# 1 Adult Census Income ¶

Predict whether income exceeds $50K/yr based on census data

## 1.1 Informations on the dataset

This data was extracted from the 1994 Census bureau database by Ronny Kohavi and Barry Becker (Data Mining and Visualization, Silicon Graphics). A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AFNLWGT>1) && (HRSWK>0)). The prediction task is to determine whether a person makes over $50K a year.

Original dataset open sourced, can be found [here (https://archive.ics.uci.edu/ml/datasets/census+income)](https://archive.ics.uci.edu/ml/datasets/census+income).

## 1.2 Goal

Predict **whether or not a person makes more than USD 50,000** from the information contained in the columns. Find clear insights on the profiles of the people that make more than 50,000USD / year. For example, which variables seem to be the most correlated with this phenomenon?

# 2 Dataset first insight

Libraries import

In [1]:

```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier
from sklearn.model_selection import GridSearchCV
```

Loading the file

In [4]:

```
df = pd.read_csv('./input/adult.csv')
df.head()
```

Out[4]:

| | age | workclass | fnlwgt | education | education.num | marital.status | occupation | relationship |
|---|---|---|---|---|---|---|---|---|
| **0** | 90 | ? | 77053 | HS-grad | 9 | Widowed | ? | Not-in-family |
| **1** | 82 | Private | 132870 | HS-grad | 9 | Widowed | Exec-managerial | Not-in-family |
| **2** | 66 | ? | 186061 | Some-college | 10 | Widowed | ? | Unmarried |
| **3** | 54 | Private | 140359 | 7th-8th | 4 | Divorced | Machine-op-inspct | Unmarried |
| **4** | 41 | Private | 264663 | Some-college | 10 | Separated | Prof-specialty | Own-child |

Columns description

- age: continuous.
- workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
- fnlwgt: continuous.
- 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: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
- 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.

In [5]:

```
df.shape
```

Out[5]:

```
(32561, 15)
```

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
age               32561 non-null int64
workclass         32561 non-null object
fnlwgt            32561 non-null int64
education         32561 non-null object
education.num     32561 non-null int64
marital.status    32561 non-null object
occupation        32561 non-null object
relationship      32561 non-null object
race              32561 non-null object
sex               32561 non-null object
capital.gain      32561 non-null int64
capital.loss      32561 non-null int64
hours.per.week    32561 non-null int64
native.country    32561 non-null object
income            32561 non-null object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

When it comes to numerical values, no information is missing. On the contrary for categorical features, there are '?', which indicated unknow information. Some rows are duplicated and need to be removed :

In [7]:

```
df.duplicated().sum()
```

Out[7]:

```
24
```

In [8]:

```
df = df.drop_duplicates()
df.shape
```

Out[8]:

```
(32537, 15)
```

In [9]:

```
cat_feat = df.select_dtypes(include=['object']).columns
cat_feat
```

Out[9]:

```
Index(['workclass', 'education', 'marital.status', 'occupation',
       'relationship', 'race', 'sex', 'native.country', 'income'],
      dtype='object')
```

The number of missing value isn't relevant

In [10]:

```
print('% of missing values :')
for c in cat_feat:
    perc = len(df[df[c] == '?']) / df.shape[0] * 100
    print(c, f'{perc:.1f} %')
```

```
% of missing values :
workclass 5.6 %
education 0.0 %
marital.status 0.0 %
occupation 5.7 %
relationship 0.0 %
race 0.0 %
sex 0.0 %
native.country 1.8 %
income 0.0 %
```

Basic statistics for numerical values:

In [11]:

```
df.describe()
```

Out[11]:

| | age | fnlwgt | education.num | capital.gain | capital.loss | hours.per.week |
|---|---|---|---|---|---|---|
| **count** | 32537.000000 | 3.253700e+04 | 32537.000000 | 32537.000000 | 32537.000000 | 32537.000000 |
| **mean** | 38.585549 | 1.897808e+05 | 10.081815 | 1078.443741 | 87.368227 | 40.440329 |
| **std** | 13.637984 | 1.055565e+05 | 2.571633 | 7387.957424 | 403.101833 | 12.346889 |
| **min** | 17.000000 | 1.228500e+04 | 1.000000 | 0.000000 | 0.000000 | 1.000000 |
| **25%** | 28.000000 | 1.178270e+05 | 9.000000 | 0.000000 | 0.000000 | 40.000000 |
| **50%** | 37.000000 | 1.783560e+05 | 10.000000 | 0.000000 | 0.000000 | 40.000000 |
| **75%** | 48.000000 | 2.369930e+05 | 12.000000 | 0.000000 | 0.000000 | 45.000000 |
| **max** | 90.000000 | 1.484705e+06 | 16.000000 | 99999.000000 | 4356.000000 | 99.000000 |

# 3 Exploratory Analysis

In [12]:

```
# Taking a look at the target (income) without distinction of sex
print(f"Ratio above 50k : {(df['income'] == '>50K').astype('int').sum() / df.shape[
```

```
Ratio above 50k : 24.09%
```

