If you run this entire notebook it will take a long time to finish and require about 16 gigabytes of RAM.

Dataset is National Corrections Reporting Program, 1991-2014: Selected Variables (ICPSR 36404) - DS1: Term Records

Available here: [http://www.icpsr.umich.edu/cgi-bin/bob/terms2?study=36404&ds=1&bundle=delimited&path=NACJD (http://www.icpsr.umich.edu/cgi-bin/bob/terms2?study=36404&ds=1&bundle=delimited&path=NACJD)](http://www.icpsr.umich.edu/cgi-bin/bob/terms2?study=36404&ds=1&bundle=delimited&path=NACJD)

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
data_path = "36404-0001-Data.tsv"
#place the file in the same directory as the notebook
```

In [2]:
```
def build_df(filename):
    df = pd.read_csv(data_path, header=0, sep="\t")
    return df
```

In [145]:
```
df = build_df(data_path)
```

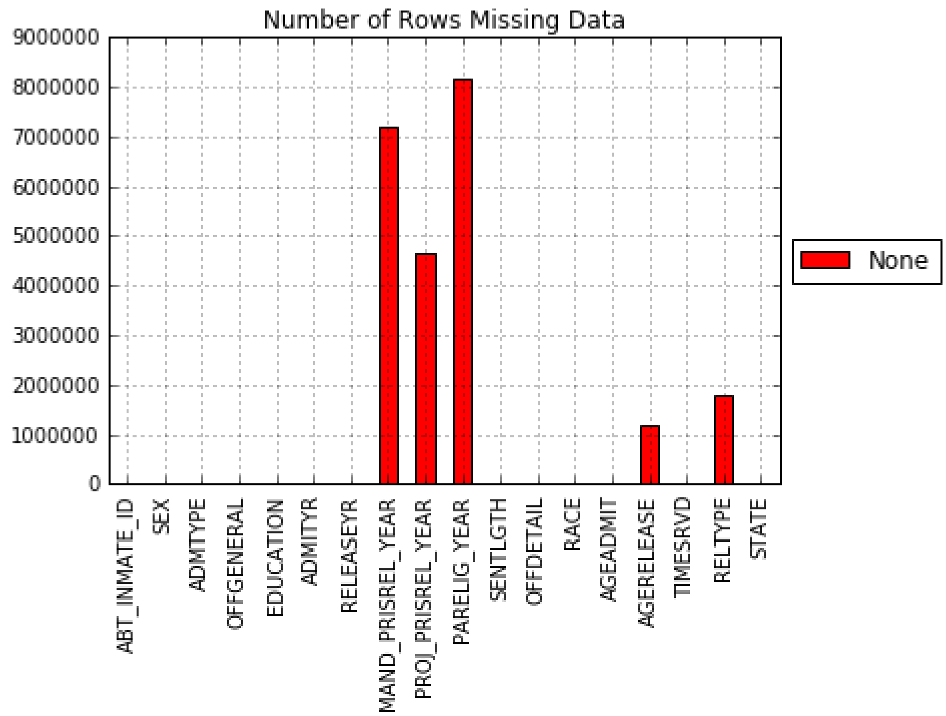
```
//anaconda/lib/python3.5/site-packages/IPython/core/interactiveshell.py:2
825: DtypeWarning: Columns (10) have mixed types. Specify dtype option on
 import or set low_memory=False.
  if self.run_code(code, result):
```

In [146]:
```
df = df.convert_objects(convert_numeric=True) # puts NAN on blank rows and c
```

```
//anaconda/lib/python3.5/site-packages/ipykernel/__main__.py:1: FutureWar
ning: convert_objects is deprecated.  Use the data-type specific converte
rs pd.to_datetime, pd.to_timedelta and pd.to_numeric.
  if __name__ == '__main__':
```

In [5]:
```
missing_data = df.isnull().sum()
missing_data.plot(kind='bar', color='Red', title="Number of Rows Missing Dat
```

Out[5]: <matplotlib.legend.Legend at 0x1117ffc18>



As we can see from the above graph some columns such as PARELIG_YEAR are missing almost 80% of their values. Therefore, we cannot impute the values in this column as more data is missing than available.

In [147]:
```
complete_rows = df.dropna()
```

In [7]:
```
print(len(complete_rows))
```

```
720189
```

Additionally, only 720,189 rows are complete which is only about 6% of the data. We will come back to this issue later for now let's make our data easier to read.

In [8]:
```
def convert_state_in_df(df):
    df.ix[(df.STATE == 1), 'STATE'] = 'Alabama'
    df.ix[(df.STATE == 2), 'STATE'] = 'Alaska'
    df.ix[(df.STATE == 4), 'STATE'] = 'Arizona'
    df.ix[(df.STATE == 5), 'STATE'] = 'Arkansas'
    df.ix[(df.STATE == 6), 'STATE'] = 'California'
    df.ix[(df.STATE == 8), 'STATE'] = 'Colorado'
    df.ix[(df.STATE == 9), 'STATE'] = 'Connecticut'
    df.ix[(df.STATE == 10), 'STATE'] = 'Delaware'
    df.ix[(df.STATE == 11), 'STATE'] = 'District of Columbia'
    df.ix[(df.STATE == 12), 'STATE'] = 'Florida'
    df.ix[(df.STATE == 13), 'STATE'] = 'Georgia'
    df.ix[(df.STATE == 15), 'STATE'] = 'Hawaii'
    df.ix[(df.STATE == 16), 'STATE'] = 'Idaho'
    df.ix[(df.STATE == 17), 'STATE'] = 'Illinois'
    df.ix[(df.STATE == 18), 'STATE'] = 'Indiana'
    df.ix[(df.STATE == 19), 'STATE'] = 'Iowa'
    df.ix[(df.STATE == 20), 'STATE'] = 'Kansas'
    df.ix[(df.STATE == 21), 'STATE'] = 'Kentucky'
    df.ix[(df.STATE == 22), 'STATE'] = 'Louisiana'
    df.ix[(df.STATE == 23), 'STATE'] = 'Maine'
    df.ix[(df.STATE == 24), 'STATE'] = 'Maryland'
    df.ix[(df.STATE == 25), 'STATE'] = 'Massachusetts'
    df.ix[(df.STATE == 26), 'STATE'] = 'Michigan'
    df.ix[(df.STATE == 27), 'STATE'] = 'Minnesota'
    df.ix[(df.STATE == 28), 'STATE'] = 'Mississippi'
    df.ix[(df.STATE == 29), 'STATE'] = 'Missouri'
    df.ix[(df.STATE == 30), 'STATE'] = 'Montana'
    df.ix[(df.STATE == 31), 'STATE'] = 'Nebraska'
    df.ix[(df.STATE == 32), 'STATE'] = 'Nevada'
    df.ix[(df.STATE == 33), 'STATE'] = 'New Hampshire'
    df.ix[(df.STATE == 34), 'STATE'] = 'New Jersey'
    df.ix[(df.STATE == 35), 'STATE'] = 'New Mexico'
    df.ix[(df.STATE == 36), 'STATE'] = 'New York'
    df.ix[(df.STATE == 37), 'STATE'] = 'North Carolina'
    df.ix[(df.STATE == 38), 'STATE'] = 'North Dakota'
    df.ix[(df.STATE == 39), 'STATE'] = 'Ohio'
    df.ix[(df.STATE == 40), 'STATE'] = 'Oklahoma'
    df.ix[(df.STATE == 41), 'STATE'] = 'Oregon'
    df.ix[(df.STATE == 42), 'STATE'] = 'Pennsylvania'
    df.ix[(df.STATE == 44), 'STATE'] = 'Rhode Island'
    df.ix[(df.STATE == 45), 'STATE'] = 'South Carolina'
    df.ix[(df.STATE == 46), 'STATE'] = 'South Dakota'
    df.ix[(df.STATE == 47), 'STATE'] = 'Tennessee'
    df.ix[(df.STATE == 48), 'STATE'] = 'Texas'
    df.ix[(df.STATE == 49), 'STATE'] = 'Utah'
    df.ix[(df.STATE == 50), 'STATE'] = 'Vermont'
    df.ix[(df.STATE == 51), 'STATE'] = 'Virgina'
    df.ix[(df.STATE == 53), 'STATE'] = 'Washington'
    df.ix[(df.STATE == 54), 'STATE'] = 'West Virginia'
    df.ix[(df.STATE == 55), 'STATE'] = 'Wisconsin'
    df.ix[(df.STATE == 56), 'STATE'] = 'Wyoming'

