In [1]:
```
%matplotlib inline

import math
from enum import IntEnum

import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import graphviz

from sklearn import tree, metrics, svm
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelBinarizer, Imputer
```

In [2]:
```
def convert_raw_csv(input_file, output_file):
    df = pd.read_csv(input_file, header = 0, sep=',', thousands=',')
    toScale = ['attr1_1','sinc1_1','intel1_1','fun1_1','amb1_1','shar1_1',
              'attr2_1','sinc2_1','intel2_1','fun2_1','amb2_1','shar2_1',
              'attr3_1','sinc3_1','intel3_1','fun3_1','amb3_1',
              'attr4_1','sinc4_1','intel4_1','fun4_1','amb4_1','shar4_1',
              'attr5_1','sinc5_1','intel5_1','fun5_1','amb5_1']

    def scaleAttrs(r):
        for group in [toScale[0:6],toScale[6:12],toScale[12:17],toScale[17:23]
,toScale[23:28]]:
            s = np.sum(r[group])
            assert not s == 0 and not s == np.isnan(s)
            r[group] = r[group]/s
        return r

    df[toScale] = df[toScale].apply(scaleAttrs, axis=1)
    df.to_csv(output_file, index=False)
```

In [3]:
```
def with_pAge(df):
    df = df.copy()
    ages = df[['iid','age']].groupby(['iid']).mean()
    df['pAge'] = df['pid'].apply(lambda x: math.nan if math.isnan(x) else ages
.age[x])
    return df
```

In [4]:
```
def impute(X, verbose=False):
    # Copy to avoid looping over the array we're modifying
    cols = X.columns.values
    for col in cols:
        if X[col].dtypes=='object':
            #print('Classifying {0}'.format(col))
            X = X.drop(col, axis=1)
            if verbose:
                print('Dropping column {0}'.format(col))
            # This is really heavy
            #classes = X[col].str.get_dummies().rename(columns=lambda x: 'fiel
d-{0}'.format(x).replace(' ',''))
            #X = pd.concat([X,classes])
        elif X[col].dtypes=='float64' and X[col].isnull().values.any():
            assert not col == 'iid' and not col == 'id' and not col == 'idg'
            #print('Imputing {0}'.format(col))
            # fill in missing values
            if col == 'field_cd' or \
                col == 'gender' or \
                col == 'undergrd' or \
                col == 'race' or \
                col == 'from' or \
                col == 'career_c':
                X[[col]]=Imputer(missing_values='NaN', strategy='most_frequent
', axis=0).fit_transform(X[[col]])
            else:
                X[[col]]=Imputer(missing_values='NaN', strategy='mean', axis=0
).fit_transform(X[[col]])
    return X
```

In [5]:
```
# Preprocess data
def preprocess(df, verbose=False):
    return impute(df.drop(columns=['iid', 'id', 'idg', 'condtn', 'wave', 'roun
d', 'position',
                            'positin1', 'order', 'partner', 'pid',
                            'zipcode', # zipcode -> income
                            #'undergra', -> {mn_sat, tuition}
                            'attr', 'sinc', 'intel', 'fun', 'amb', 'shar', 'li
ke', 'prob',
                            'match',
                            #'gender',
                            'you_call', 'them_cal', 'date_3', 'numdat_3', 'num
_in_3',
                           ], errors='ignore'), verbose=verbose)
```

In [6]:
```
def splitBy(df, attr):
    return df.drop(columns=[attr]), df[attr]
```