Distinction between numerical vs. text values

In [13]:

```
num_feat = df.select_dtypes(include=['int64']).columns
num_feat
```

Out[13]:

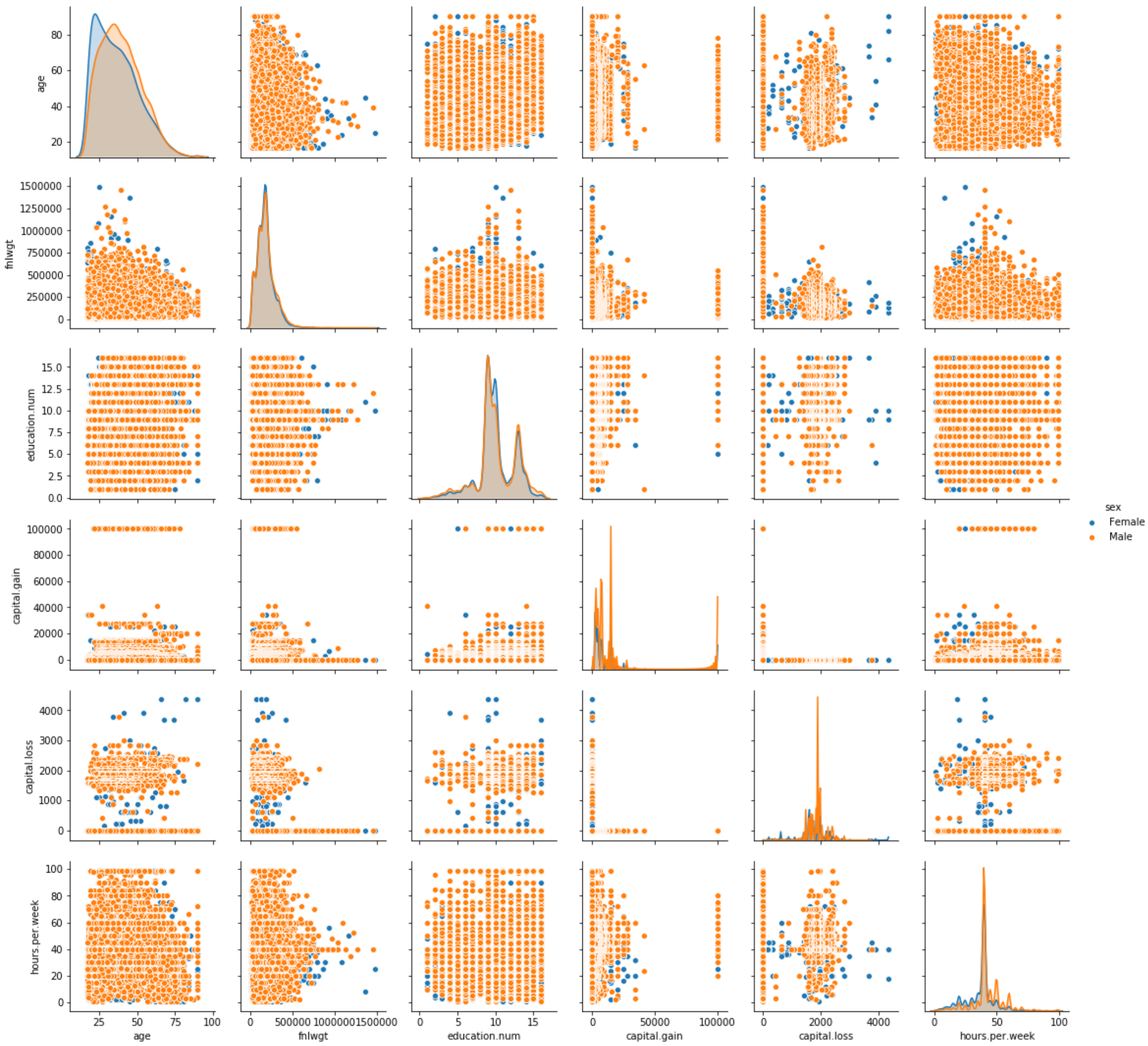
```
Index(['age', 'fnlwgt', 'education.num', 'capital.gain', 'capital.los
s',
       'hours.per.week'],
      dtype='object')
```

Plot pairwise relationships in a dataset.

In [14]:

```
plt.figure(1, figsize=(16,10))
sns.pairplot(data=df, hue='sex')
plt.show()
```

```
<Figure size 1152x720 with 0 Axes>
```