    return df
```

In [9]:
```
def add_sex_to_df(df):
    df.ix[(df.SEX == 1), 'SEX'] = 'Male'
    df.ix[(df.SEX == 2), 'SEX'] = 'Female'

    return df
```

In [10]:
```
def add_offgeneral_to_df(df):
    df.ix[(df.OFFGENERAL == 1), 'OFFGENERAL'] = 'Violent'
    df.ix[(df.OFFGENERAL == 2), 'OFFGENERAL'] = 'Property'
    df.ix[(df.OFFGENERAL == 3), 'OFFGENERAL'] = 'Drugs'
    df.ix[(df.OFFGENERAL == 4), 'OFFGENERAL'] = 'Public Order'
    df.ix[(df.OFFGENERAL == 5), 'OFFGENERAL'] = 'Other'
    df.ix[(df.OFFGENERAL == 9), 'OFFGENERAL'] = 'Missing'

    return df
```

In [11]:
```
def add_race_to_df(df):
    df.ix[(df.RACE == 1), 'RACE'] = 'White'
    df.ix[(df.RACE == 2), 'RACE'] = 'Black'
    df.ix[(df.RACE == 3), 'RACE'] = 'Hispanic'
    df.ix[(df.RACE == 4), 'RACE'] = 'Other'
    df.ix[(df.RACE == 9), 'RACE'] = 'Missing'

    return df
```

In [12]:
```
def add_sentlgth_to_df(df):
    df.ix[(df.SENTLGTH == 0), 'SENTLGTH'] = '0 - 1'
    df.ix[(df.SENTLGTH == 1), 'SENTLGTH'] = '1 - 1.9'
    df.ix[(df.SENTLGTH == 2), 'SENTLGTH'] = '2 - 4.9'
    df.ix[(df.SENTLGTH == 3), 'SENTLGTH'] = '5 - 9.9'
    df.ix[(df.SENTLGTH == 4), 'SENTLGTH'] = '10 - 24.9'
    df.ix[(df.SENTLGTH == 5), 'SENTLGTH'] = '25+'
    df.ix[(df.SENTLGTH == 6), 'SENTLGTH'] = 'Life'
    df.ix[(df.SENTLGTH == 9), 'SENTLGTH'] = 'Missing'

    return df
```

In [13]:
```
def add_off_detail_to_df(df):
    df.ix[(df.OFFDETAIL == 1), 'OFFDETAIL'] = 'Murder'
    df.ix[(df.OFFDETAIL == 2), 'OFFDETAIL'] = 'Negligent Manslaughter'
    df.ix[(df.OFFDETAIL == 3), 'OFFDETAIL'] = 'Rape / Sexual Assault'
    df.ix[(df.OFFDETAIL == 4), 'OFFDETAIL'] = 'Robbery'
    df.ix[(df.OFFDETAIL == 5), 'OFFDETAIL'] = 'Assault'
    df.ix[(df.OFFDETAIL == 6), 'OFFDETAIL'] = 'Other Violent'
    df.ix[(df.OFFDETAIL == 7), 'OFFDETAIL'] = 'Burglary'
    df.ix[(df.OFFDETAIL == 8), 'OFFDETAIL'] = 'Larceny'
    df.ix[(df.OFFDETAIL == 9), 'OFFDETAIL'] = 'GTA'
    df.ix[(df.OFFDETAIL == 10), 'OFFDETAIL'] = 'Fraud'
    df.ix[(df.OFFDETAIL == 11), 'OFFDETAIL'] = 'Other Property'
    df.ix[(df.OFFDETAIL == 12), 'OFFDETAIL'] = 'Drugs'
    df.ix[(df.OFFDETAIL == 13), 'OFFDETAIL'] = 'Public Order'
    df.ix[(df.OFFDETAIL == 14), 'OFFDETAIL'] = 'Other'
    df.ix[(df.OFFDETAIL == 99), 'OFFDETAIL'] = 'Missing'