In [7]:
```
def model(X,y,test_size=0.2,random_state=0,min_samples_split=0.02, max_depth=1
0, accuracy_file=None, print_stats=True):
    X_train, X_test, y_train, y_test = train_test_split(
     X, y, test_size=test_size, random_state=random_state)

    clf = tree.DecisionTreeClassifier(min_samples_split=min_samples_split, max
_depth=max_depth)
    clf = clf.fit(X_train, y_train)

    y_predict = clf.predict(X_test)

    accuracy = metrics.accuracy_score(y_test, y_predict)
    tn, fp, fn, tp = metrics.confusion_matrix(y_test, y_predict).ravel()/len(y
_test)
    if print_stats:
        accuracy_str = """Accuracy: {0:.2f}%
True negatives: {1:.2f}%\tFalse negatives: {2:.2f}%
False positives: {3:.2f}%\tTrue positives: {4:.2f}%\n""".format(
            accuracy*100, tn*100, fp*100, fn*100, tp*100)
        print(accuracy_str)

    if not accuracy_file == None:
        with open(accuracy_file, 'w') as f:
            f.write(accuracy_str)
    return clf
```

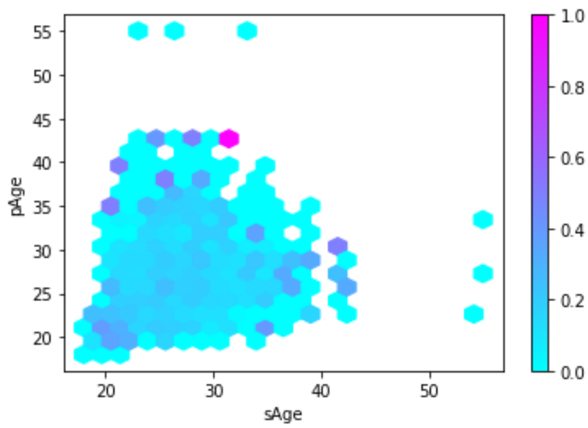
In [8]:
```
def vizualize(model, columns, out_file=None):
    graph = graphviz.Source(
        tree.export_graphviz(model, out_file=None,
                                feature_names=columns,
                                filled=True, rounded=True,
                                special_characters=True))
    if not out_file == None:
        graph.render(out_file)

    return graph
```

In [9]:
```
class Gender(IntEnum):
    FEMALE = 0;
    MALE = 1;
```

In [10]:
```
# Scaling the attrs turned out to be really slow, so store preprocessed data.
#convert_raw_csv("data.csv", "data_converted.csv")
```

In [11]:
```
df = pd.read_csv("data_converted.csv", header=0, sep=',')
```

In [12]:
```
with_pAge(df).rename({'age':'sAge'}, axis='columns').plot.hexbin(
    x='sAge', y='pAge', C='match',
    cmap=plt.cm.cool,
    reduce_C_function=np.mean,
    gridsize=22,
    sharex=False, sharey=False)
plt.show()
```

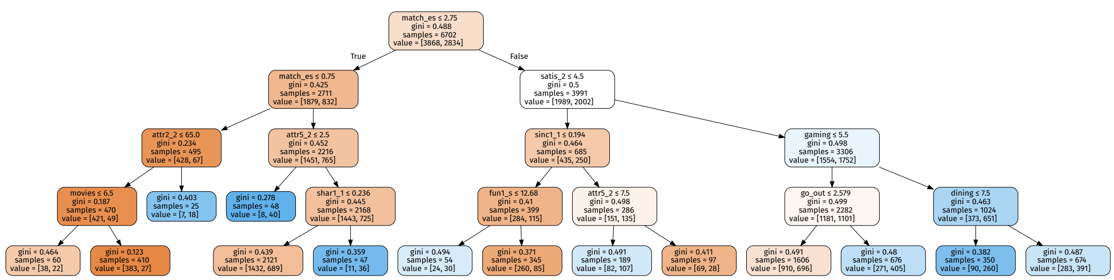


In [13]:
```
X, Y = splitBy(preprocess(df), 'dec')
X = X.drop(columns=['gender'])
```

In [14]:
```
uni_model = model(X, Y, test_size=0.2)
vizualize(model(X, Y, test_size=0.2, max_depth=4, print_stats=False), X.column
s)
```

```
Accuracy: 68.26%
True negatives: 47.37%  False negatives: 11.81%
False positives: 19.93% True positives: 20.88%
```