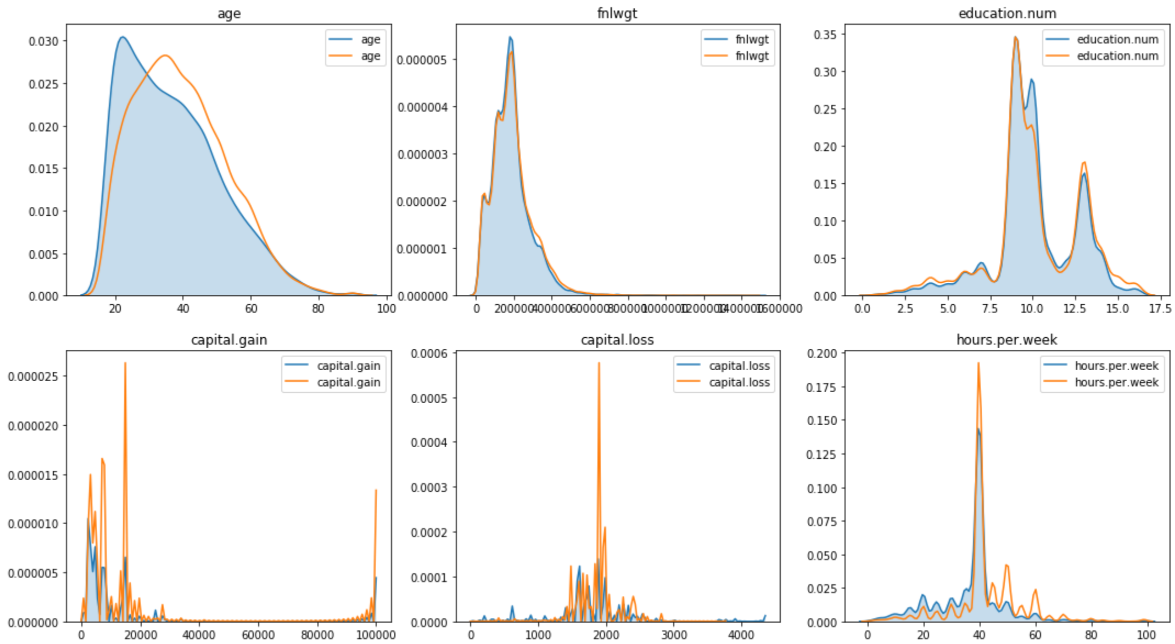



Distributions of numerical values

In [15]:

```
plt.figure(figsize=(18,10))
plt.subplot(231)

i=0
for c in num_feat:
    plt.subplot(2, 3, i+1)
    i += 1
    sns.kdeplot(df[df['sex'] == 'Female'][c], shade=True, )
    sns.kdeplot(df[df['sex'] == 'Male'][c], shade=False)
    plt.title(c)

plt.show()
```

```
/home/sunflowa/Anaconda/lib/python3.7/site-packages/matplotlib/figure.
py:98: MatplotlibDeprecationWarning:
Adding an axes using the same arguments as a previous axes currently r
euses the earlier instance.  In a future version, a new instance will
always be created and returned.  Meanwhile, this warning can be suppre
ssed, and the future behavior ensured, by passing a unique label to ea
ch axes instance.
  "Adding an axes using the same arguments as a previous axes "
```