    return df
```

In [14]:
```
df = add_race_to_df(df)
df = add_offgeneral_to_df(df)
df = add_sex_to_df(df)
df = convert_state_in_df(df)
df = add_sentlgth_to_df(df)
df['count'] = 1
```

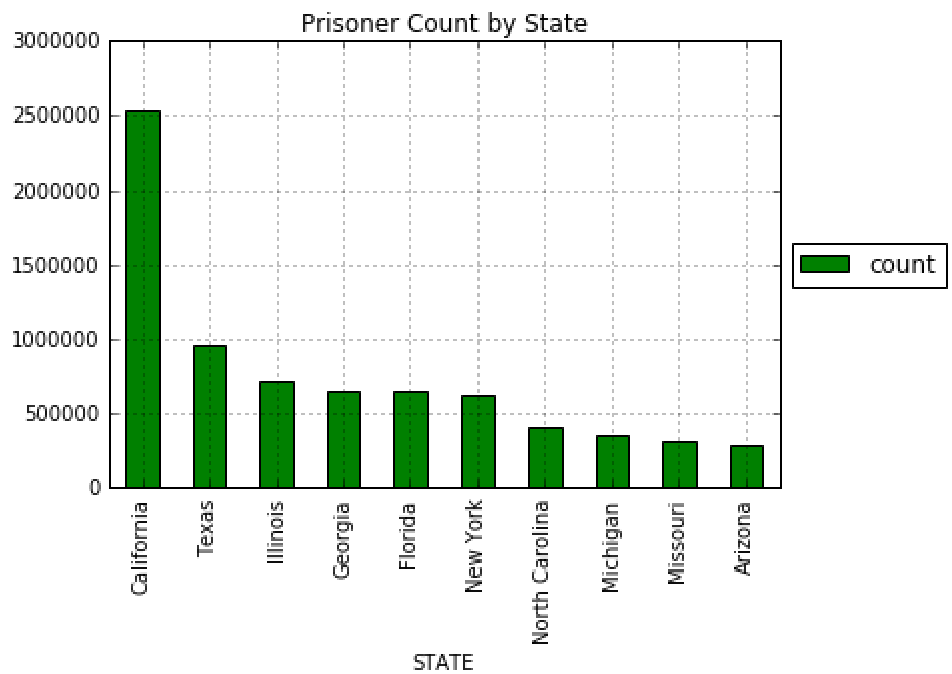
In [98]:
```
df = add_off_detail_to_df(df)
```

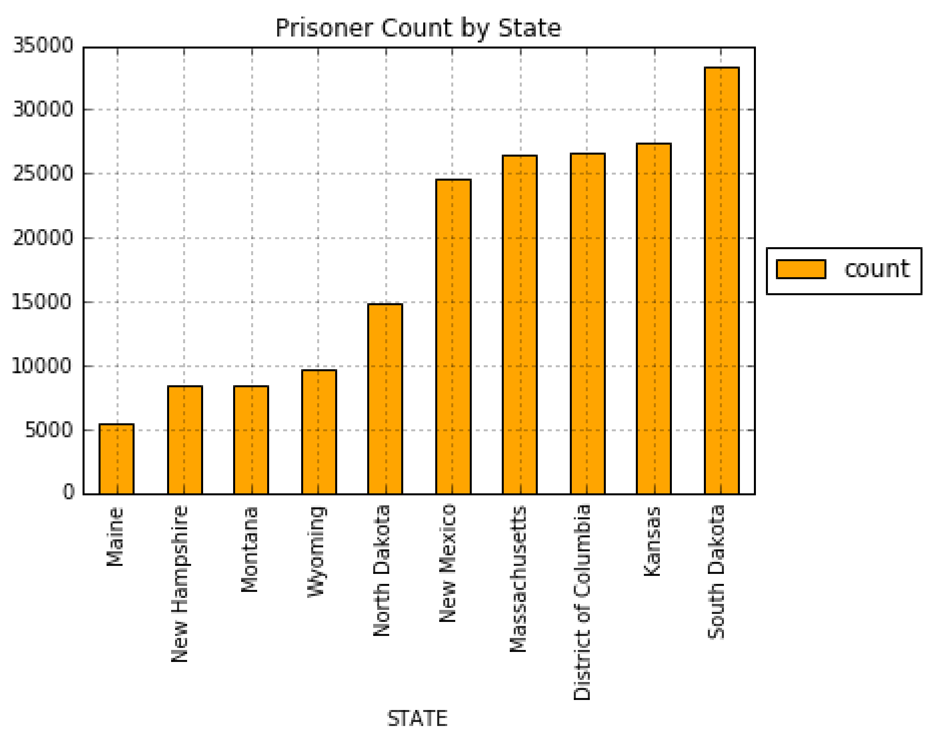
Next I add in class_label to mark repeat offenders where 2 means they are a repeat offender and 1 means they are not a repeat offender

In [71]:
```
dup = df.set_index('ABT_INMATE_ID').index.duplicated(keep=False)
dup = dup * 1
class_label = [x + 1 for x in dup]
se = pd.Series(class_label)
df.insert(0, 'class_label', se.values)
# df.drop('ABT_INMATE_ID', axis=1, inplace = True)
```

Basic Visuals and Statistics

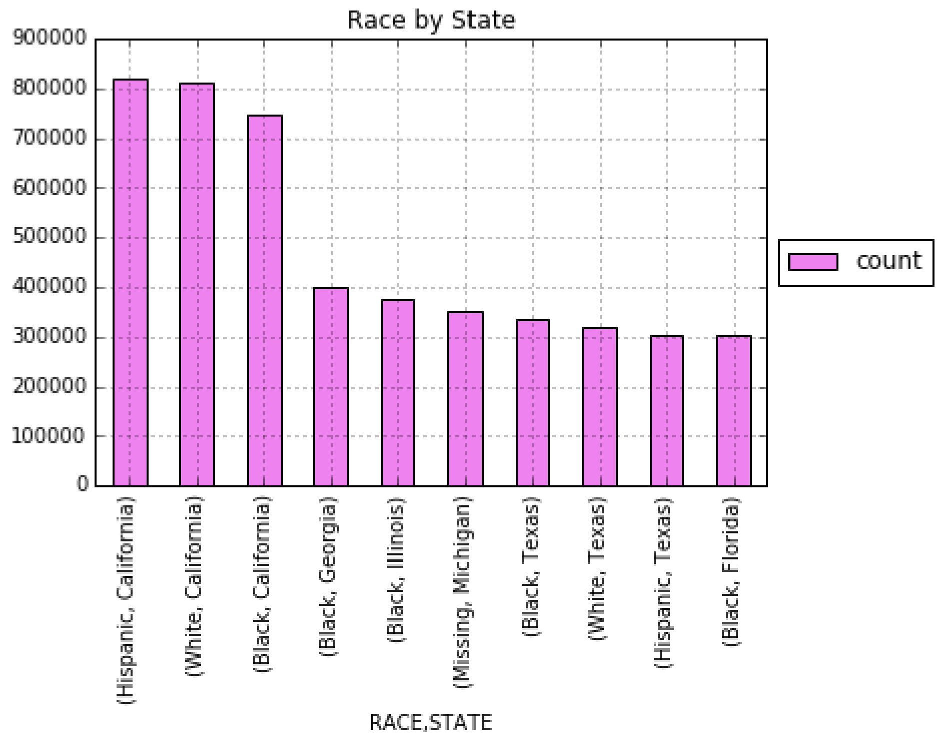
In [75]:
```
state_stats = df.groupby(by=['STATE'])['count'].sum().nlargest(10)
state_stats.plot(kind='bar', color='green', title="High Prisoner Count by St
plt.show()
state_stats2 = df.groupby(by=['STATE'])['count'].sum().nsmallest(10)
state_stats2.plot(kind='bar', color='orange', title="Low Prisoner Count by S
plt.show()
```





In [85]:
```
race_by_state = df.groupby(by=['RACE', 'STATE'])['count'].sum().nlargest(10)
race_by_state.plot(kind='bar', color='violet', title="Race by State", stacke
```

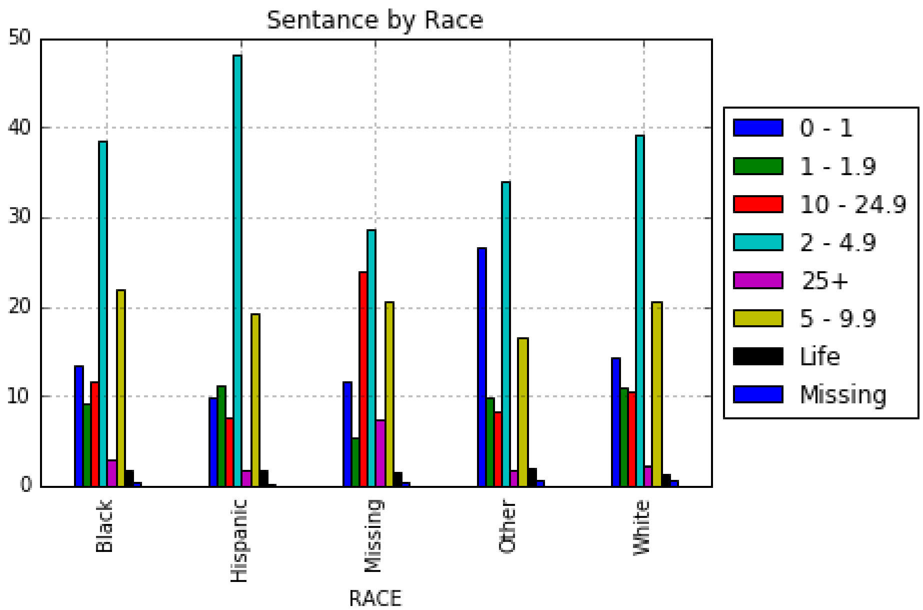
Out[85]: <matplotlib.legend.Legend at 0x1b7e2d9b0>



States appear to be locking up an equal number of black, white, and hispanic people. We'd need more information about specific state demographics, but it initially appears that some groups are over represented.

In [90]:
```
sentance_length_by_race = pd.crosstab(df.RACE, df.SENTLGTH, margins=False).a
sentance_length_by_race.plot(kind='bar', title="Sentance by Race", grid=True
```

Out[90]: <matplotlib.legend.Legend at 0x1bd7b85c0>



I expected there to be some racial bias in sentancing, but that does not appear to be the case. This is more clearly illustrated in the crosstab below

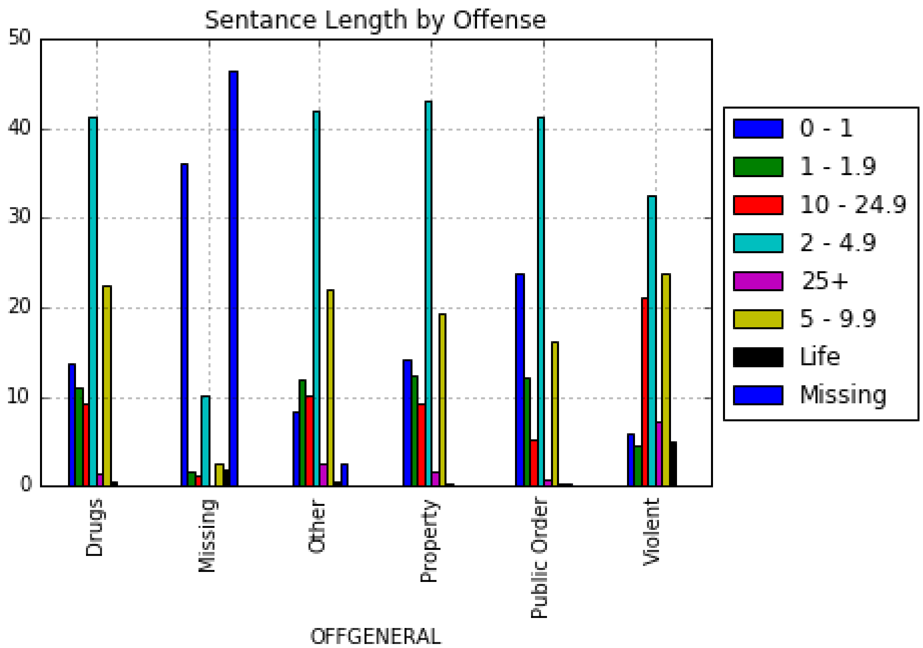
In [91]:
```
sentance_length_by_race
```

Out[91]:

SENTLGTH	0 - 1	1 - 1.9	10 - 24.9	2 - 4.9	25+	5 - 9.9	Life	Mi
RACE								
Black	13.452908	9.101673	11.580064	38.617899	2.968310	22.018191	1.752757	0.5
Hispanic	9.946263	11.103155	7.653948	48.102016	1.878019	19.360450	1.775519	0.1
Missing	11.614201	5.339084	24.076792	28.722387	7.404945	20.686627	1.685146	0.4
Other	26.586445	9.963377	8.280232	33.987095	1.861118	16.542577	2.107061	0.6
White	14.295786	10.993842	10.488890	39.322407	2.232418	20.728668	1.299821	0.6

In [92]:
```
sentance_length_by_offense = pd.crosstab(df.OFFGENERAL, df.SENTLGTH, margins
sentance_length_by_offense.plot(kind='bar', title="Sentance Length by Offens
```

Out[92]: <matplotlib.legend.Legend at 0x1c2fcb240>



In [93]:
```
sentance_length_by_offense
```

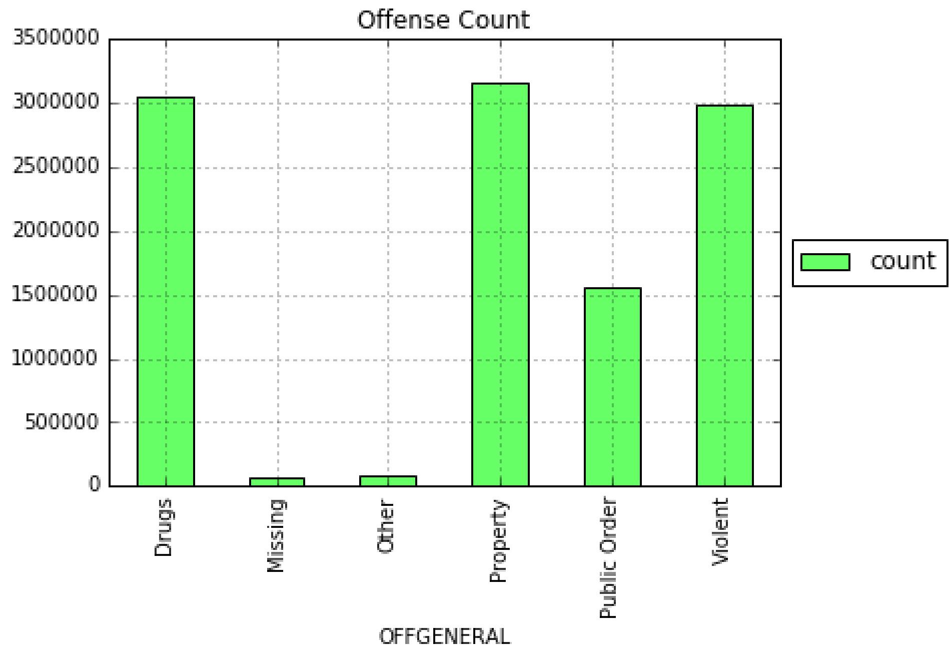
Out[93]:

SENTLGTH	0 - 1	1 - 1.9	10 - 24.9	2 - 4.9	25+	5 - 9.9	Life
OFFGENERAL							
Drugs	13.681003	11.017551	9.276840	41.358339	1.513696	22.494780	0.520735
Missing	36.080674	1.692910	1.192924	10.063097	0.170418	2.502746	1.856286
Other	8.303531	11.916562	10.197440	41.900578	2.533261	22.089854	0.564608
Property	14.268174	12.343258	9.165766	43.076718	1.575717	19.243617	0.195987
Public Order	23.732960	12.088864	5.286476	41.321555	0.827589	16.183378	0.190258
Violent	5.788639	4.459756	21.032803	32.595915	7.209000	23.785353	4.952593

Interesting that 2-4.9 years is the most common sentance for any offense. Also notice how much higher life sentance is for violent when compared to other crimes.

In [96]:
```
offense_stats = df.groupby(by=['OFFGENERAL'])['count'].sum()
offense_stats.plot(kind='bar', color='#66ff66', title="Offense Count", grid=
```

Out[96]: <matplotlib.legend.Legend at 0x1cf4794a8>



We can clearly see that we are locking up more non-violent drug offenders than violent offenders. Interestingly property offenses are the most common. Let's take another look at offense verse sentence length.

In [120]:
```
# THE GRAPHS WORKS BUT HAVE A LOT OF DATA SO IT'S HARD TO DRAW CONCLUSIONS
# from pylab import rcParams
# rcParams['figure.figsize'] = 14, 10
# sentance_length_by_offense_detail = pd.crosstab(df.OFFDETAIL, df.SENTLGTH,
# sentance_length_by_offense_detail.plot(kind='bar', title="Sentance Length
```

In [121]:
```
# sentance_length_by_offense_detail.plot(kind='bar', title="Sentance Length
```

In [125]:
```
rcParams['figure.figsize'] = 10, 5
sentance_length_by_offense_detail
```

Out[125]:

SENTLGTH	0 - 1	1 - 1.9	10 - 24.9	2 - 4.9	25+	5 - 9.9	Life
OFFDETAIL							
Assault	10.826631	6.337671	11.659781	47.298930	2.328681	20.689201	0.742615
Burglary	8.809195	8.301510	13.721045	41.560686	2.621558	24.496743	0.362520
Drugs	13.681003	11.017551	9.276840	41.358339	1.513696	22.494780	0.520735
Fraud	19.501422	13.416317	8.175684	40.064343	1.260291	17.347805	0.064613
GTA	10.739043	17.535598	3.326040	51.872265	0.715427	15.708828	0.048274
Larceny	20.193848	15.318514	5.302954	44.517715	0.695440	13.756000	0.082572
Missing	36.080674	1.692910	1.192924	10.063097	0.170418	2.502746	1.856286
Murder	0.878522	0.237286	26.744420	2.720663	22.228931	10.963867	35.41452
Negligent Manslaughter	2.391671	2.950140	34.759673	26.265064	5.491870	27.425318	0.652836
Other	8.303531	11.916562	10.197440	41.900578	2.533261	22.089854	0.564608
Other Property	16.886083	14.570118	7.465466	41.991962	0.903251	17.892578	0.137839
Other Violent	9.521945	10.280867	13.196009	38.718675	4.298360	21.392809	2.450989
Public Order	23.732960	12.088864	5.286476	41.321555	0.827589	16.183378	0.190258
Rape / Sexual Assault	2.600480	3.398252	30.529121	21.902889	10.873597	26.723712	3.811843
Robbery	3.049892	3.001414	24.703500	31.475919	6.366986	29.899008	1.439824

Comparing drugs to assault or fraud we can see some interesting results. It appears that most drugs offenses warrent longer sentances than assault or fraud

In [132]:
```
sex_stats = df.groupby(by=['SEX'])['count'].sum()
sex_stats
```

Out[132]:
```
SEX
Female    1147078
Male      9759759
Name: count, dtype: int64
```

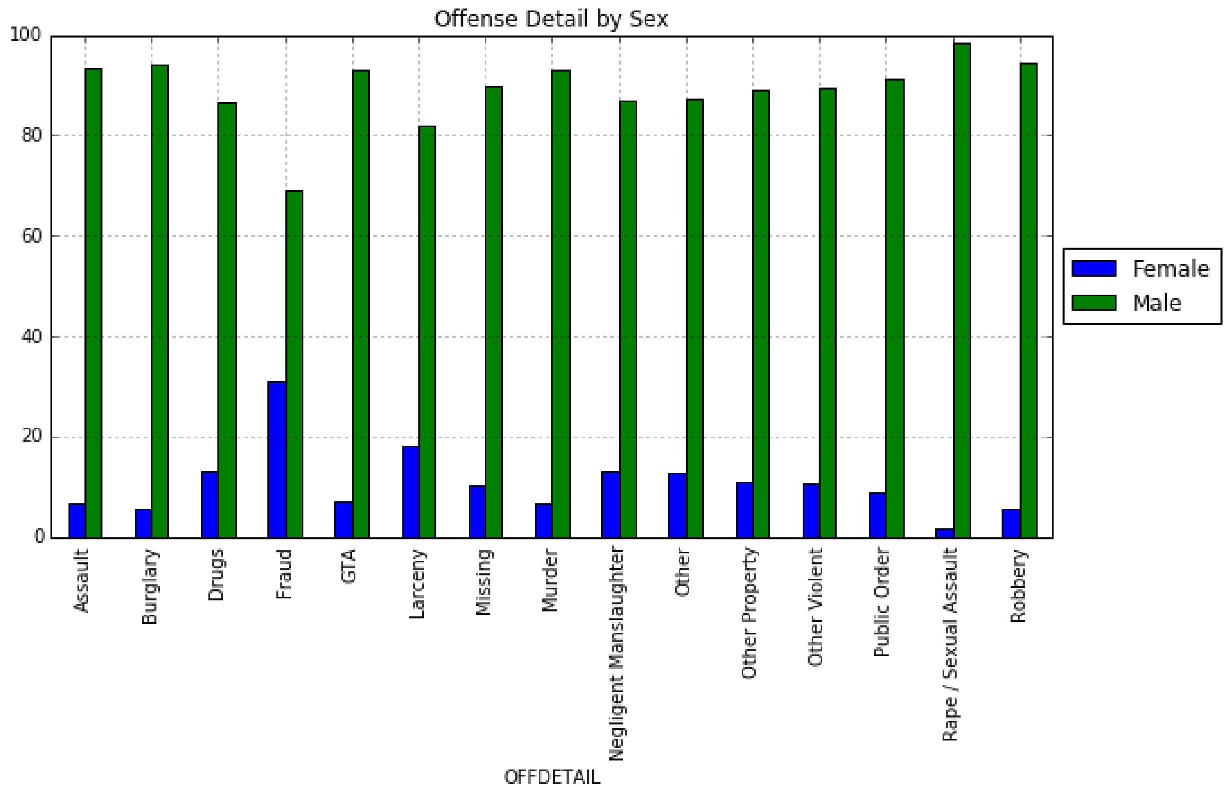
10.5 % Women

90.5 % Men

Incredible that there is such a large difference

In [128]:
```
offense_detail_vs_sex = pd.crosstab(df.OFFDETAIL, df.SEX, margins=False).appl
offense_detail_vs_sex.plot(kind='bar', title="Offense Detail by Sex", grid=Tr
```

Out[128]: <matplotlib.legend.Legend at 0x1df991320>



In [133]:
```
repeat_offenders = df.groupby(by=['class_label'])['count'].sum()
repeat_offenders
```

Out[133]:
```
class_label
1    3925136
2    6981701
Name: count, dtype: int64
```

64% are repeat offenders

Let’s see if we can figure out what characteristics are the best predictors of whether someone will be a repeat offender.

I will use the complete rows from the original data as my sample. I used logistic regression because

there are only 2 labels.

In [148]:
```
repeat = complete_rows.set_index('ABT_INMATE_ID').index.duplicated(keep=Fals
repeat = repeat * 1
class_label = [x + 1 for x in repeat]
se = pd.Series(class_label)
complete_rows.insert(0, 'class_label', se.values)
complete_rows.drop('ABT_INMATE_ID', axis=1, inplace = True) # drop the ID be
```