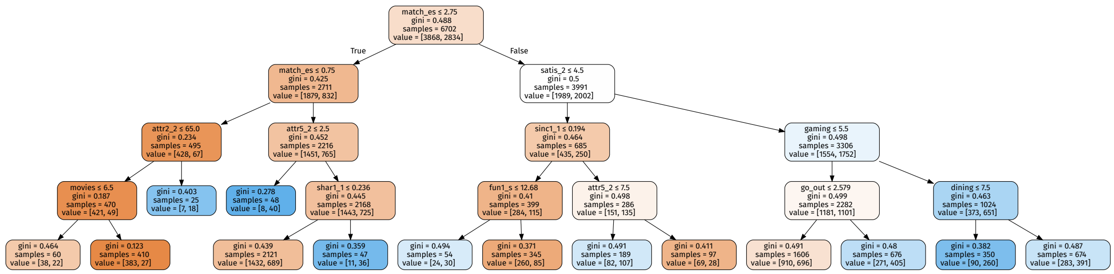
Out[14]:



In [15]:
```
X_nobias = impute(X.drop(["race","imprace","imprelig","income"], axis=1))
nobias_model = model(X_nobias,Y, test_size=0.2)
vizualize(model(X_nobias,Y, max_depth=4, test_size=0.2, print_stats=False), X_
nobias.columns)
```

```
Accuracy: 68.32%
True negatives: 47.32%  False negatives: 11.87%
False positives: 19.81% True positives: 21.00%
```

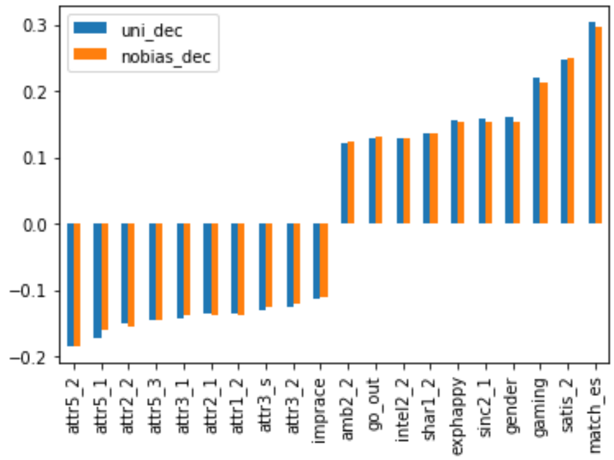
Out[15]:

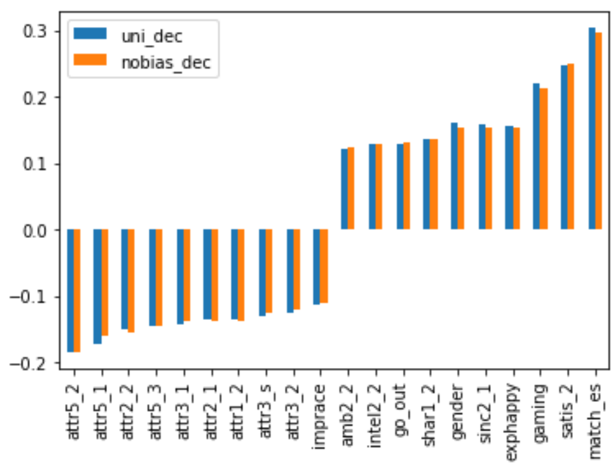


In [16]:
```
def printDiscriminationScore(attr, d_uni, d_nobias):
    print("""Discrimination score(slift) towards {0}:
 Unisex model: {1}
 No bias model: {2}""".format(attr, d_uni, d_nobias))
```

In [17]:
```
def discriminationScore(df):
    means = df[['dec','nobias_dec','uni_dec']].mean()
    d_uni = abs(means['dec']-means['uni_dec'])
    d_nobias = abs(means['dec']-means['nobias_dec'])
    return d_uni, d_nobias
```