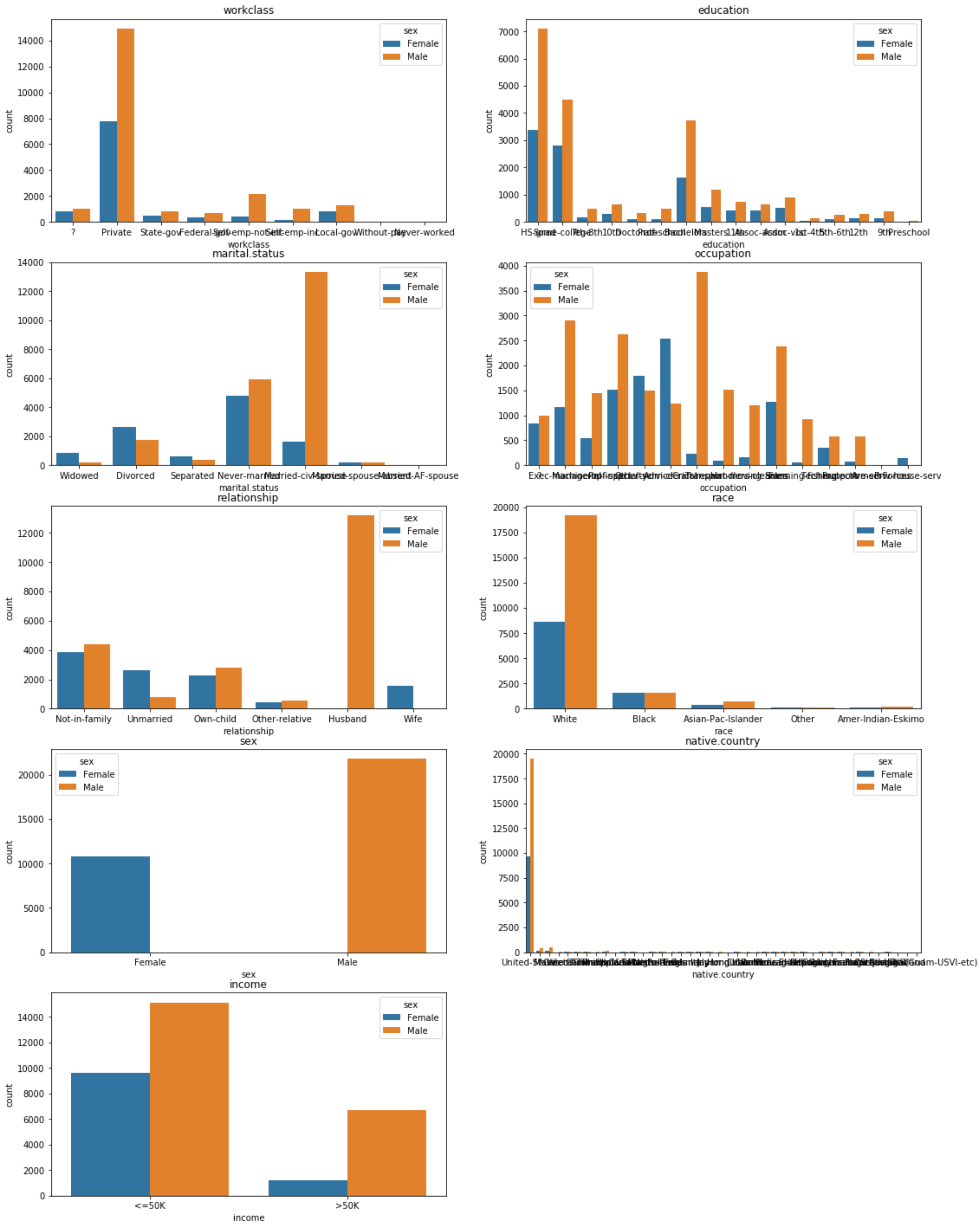



There are significant differences when it comes to capital gain / loss and hours per week.

In [16]:

```
plt.figure(figsize=(18,25))
plt.subplot(521)

i=0
for c in cat_feat:
    plt.subplot(5, 2, i+1)
    i += 1
    sns.countplot(x=c, data=df, hue='sex')
    plt.title(c)

plt.show()
```

```
/home/sunflowa/Anaconda/lib/python3.7/site-packages/matplotlib/figure.
py:98: MatplotlibDeprecationWarning:
Adding an axes using the same arguments as a previous axes currently r
euses the earlier instance.  In a future version, a new instance will
always be created and returned.  Meanwhile, this warning can be suppre
ssed, and the future behavior ensured, by passing a unique label to ea
ch axes instance.
  "Adding an axes using the same arguments as a previous axes "
```




There are far more male earning >50k than female, but at the same time there are also more male earning <50k and even more males recorded in general. The counts need to be normalized.

In [17]:

```
# nb of female / male
nb_female = (df.sex == 'Female').astype('int').sum()
nb_male = (df.sex == 'Male').astype('int').sum()
nb_female, nb_male
```

Out[17]:

```
(10762, 21775)
```

In [18]:

```
# nb of people earning more or less than 50k per gender
nb_male_above = len(df[(df.income == '>50K') & (df.sex == 'Male')])
nb_male_below = len(df[(df.income == '<=50K') & (df.sex == 'Male')])
nb_female_above = len(df[(df.income == '>50K') & (df.sex == 'Female')])
nb_female_below = len(df[(df.income == '<=50K') & (df.sex == 'Female')])
nb_male_above, nb_male_below, nb_female_above, nb_female_below
```

Out[18]:

```
(6660, 15115, 1179, 9583)
```

In [19]:

```
print(f'Among Males   : {nb_male_above/nb_male*100:.0f}% earn >50K // {nb_male_belo
print(f'Among Females : {nb_female_above/nb_female*100:.0f}% earn >50K // {nb_femal
```

```
Among Males   : 31% earn >50K // 69% earn <=50K
Among Females : 11% earn >50K // 89% earn <=50K
```

In [20]:

```
# normalization
nb_male_above /= nb_male
nb_male_below /= nb_male
nb_female_above /= nb_female
nb_female_below /= nb_female
nb_male_above, nb_male_below, nb_female_above, nb_female_below
```

Out[20]:

```
(0.3058553386911596,
 0.6941446613088404,
 0.1095521278572756,
 0.8904478721427244)
```

In [21]:

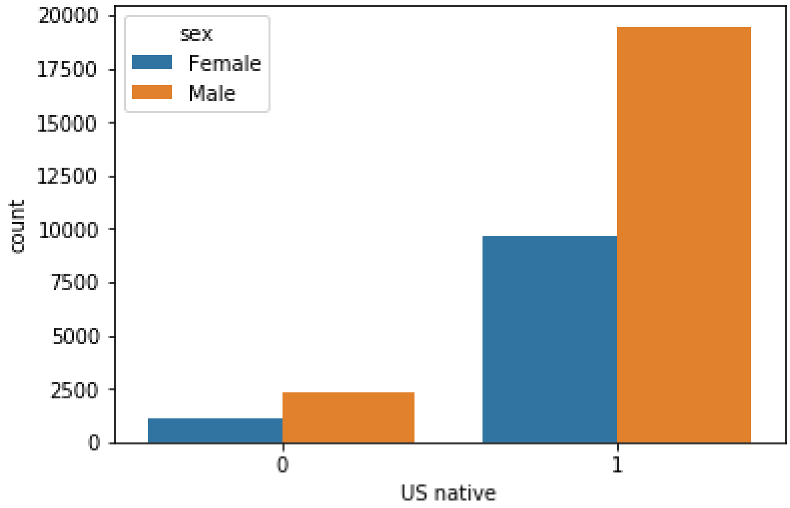
```
print(f'Among people earning >50K  : {nb_male_above / (nb_male_above + nb_female_ab
print(f'Among people earning =<50K : {nb_male_below / (nb_male_below + nb_female_be
```

```
Among people earning >50K  : 74% are Females and 26% are Males
Among people earning =<50K : 44% are Females and 56% are Males
```