```
//anaconda/lib/python3.5/site-packages/ipykernel/__main__.py:6: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-doc
s/stable/indexing.html#indexing-view-versus-copy (http://pandas.pydata.or
g/pandas-docs/stable/indexing.html#indexing-view-versus-copy)
```

Now I remove all the rows that have "missing"

In [149]:
```
complete_rows = complete_rows[complete_rows.RELEASEYR != 9999]
complete_rows = complete_rows[complete_rows.ADMTYPE != 9]
complete_rows = complete_rows[complete_rows.OFFGENERAL != 9]
complete_rows = complete_rows[complete_rows.ADMITYR != 9999]
complete_rows = complete_rows[complete_rows.OFFDETAIL != 99]
complete_rows = complete_rows[complete_rows.RACE != 9]
complete_rows = complete_rows[complete_rows.AGEADMIT != 9]
complete_rows.drop('EDUCATION', axis=1, inplace=True) # missing all values
complete_rows = complete_rows[complete_rows.MAND_PRISREL_YEAR != 9999]
complete_rows = complete_rows[complete_rows.PROJ_PRISREL_YEAR != 9999]
complete_rows = complete_rows[complete_rows.PARELIG_YEAR != 9999]
complete_rows = complete_rows[complete_rows.OFFDETAIL != 9]
complete_rows = complete_rows[complete_rows.SENTLGTH != 9]
complete_rows = complete_rows[complete_rows.AGERELEASE != 9]
complete_rows = complete_rows[complete_rows.RELTYPE != 9]
```

Now we need to Standardize our data. Complete rows still has over 660k rows which is too much so I'll take a sample.

In [150]:
```
# take 10% of complete rows
sample = complete_rows.sample(frac=0.10, random_state=0)
```

Split into Training and Test data

In [102]:
```
```

