        below50.append(len(train_set[(train_set[col] == i) & (train_set[
```

```
    p1 = ax.bar(.10 + ind, below50, width)
    p2 = ax.bar(.10 + ind + width,above50, width)

    ax.set_title(col)
    plt.xlabel('Values for '+ col)
    plt.ylabel('Amount per value')
    ax.set_xticks(ind + width + width)
    ax.set_xticklabels(train_set[col].unique())
    ax.legend((p1[0],p2[0]),('Below $50,000','Above $50,000'))
    ax.yaxis.set_units(1)
    ax.autoscale_view()
    plt.xticks(rotation=90)
    fig = plt.gcf()
    fig.set_size_inches(10,10)
    plt.show()
```

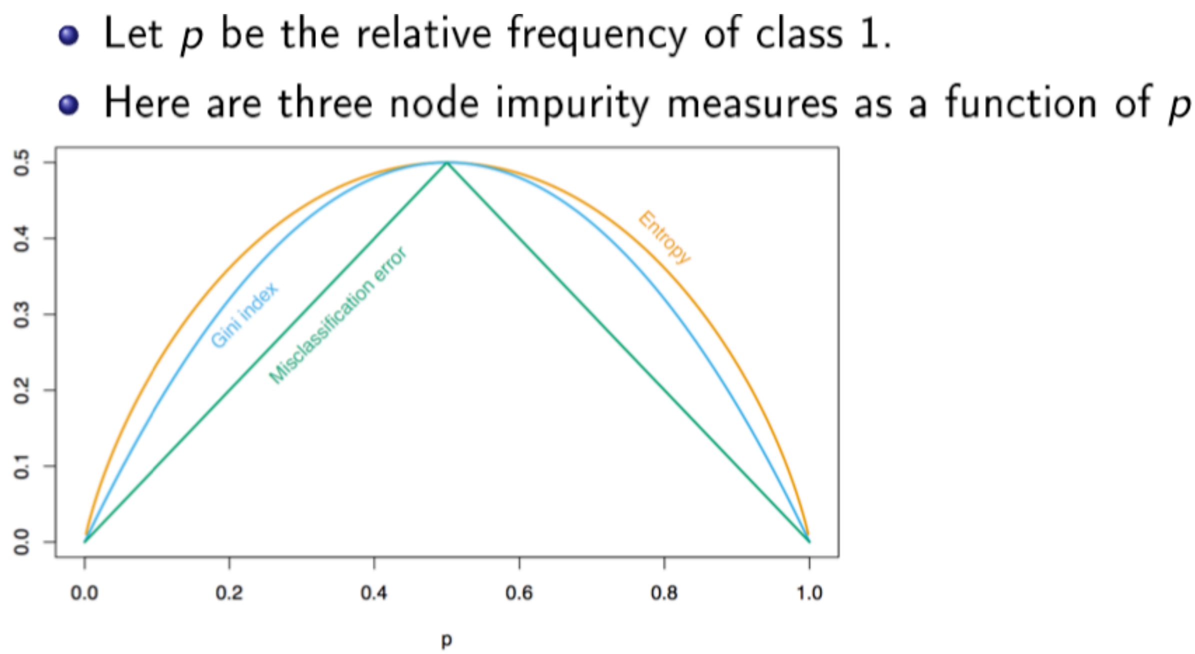


Some general insights about people who make above $50,000 per year from some of the original categorical variables include: the person is more likely to be male, the person is more likely to be employed full time, and more likely to be a householder or spouse of a householder.

Model Testing

To verify whether the features I identified really had a stronger correlation to the target than other variables in the dataset, I decided to build two decision tree classifier models. The first model is a baseline model trained using all of the features in the dataset (excluding those with high percentage of values missing). The second model is trained using only those variables that I thought were most important based upon my chi square analysis. By comparing the performance of the two models, I would recieve insights into whether the variables/features I chose had a stronger correlation with whether someone makes more or less than $50,000.

Note: When creating both decision tree models I decided to use entropy over the gini index as it is the more stringent of the two when it comes to measuring node purity.



In [21]:
```
#removing original continuous variables since they are being replaced by
train_set = train_set.loc[:,~train_set.columns.isin(['age','wage per hou
test_set = test_set.loc[:,~test_set.columns.isin(['age','wage per hour',
```

Part 1: The first model is built using all the features in the original dataset.

In [22]:
```
#decision tree classifier is initialized
clf = DecisionTreeClassifier(criterion = 'entropy')