The distinction between american natives and the others should also be made

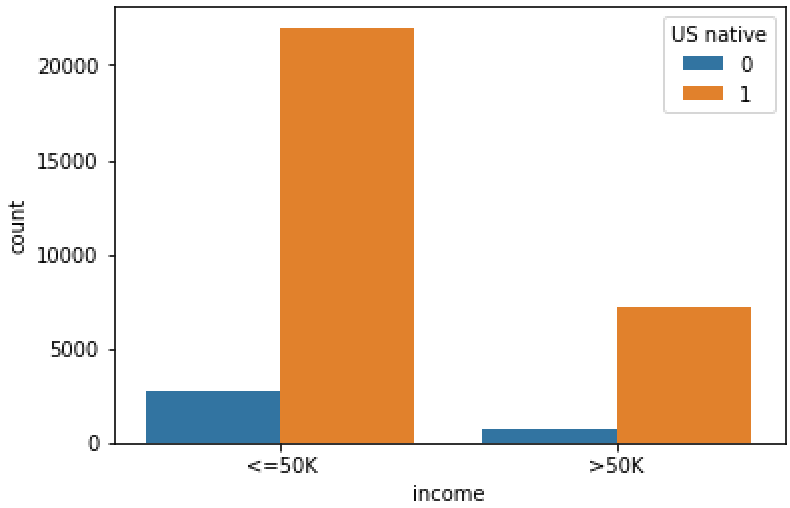
In [22]:

```
df['US native'] = (df['native.country'] == 'United-States').astype('int')
plt.figure(figsize=(6,4))
sns.countplot(x='US native', data=df, hue='sex')
plt.show()
```




In [23]:

```
plt.figure(figsize=(6,4))
sns.countplot(x='income', data=df, hue='US native')
plt.show()
```




In [24]:

```
# nb of people earning more or less than 50k per origin
nb_native_above = len(df[(df.income == '>50K') & (df['US native'] == 1)])
nb_native_below = len(df[(df.income == '<=50K') & (df['US native'] == 1)])
nb_foreign_above = len(df[(df.income == '>50K') & (df['US native'] == 0)])
nb_foreign_below = len(df[(df.income == '<=50K') & (df['US native'] == 0)])
nb_native_above, nb_native_below, nb_foreign_above, nb_foreign_below
```

Out[24]:

```
(7169, 21984, 670, 2714)
```

In [25]:

```
nb_native = (df['US native'] == 1).astype('int').sum()
nb_foreign = df.shape[0] - nb_native
nb_native, nb_foreign
```

Out[25]:

```
(29153, 3384)
```

In [26]:

```
print(f'Among natives    : {nb_native_above/nb_native*100:.0f}% earn >50K // {nb_na
print(f'Among foreigners : {nb_foreign_above/nb_foreign*100:.0f}% earn >50K // {nb_
```

```
Among natives    : 25% earn >50K // 75% earn <=50K
Among foreigners : 20% earn >50K // 80% earn <=50K
```

In [27]:

```
# normalization
nb_native_above /= nb_native
nb_native_below /= nb_native
nb_foreign_above /= nb_foreign
nb_foreign_below /= nb_foreign
nb_native_above, nb_native_below, nb_foreign_above, nb_foreign_below
```

Out[27]:

```
(0.24590951188556923,
 0.7540904881144308,
 0.1979905437352246,
 0.8020094562647754)
```

In [28]:

```
print(f'Among people earning >50K  : {nb_native_above / (nb_native_above + nb_forei
print(f'Among people earning =<50K : {nb_native_below / (nb_native_below + nb_forei
```

```
Among people earning >50K  : 55% are natives and 45% are foreigners
Among people earning =<50K : 48% are natives and 52% are foreigners
```

In [29]:

```
num_feat = df.select_dtypes(include=['float', 'int']).columns
num_feat
```

Out[29]:

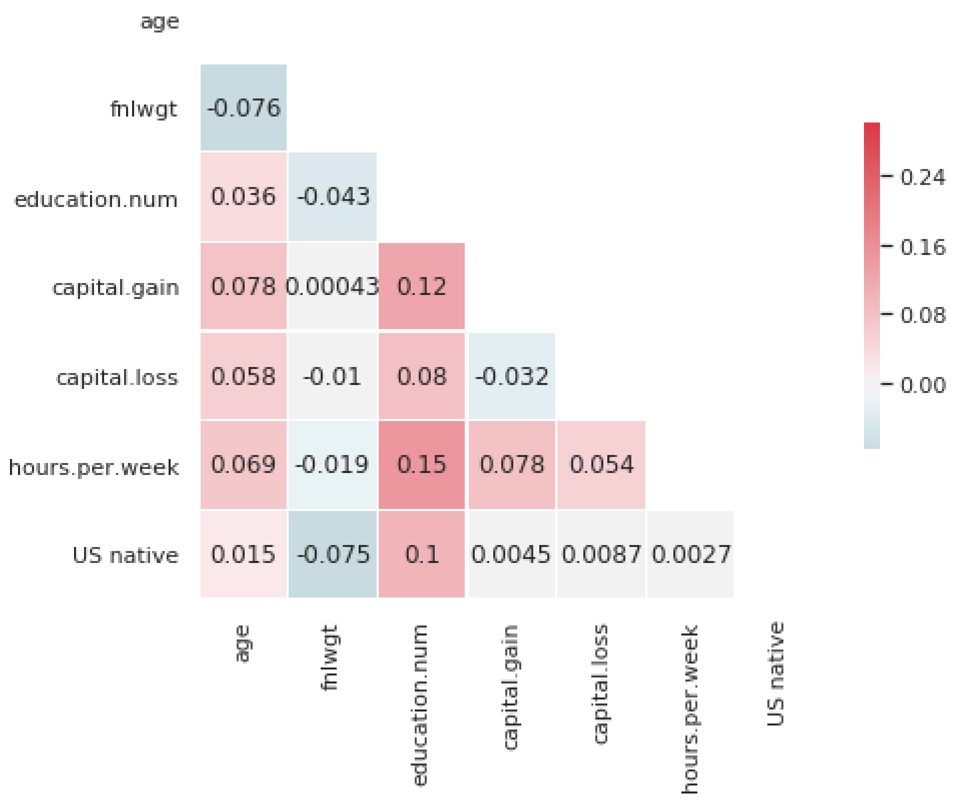
```
Index(['age', 'fnlwgt', 'education.num', 'capital.gain', 'capital.los
s',
       'hours.per.week', 'US native'],
      dtype='object')
```

In [30]:

```
sns.set(style="white")

# Compute the correlation matrix
corr = df[num_feat].corr()

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(7, 6))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, annot=True, cbar_kws={"shrink": .5})
```

Out[30]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc5c8dda3c8>
```




# 4 Preparing data

In [31]:

```
df['income'] = pd.get_dummies(df['income'], prefix='income', drop_first=True)
```

In [32]:

```
y = df.income
df = df.drop(columns=['income'])
```

In [33]:

```
print(f'Ratio above 50k:  {y.sum()/len(y)*100:.2f}%')
```

```
Ratio above 50k:  24.09%
```

In [34]:

```
#cat_columns = ['workclass', 'education', 'marital-status', 'occupation', 'relation
```

In [36]:

```
df.head()
```

Out[36]:

| | age | workclass | fnlwgt | education | education.num | marital.status | occupation | relationship |
|---|---|---|---|---|---|---|---|---|
| **0** | 90 | ? | 77053 | HS-grad | 9 | Widowed | ? | Not-in-family |
| **1** | 82 | Private | 132870 | HS-grad | 9 | Widowed | Exec-managerial | Not-in-family |
| **2** | 66 | ? | 186061 | Some-college | 10 | Widowed | ? | Unmarried |
| **3** | 54 | Private | 140359 | 7th-8th | 4 | Divorced | Machine-op-inspct | Unmarried |
| **4** | 41 | Private | 264663 | Some-college | 10 | Separated | Prof-specialty | Own-child |

In [37]:

```
cols = list(df.columns)
cols
```

Out[37]:

```
['age',
 'workclass',
 'fnlwgt',
 'education',
 'education.num',
 'marital.status',
 'occupation',
 'relationship',
 'race',
 'sex',
 'capital.gain',
 'capital.loss',
 'hours.per.week',
 'native.country',
 'US native']
```

In [38]:

```
selected_feat = cols.copy()
selected_feat.remove('US native')
selected_feat
```

Out[38]:

```
['age',
 'workclass',
 'fnlwgt',
 'education',
 'education.num',
 'marital.status',
 'occupation',
 'relationship',
 'race',
 'sex',
 'capital.gain',
 'capital.loss',
 'hours.per.week',
 'native.country']
```

In [39]:

```
df_final = df[selected_feat]
```

In [40]:

```
cat_feat = df_final.select_dtypes(include=['object']).columns
X = pd.get_dummies(df_final[cat_feat], drop_first=True)
```

In [41]:

```
#X = pd.concat([df_final[continuous_columns], df_dummies], axis=1)
```

In [42]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

# 5 Model training and predictions

In [43]:

```
def print_score(model, name):
    model.fit(X_train, y_train)
    print('Accuracy score of the', name, f': on train = {model.score(X_train, y_tra
```

## 5.1 Baseline LogisticRegression

In [44]:

```
print_score(LogisticRegression(), 'LogisticReg')
```

```
Accuracy score of the LogisticReg : on train = 83.26%, on test = 83.2
8%
```

## 5.2 Decision Tree

In [45]:

```
print_score(DecisionTreeClassifier(), 'DecisionTreeClf')
```

```
Accuracy score of the DecisionTreeClf : on train = 86.72%, on test = 8
1.59%
```

## 5.3 Random Forest

In [46]:

```
rf = RandomForestClassifier().fit(X_train, y_train)
print(f'Accuracy score of the RandomForrest: on train = {rf.score(X_train, y_train)
```

```
Accuracy score of the RandomForrest: on train = 86.42%, on test = 82.1
6%
```

## 5.4 ExtraTreesClassifier

In [47]:

```
# fit an Extra Tree model to the data
print_score(DecisionTreeClassifier(), 'ExtraTreesClf')
```

```
Accuracy score of the ExtraTreesClf : on train = 86.72%, on test = 81.
65%
```

## 5.5 Tuned model

In [48]:

```
rfc = RandomForestClassifier()
param_grid = {
    'n_estimators': [50, 100, 150, 200, 250],
    'max_features': [1, 2, 3, 4, 5],
    'max_depth' : [4, 6, 8]
}
```

In [49]:

```
rfc_cv = GridSearchCV(estimator=rfc, param_grid=param_grid, cv=5)
rfc_cv.fit(X_train, y_train)
```

Out[49]:

```
GridSearchCV(cv=5, error_score='raise-deprecating',
       estimator=RandomForestClassifier(bootstrap=True, class_weight=N
one, criterion='gini',
            max_depth=None, max_features='auto', 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, n_estimators='warn', n_jobs=
None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid={'n_estimators': [50, 100, 150, 200, 250], 'max_feat
ures': [1, 2, 3, 4, 5], 'max_depth': [4, 6, 8]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

In [50]:

```
rfc_cv.best_params_
```

Out[50]:

```
{'max_depth': 8, 'max_features': 5, 'n_estimators': 50}
```

In [51]:

```
rfc_best = RandomForestClassifier(max_depth=8, max_features=5, n_estimators=250).fi
print(f'Accuracy score of the RandomForrest: on train = {rfc_best.score(X_train, y_
```

```
Accuracy score of the RandomForrest: on train = 80.26%, on test = 80.2
4%
```

# 6 Profiling

Let's find clear insights on the profiles of the people that make more than USD 50K a year. Which features seem to be the most correlated with this phenomenon.

## 6.1 Based on the rf model

In [52]:

```
# indexes of columns which are the most important
np.argsort(rf.feature_importances_)[-16:]
```

Out[52]:

```
array([22,  5,  3, 21, 18, 46, 47, 43, 19, 38, 32, 52, 45, 16, 26, 2
4])
```

In [53]:

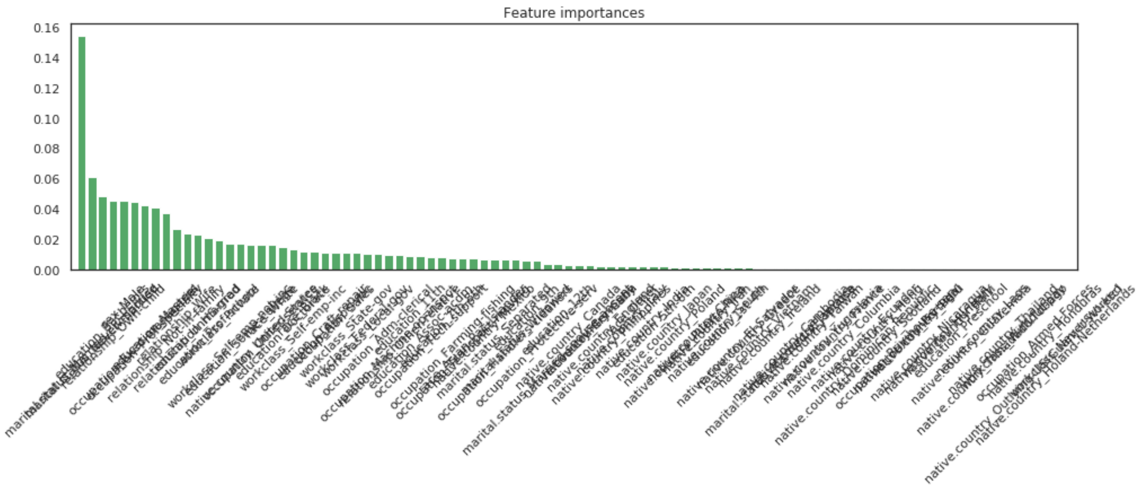
```
# most important features
[list(X.columns)[i] for i in np.argsort(rf.feature_importances_)[-16:]][::-1]
```