```
# test set is 20%
from sklearn.cross_validation import train_test_split
X, y = sample.iloc[:, 1:].values, sample.iloc[:, 0].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, ra
```

Standardize Values so larger numbers such as year don't skew the results

In [103]:

```
from sklearn.preprocessing import StandardScaler
stdsc = StandardScaler()
X_train_std = stdsc.fit_transform(X_train)
X_test_std = stdsc.transform(X_test)
```

Calculate Accuracy

In [28]:

```
from sklearn.linear_model import LogisticRegression
LogisticRegression(penalty='l1')
lr = LogisticRegression(penalty='l1', C=0.1)
lr.fit(X_train_std, y_train)
print('Training accuracy:', lr.score(X_train_std, y_train))
print('Test accuracy:', lr.score(X_test_std, y_test))
```

```
Training accuracy: 0.639990923187
Test accuracy: 0.645942061871
```

At this point I was disappointed with the results so I decided to explore the importance of each feature. The dataset currently has 16 dimensions. To evaluate each variable I used a random forest to see which variables are the most important to predict repeat offenders.

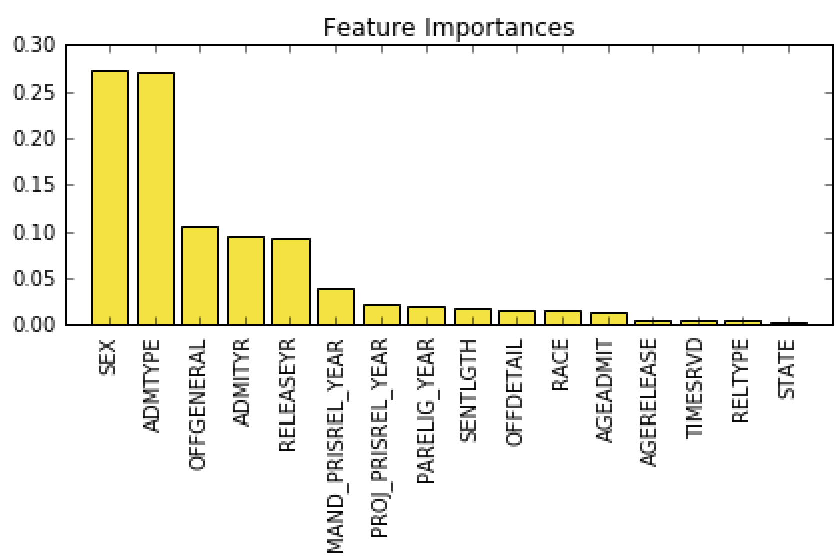
In [20]:

```
from sklearn.ensemble import RandomForestClassifier
feat_labels = complete_rows.columns[1:]
forest = RandomForestClassifier(n_estimators=1000, max_depth=5,  random_stat
```

In [56]:
```
%%time
forest.fit(X_train, y_train)
importances = forest.feature_importances_
indices = np.argsort(importances)[::-1]
for f in range(X_train.shape[1]):
    print ("%2d) %-*s %f" % (f + 1, 30, feat_labels[f], importances[indices[
```