#the target variable is saved seperately
target = train_set['year'].values

#new training dataframe is created with the target dropped
newtrain_set = train_set.loc[:,~train_set.columns.isin(['year'])]
```

In [23]:
```
#label encoder is applied for the categorical values for each variable
newtrain_set = newtrain_set.apply(preprocessing.LabelEncoder().fit_trans

#the model is then fitted using the training set
clf.fit(newtrain_set,target)
```

Out[23]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_dep
th=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=
None,
            splitter='best')
```

In [24]:
```
#the target variable is dropped from the test set
newtest_set = test_set.drop('year', 1)

#label encoder is applied for the categorical values for each variable i
newtest_set = newtest_set.apply(preprocessing.LabelEncoder().fit_transfo

#performance score is calculated on the test set
testScore = clf.score(newtest_set,test_set['year'].values)

print('Testing Accuracy: ', testScore)
```

```
Testing Accuracy:  0.9256029349852649
```

Part 2: The second model is built using only those features I deemed most important from my chi square analysis.

In [25]:
```
#the target is saved seperately
target = train_set['year'].values

#a training set with only the best features is created
best_feats_train = train_set.loc[:,feats]

#label encoder is applied for the categorical values for each variable i
best_feats_train = best_feats_train.apply(preprocessing.LabelEncoder().f

#the model is then fitted using the training set with only the best feat
clf.fit(best_feats_train,target)
```

Out[25]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_dep
th=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=
None,
            splitter='best')
```

In [26]:
```
#target is saved seperately
target = test_set['year'].values

#a test set with only the best features is created
best_feats_test = test_set.loc[:,feats]

#label encoder is applied for the categorical values for each variable i
best_feats_test = best_feats_test.apply(preprocessing.LabelEncoder().fit_

#performance score is calculated on the test set
testScore = clf.score(best_feats_test,target)
print('Testing Accuracy: ', testScore)
```

```
Testing Accuracy:  0.9284296625969808
```

As you can see, my second model built using only those features I deemed most important slightly improved over my baseline model which includes all of the features. My baseline model has a test score accuracy of about 92.56% while my second model has a test score accuracy of about 92.84%.

Conclusion

The following features seem to have a heavier correlation with whether someone makes more or less than $50,000 than the others:

In [27]:
```
feats
```

Out[27]:
```
['class of worker',
 'age - binned',
 'veterans benefits',
 "fill inc questionnaire for veteran's admin",
 'num persons worked for employer',
 'capital losses - binned',
 'dividends from stocks - binned',
 'num persons worked for employer - binned',
 'detailed household and family stat',
 'tax filer stat',
 'detailed household summary in household',
 'sex',
 'detailed industry recode',
 'detailed occupation recode',
 'education',
 'full or part time employment stat',
 'marital stat',
 'capital gains - binned',
 'major occupation code',
 'major industry code']
```

Challenges: I would say the biggest challenge I experienced was understanding why there were p-values equal to zero.I find it to be a bit suspicious that this is the case. However, I did try to double check and analyze my chi square analysis calculations. I made sure all of my observations were more than 1 dimenisional and made sure that the observed and expected frequency in each cell was at least 5, as these factors would invalidate my calculations according to the chi square documentation. I believe future work on this assignment could possibly include performing other tests that could indicate feature importance and see how similar the most important feaures generated from that are to the ones from my chi square analysis.

In [ ]:
```
```