Out[53]:

```
['marital.status_Married-civ-spouse',
 'marital.status_Never-married',
 'education_Bachelors',
 'relationship_Own-child',
 'sex_Male',
 'occupation_Exec-managerial',
 'occupation_Prof-specialty',
 'education_Masters',
 'relationship_Not-in-family',
 'relationship_Wife',
 'relationship_Unmarried',
 'education_HS-grad',
 'education_Prof-school',
 'workclass_Private',
 'workclass_Self-emp-not-inc',
 'education_Some-college']
```

In [54]:

```
# Feature importances
features = X.columns
importances = rf.feature_importances_
indices = np.argsort(importances)[::-1]
num_features = len(importances)

# Plot the feature importances of the tree
plt.figure(figsize=(16, 4))
plt.title("Feature importances")
plt.bar(range(num_features), importances[indices], color="g", align="center")
plt.xticks(range(num_features), [features[i] for i in indices], rotation='45')
plt.xlim([-1, num_features])
plt.show()

# Print values
for i in indices:
    print ("{0} - {1:.3f}".format(features[i], importances[i]))
```

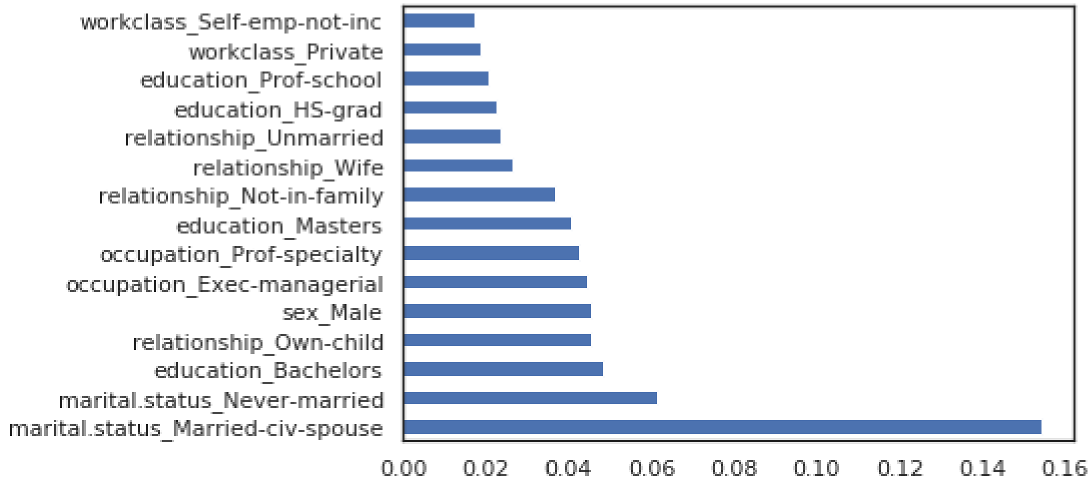


In [55]:

```
(pd.Series(rf.feature_importances_, index=X_train.columns)
   .nlargest(15)
   .plot(kind='barh'))
```

Out[55]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc5c8de0978>
```



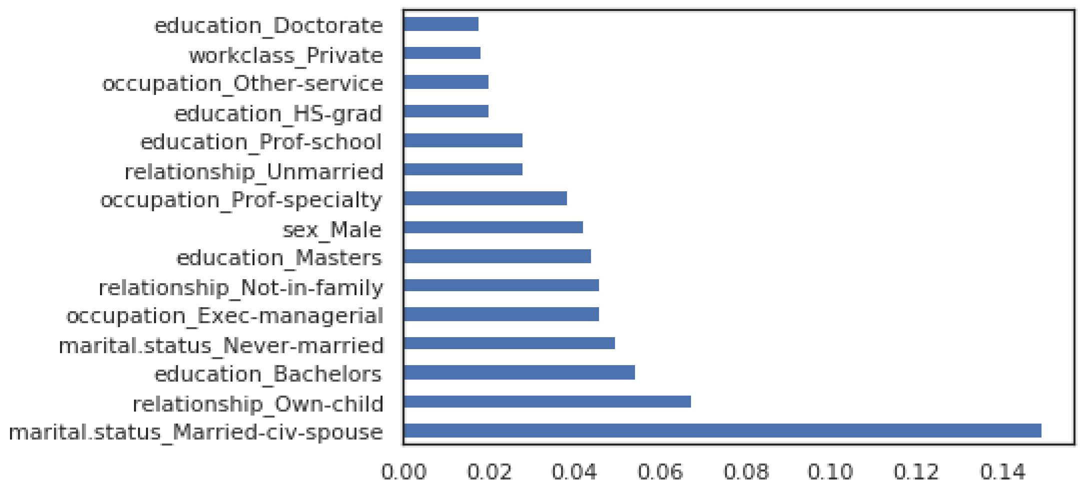

## 6.2 Based on the ExtraTree model

In [56]:

```
extree = ExtraTreesClassifier().fit(X_train, y_train)
(pd.Series(extree.feature_importances_, index=X_train.columns)
   .nlargest(15)
   .plot(kind='barh'))
```

Out[56]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc5c9031438>
```




The same features come first.