```
 1) SEX                            0.273661
 2) ADMTYPE                        0.269934
 3) OFFGENERAL                     0.106134
 4) ADMITYR                        0.095203
 5) RELEASEYR                      0.092483
 6) MAND_PRISREL_YEAR              0.038753
 7) PROJ_PRISREL_YEAR              0.023060
 8) PARELIG_YEAR                   0.019957
 9) SENTLGTH                       0.018406
10) OFFDETAIL                      0.016320
11) RACE                           0.014892
12) AGEADMIT                       0.012895
13) AGERELEASE                     0.005550
14) TIMESRVD                       0.004666
15) RELTYPE                        0.004262
16) STATE                          0.003822
CPU times: user 39.4 s, sys: 571 ms, total: 39.9 s
Wall time: 41.5 s
```

In [57]:
```
plt.title('Feature Importances')
plt.bar(range(X_train.shape[1]), importances[indices], color='#f4e242', alig
plt.xticks(range(X_train.shape[1]), feat_labels, rotation=90)
plt.xlim([-1, X_train.shape[1]])
plt.tight_layout()
plt.show()
```



Checking results using KNN and Sequential Backward Selection

In [104]:
```
from sklearn.base import clone
from itertools import combinations
from sklearn.cross_validation import train_test_split
from sklearn.metrics import accuracy_score
```

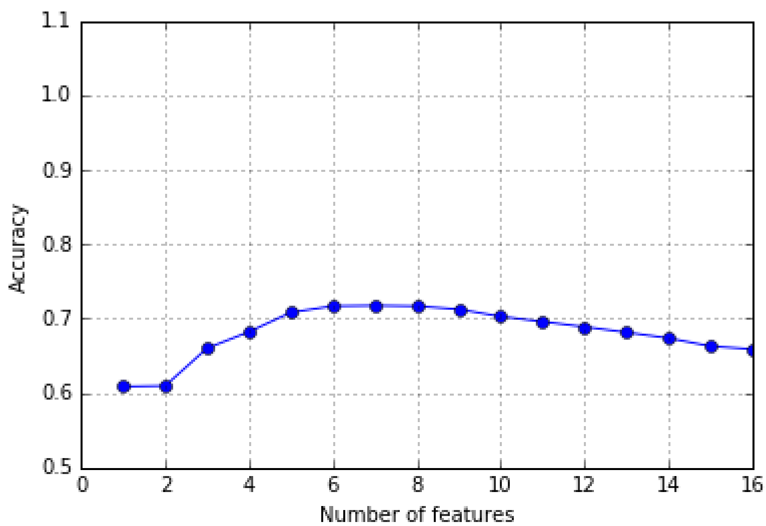
In [105]:

```
# Not in Sklearn
class SBS():
    def __init__(self, estimator, k_features,
                 scoring=accuracy_score,
                 test_size=0.25, random_state=1):
        self.scoring = scoring
        self.estimator = clone(estimator)
        self.k_features = k_features
        self.test_size = test_size
        self.random_state = random_state

    def fit(self, X, y):
        X_train, X_test, y_train, y_test = \
            train_test_split(X, y, test_size=self.test_size, random_state=se

        dim = X_train.shape[1]
        self.indices_ = tuple(range(dim))
        self.subsets_ = [self.indices_]
        score = self._calc_score(X_train, y_train, X_test, y_test, self.indi
        self.scores_ = [score]

        while dim > self.k_features:
            scores = []
            subsets = []

            for p in combinations(self.indices_, r = (dim - 1)):
                score = self._calc_score(X_train, y_train, X_test, y_test, p

                scores.append(score)
                subsets.append(p)

            best = np.argmax(scores)
            self.indices_ = subsets[best]
            self.subsets_.append(self.indices_)
            dim -= 1
            self.scores_.append(scores[best])
        self.k_score_ = self.scores_[-1]

        return self


    def transform(self, X):
        return X[:, self.indices_]

    def _calc_score(self, X_train, y_train, X_test, y_test, indices):

        self.estimator.fit(X_train[:, indices], y_train)
        y_pred = self.estimator.predict(X_test[:, indices])
        score = self.scoring(y_test, y_pred)
        return score
```

In [111]:
```
# Takes about 10 minutes to run
from sklearn.neighbors import KNeighborsClassifier
%timeit
knn = KNeighborsClassifier(n_neighbors=2)
sbs = SBS(knn, k_features=1)
sbs.fit(X_train_std, y_train)
```

Out[111]:
```
<__main__.SBS at 0x1086f04a8>
```

In [112]:
```
k_feat = [len(k) for k in sbs.subsets_]
plt.plot(k_feat, sbs.scores_, marker='o')
plt.ylim([0.5, 1.1])
plt.ylabel('Accuracy')
plt.xlabel('Number of features')
plt.grid()
plt.show()
```



In [113]:
```
sbs.scores_
```

Out[113]:
```
[0.65880039331366769,
 0.6627335299901671,
 0.67354965585054083,
 0.68141592920353977,
 0.68882837909386585,
 0.69578700552151884,
 0.70274563194917172,
 0.7124271991528629,
 0.71666288480447771,
 0.71741925724226607,
 0.71673852204825661,
 0.70819151350124798,
 0.68209666439754935,
 0.66001058921412903,
 0.60940927312608728,
 0.60850162620074122]
```

In [91]:
```
k1 = list(sbs.subsets_[10])
print(sample.columns[1:][k1])
```

```
Index(['ADMTYPE', 'RELEASEYR', 'MAND_PRISREL_YEAR', 'PARELIG_YEAR', 'TIME
SRVD',
       'STATE'],
      dtype='object')
```

The above code shows the 6 features that result in the best accuracy score. This implies that we can remove 10 feature from our dataset. Let's try it

In [22]:
```
# reduce to 6 dimensions
def drop_columns_for_lr(df):
    df.drop('STATE', axis=1, inplace=True)
    df.drop('RELTYPE', axis=1, inplace=True)
    df.drop('TIMESRVD', axis=1, inplace=True)
    df.drop('AGERELEASE', axis=1, inplace=True)
    df.drop('AGEADMIT', axis=1, inplace=True)
    df.drop('RACE', axis=1, inplace=True)
    df.drop('OFFDETAIL', axis=1, inplace=True)
    df.drop('SENTLGTH', axis=1, inplace=True)
    df.drop('PARELIG_YEAR', axis=1, inplace=True)
    df.drop('PROJ_PRISREL_YEAR', axis=1, inplace=True)
    return df
```

In [47]:
```
# since we are dropping columns we need to make a copy of the df
copy = complete_rows.copy()
copy2 = complete_rows.copy()
```

In [168]:
```
male_df = complete_rows.copy()
female_df = complete_rows.copy()
```

In [48]:
```
smaller_lr = drop_columns_for_lr(copy)
```

Since we reduced the dimensionality of the set we can now run logistic regression on the entire set smaller_lr

In [49]:
```
X, y = smaller_lr.iloc[:, 1:].values, smaller_lr.iloc[:, 0].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, ra
stdsc = StandardScaler()
X_train_std = stdsc.fit_transform(X_train)
X_test_std = stdsc.transform(X_test)
LogisticRegression(penalty='l1')
lr = LogisticRegression(penalty='l1', C=0.1)
lr.fit(X_train_std, y_train)
print('Training accuracy:', lr.score(X_train_std, y_train))
print('Test accuracy:', lr.score(X_test_std, y_test))
```