In [22]:
```
df_dec = impute(preprocess(df.copy()))

df_dec['uni_dec'] = uni_model.predict(X.as_matrix())
df_dec['nobias_dec'] = nobias_model.predict(X_nobias.as_matrix())

print()

### Pearson coefficent of correlation between attributes and decisions
corr = df_dec.corr().drop(['uni_dec', 'nobias_dec', 'dec'])

### Sorted by unisex model correlation
uni_corr = corr[['uni_dec', 'nobias_dec']].sort_values(by='uni_dec')
uni_corr.head(10).append(uni_corr.tail(10)).plot.bar()
plt.show()

### Sorted by no-bias model correlation
nobias_corr = corr[['uni_dec', 'nobias_dec']].sort_values(by='nobias_dec')
nobias_corr.head(10).append(nobias_corr.tail(10)).plot.bar()
plt.show()

printDiscriminationScore('gender', *discriminationScore(df_dec[df_dec.gender =
= 1]))

not_equal = df_dec[df_dec.nobias_dec != df_dec.uni_dec]

### Cases where model decisions differ
print("Average values:")
display(not_equal.mean().drop(['uni_dec', 'nobias_dec']).sort_values().head(60
))
print()
print("mn_sat stats:")
display(not_equal.mn_sat.describe())
```






```
Discrimination score(slift) towards gender:
 Unisex model: 0.06938483547925606
 No bias model: 0.06819265617548875
Average values:
```

```
shar1_1     0.088446
sinc2_1     0.101208
shar2_1     0.102880
sinc4_1     0.105119
shar4_1     0.114530
intel4_1    0.126004
sinc1_1     0.126129
gender      0.131579
intel2_1    0.131880
sinc5_1     0.133858
intel1_1    0.146563
sinc3_1     0.175633
fun1_1      0.185643
fun4_1      0.193753
attr3_1     0.193955
fun2_1      0.194866
fun5_1      0.199152
amb3_1      0.199279
fun3_1      0.212357
amb5_1      0.213737
attr5_1     0.217097
intel3_1    0.218776
amb4_1      0.219359
amb1_1      0.222051
amb2_1      0.226933
attr1_1     0.231169
intel5_1    0.236156
attr4_1     0.241235
attr2_1     0.242234
dec         0.710526
met         1.127534
race        1.526316
length      1.662708
match_es    2.000000
gaming      2.052632
numdat_2    2.160146
go_out      2.447368
sports      2.578947
tvsports    2.842105
goal        2.894737
exercise    3.447368
imprelig    3.500000
hiking      4.157895
imprace     4.289474
yoga        4.289474
concerts    5.210526
exphappy    5.263158
reading     5.552632
expnum      5.570556
theater     5.763158
date        5.868421
tv          5.921053
art         6.157895
museums     6.157895
satis_2     6.258084
field_cd    6.368421
attr5_3     6.810020
attr5_2     6.827964
amb5_3      7.048611
fun5_3      7.155258
dtype: float64
```

```
mn_sat stats:
```

```
count    3.800000e+01
mean     1.299655e+03
std      2.304258e-13
min      1.299655e+03
25%      1.299655e+03
50%      1.299655e+03
75%      1.299655e+03
max      1.299655e+03
Name: mn_sat, dtype: float64
```

In [19]:

```
df = preprocess(df)

### Pearson coefficent of correlation between gender and attributes
corr = df.corr()['gender'].drop('gender').sort_values()
corr.head(13).append(corr.tail(13)).plot.bar()
plt.show()

#male_mean = df[df.gender == Gender.MALE].mean()
#fem_mean = df[df.gender == Gender.FEMALE].mean()

# Difference in attribute means in percent:
#diff = ((male_mean-fem_mean)/male_mean).drop('gender')
#display(diff.sort_values()*100)
#(male_mean-).drop(columns=['gender']).sort_values()

#df.corr()['gender'].drop('gender').sort_values()
#df.corr()['gender'].drop('gender').sort_values()[10:]
```