```
Training accuracy: 0.637769322991
Test accuracy: 0.636569924437
```

We removed 10 dimensions but only lost ~1% in our accuracy which is amazing

In [50]:
```
def drop_columns_for_knn(df):
    df.drop('SEX', axis=1, inplace=True)
    df.drop('OFFGENERAL', axis=1, inplace=True)
    df.drop('ADMITYR', axis=1, inplace=True)
    df.drop('AGEADMIT', axis=1, inplace=True)
    df.drop('RACE', axis=1, inplace=True)
    df.drop('OFFDETAIL', axis=1, inplace=True)
    df.drop('PROJ_PRISREL_YEAR', axis=1, inplace=True)
    df.drop('AGERELEASE', axis=1, inplace=True)
    df.drop('RELTYPE', axis=1, inplace=True)
    df.drop('SENTLGTH', axis=1, inplace=True)

    return df
```

In [51]:
```
smaller_knn = drop_columns_for_knn(copy2)
```

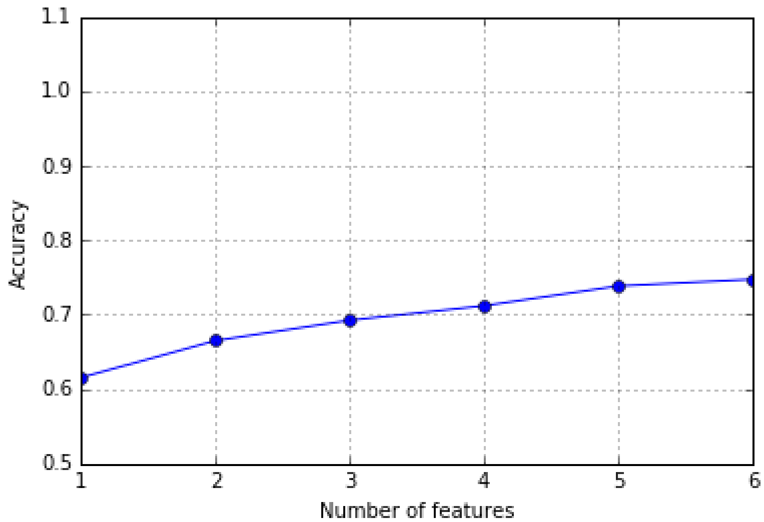
In [97]:
```
knn_sample = smaller_knn.sample(frac=0.20, random_state=0)
```

Increase n_neighbors to 7 and doubled the sample size

In [98]:
```
%%time
X, y = knn_sample.iloc[:, 1:].values, knn_sample.iloc[:, 0].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, ra
stdsc = StandardScaler()
X_train_std = stdsc.fit_transform(X_train)
X_test_std = stdsc.transform(X_test)
knn = KNeighborsClassifier(n_neighbors=7)
sbs = SBS(knn, k_features=1)
sbs.fit(X_train_std, y_train)
```

```
CPU times: user 1min 9s, sys: 677 ms, total: 1min 10s
Wall time: 1min 20s
```

In [99]:
```
k_feat = [len(k) for k in sbs.subsets_]
plt.plot(k_feat, sbs.scores_, marker='o')
plt.ylim([0.5, 1.1])
plt.ylabel('Accuracy')
plt.xlabel('Number of features')
plt.grid()
plt.show()
```



In [100]:
```
sbs.scores_
```

Out[100]:
```
[0.74733378715679599,
 0.73833295514711439,
 0.71174646395885333,
 0.6922320550639135,
 0.66481355419408517,
 0.61515770365327882]
```

KNN Another Try

Here I split the dataset into two seperate dataframes one for male prisoners and one for female.

In [151]:
```
def remove_women(df, string=False):
    if string:
        filter = df["SEX"] != 'Female'
    else:
        filter = df["SEX"] != 2

    df = df[filter]
    return df

def remove_men(df, string=False):
    if string:
        filter = df["SEX"] != "Male"
    else:
        filter = df["SEX"] != 1

    df = df[filter]
    return df
```

In [169]:
```
male_df = remove_women(male_df)
female_df = remove_men(female_df)
male_df.drop('SEX', axis=1, inplace=True)
female_df.drop('SEX', axis=1, inplace=True)
```

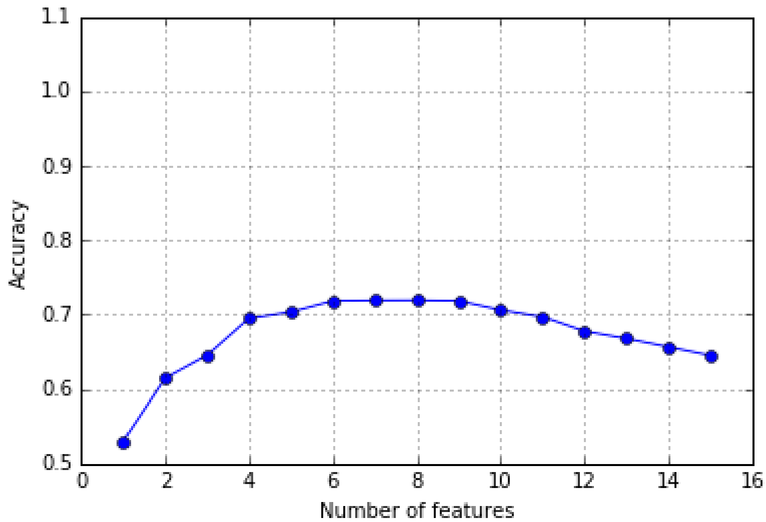
Now we can analyze each features value in the seperate dataframes to see if we can get better predictions or if different features become more or less valuable.

Men KNN

In [171]:
```
%%time
male_sample = male_df.sample(frac=0.10, random_state=0)
X, y = male_sample.iloc[:, 1:].values, male_sample.iloc[:, 0].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, ra
stdsc = StandardScaler()
X_train_std = stdsc.fit_transform(X_train)
X_test_std = stdsc.transform(X_test)
knn = KNeighborsClassifier(n_neighbors=2)
sbs = SBS(knn, k_features=1)
sbs.fit(X_train_std, y_train)
```

```
CPU times: user 4min 42s, sys: 1.93 s, total: 4min 44s
Wall time: 6min 24s
```

In [172]:
```
k_feat = [len(k) for k in sbs.subsets_]
plt.plot(k_feat, sbs.scores_, marker='o')
plt.ylim([0.5, 1.1])
plt.ylabel('Accuracy')
plt.xlabel('Number of features')
plt.grid()
plt.show()
```



In [173]:
```
sbs.scores_
```

Out[173]:
```
[0.64500941619585683,
 0.65639445300462251,
 0.66777948981338808,
 0.6776236945728471,
 0.69688409518917993,
 0.7060434857045027,
 0.71828454031843858,
 0.71905495634309191,
 0.71888375278205785,
 0.71819893853792161,
 0.70338983050847459,
 0.69482965245677109,
 0.64526622153740798,
 0.61462078411230958,
 0.52996062318096215]
```

It appears that 6 features is still the best, let's see if they are the same six.

In [176]:
```
k1 = list(sbs.subsets_[9])
print(male_sample.columns[1:][k1])
```

```
Index(['ADMTYPE', 'ADMITYR', 'MAND_PRISREL_YEAR', 'PARELIG_YEAR', 'TIMESR
VD',
       'STATE'],
      dtype='object')
```

'ADMTYPE', 'RELEASEYR', 'MAND_PRISREL_YEAR', 'PARELIG_YEAR', 'TIMESRVD', 'STATE'

VS

ADMTYPE', 'ADMITYR', 'MAND_PRISREL_YEAR', 'PARELIG_YEAR', 'TIMESRVD', 'STATE'

The whole group and the male group share all but one common feature "ADMITYR". Interestingly the accuracy is almost exactly the same 71.7% vs 71.8%.

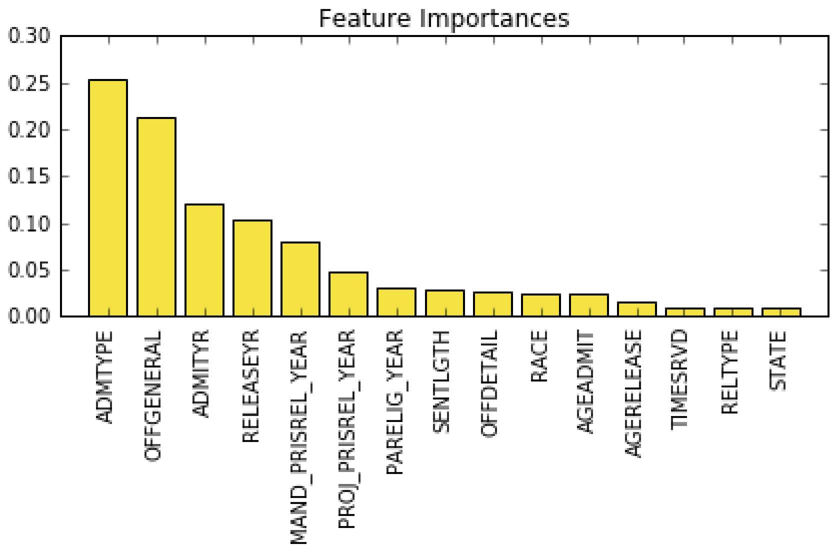
Men's Random Forest

In [186]:
```
feat_labels = male_sample.columns[1:]
forest = RandomForestClassifier(n_estimators=1000, max_depth=7,  random_stat
```

In [187]:
```
%%time
forest.fit(X_train, y_train)
importances = forest.feature_importances_
indices = np.argsort(importances)[::-1]
for f in range(X_train.shape[1]):
    print ("%2d) %-*s %f" % (f + 1, 30, feat_labels[f], importances[indices[
```

```
 1) ADMTYPE                        0.254524
 2) OFFGENERAL                     0.213256
 3) ADMITYR                        0.119919
 4) RELEASEYR                      0.103387
 5) MAND_PRISREL_YEAR              0.079867
 6) PROJ_PRISREL_YEAR              0.047442
 7) PARELIG_YEAR                   0.031747
 8) SENTLGTH                       0.028873
 9) OFFDETAIL                      0.027470
10) RACE                           0.024640
11) AGEADMIT                       0.024065
12) AGERELEASE                     0.016338
13) TIMESRVD                       0.010263
14) RELTYPE                        0.009174
15) STATE                          0.009035
CPU times: user 33.4 s, sys: 227 ms, total: 33.6 s
Wall time: 34.3 s
```

In [188]:
```
plt.title('Feature Importances')
plt.bar(range(X_train.shape[1]), importances[indices], color='#f4e242', alig
plt.xticks(range(X_train.shape[1]), feat_labels, rotation=90)
plt.xlim([-1, X_train.shape[1]])
plt.tight_layout()
plt.show()
```



Random forest classified feature importance in the exact same order even though the set only contains men now.

Men's Logistic Regression

In [189]:
```
LogisticRegression(penalty='l1')
lr = LogisticRegression(penalty='l1', C=0.1)
lr.fit(X_train_std, y_train)
print('Training accuracy:', lr.score(X_train_std, y_train))
print('Test accuracy:', lr.score(X_test_std, y_test))
```

```
Training accuracy: 0.644260400616
Test accuracy: 0.639958911145
```

Almost exactly the same accuracy as before

Women's KNN

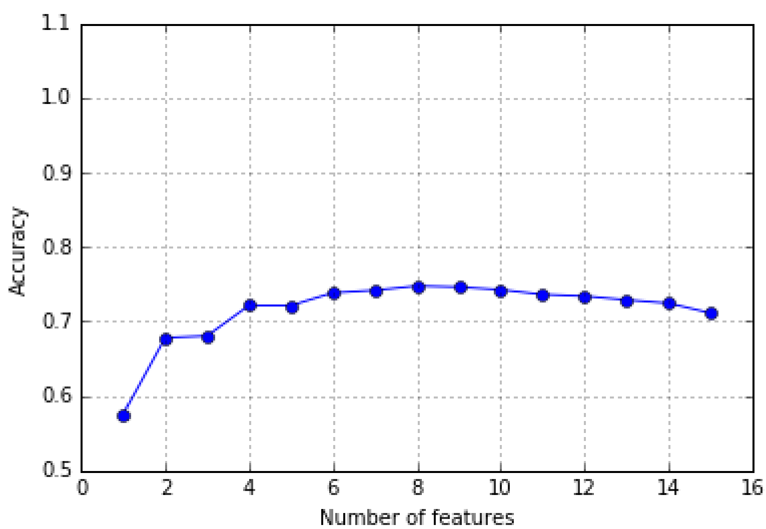
In [190]:

```
# Almost 10 minutes to run
# Ran on entire group of women not a sample
%%time
X, y = female_df.iloc[:, 1:].values, female_df.iloc[:, 0].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, ra
stdsc = StandardScaler()
X_train_std = stdsc.fit_transform(X_train)
X_test_std = stdsc.transform(X_test)
knn = KNeighborsClassifier(n_neighbors=5)
sbs = SBS(knn, k_features=1)
sbs.fit(X_train_std, y_train)
```

```
CPU times: user 7min 39s, sys: 3.59 s, total: 7min 43s
Wall time: 9min 52s
```

In [191]:

```
k_feat = [len(k) for k in sbs.subsets_]
plt.plot(k_feat, sbs.scores_, marker='o')
plt.ylim([0.5, 1.1])
plt.ylabel('Accuracy')
plt.xlabel('Number of features')
plt.grid()
plt.show()
```



In [192]:
```
sbs.scores_
```

Out[192]:
```
[0.71105478650809129,
 0.72431273152661335,
 0.72879703645934879,
 0.73386625073113665,
 0.73607590823422364,
 0.74244492103723925,
 0.74608435692467667,
 0.74757912523558845,
 0.74166504191850258,
 0.73835055566387209,
 0.721193215051667,
 0.7213231949047898,
 0.68037954117111843,
 0.67790992396178595,
 0.57529082992136216]
```

Eight features provides the best results with 74.75% accuracy which is a 3 percent improvement over the mens set and the total set.

In [194]:
```
k1 = list(sbs.subsets_[7])
print(female_df.columns[1:][k1])
```

```
Index(['ADMTYPE', 'RELEASEYR', 'MAND_PRISREL_YEAR', 'PARELIG_YEAR', 'SENT
LGTH',
       'TIMESRVD', 'RELTYPE', 'STATE'],
      dtype='object')
```

We see that the womens results vary in that there are two extra features "SENTLGTH" AND "RELTYPE" other than that the features are identical. So it appears there is some correlation between these values and repeat female offenders.

Women's Random Forest

In [195]:
```
feat_labels = female_df.columns[1:]
forest = RandomForestClassifier(n_estimators=2000, max_depth=7,  random_stat
```

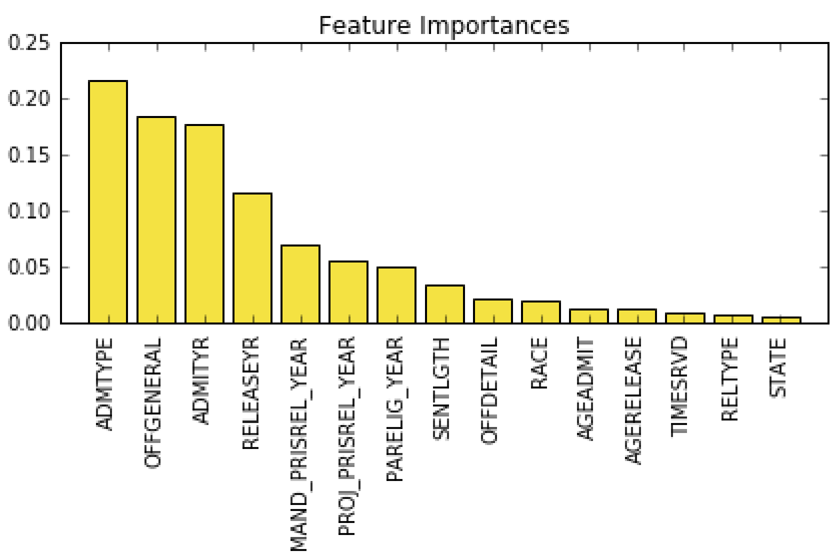
In [196]:

```
%%time
forest.fit(X_train, y_train)
importances = forest.feature_importances_
indices = np.argsort(importances)[::-1]
for f in range(X_train.shape[1]):
    print ("%2d) %-*s %f" % (f + 1, 30, feat_labels[f], importances[indices[
```

```
 1) ADMTYPE                        0.215934
 2) OFFGENERAL                     0.184211
 3) ADMITYR                        0.176604
 4) RELEASEYR                      0.117496
 5) MAND_PRISREL_YEAR              0.070212
 6) PROJ_PRISREL_YEAR              0.056362
 7) PARELIG_YEAR                   0.050029
 8) SENTLGTH                       0.035556
 9) OFFDETAIL                      0.021846
10) RACE                           0.019682
11) AGEADMIT                       0.013907
12) AGERELEASE                     0.013781
13) TIMESRVD                       0.009618
14) RELTYPE                        0.008661
15) STATE                          0.006100
CPU times: user 1min 34s, sys: 2.75 s, total: 1min 37s
Wall time: 2min 22s
```

In [197]:

```
plt.title('Feature Importances')
plt.bar(range(X_train.shape[1]), importances[indices], color='#f4e242', alig
plt.xticks(range(X_train.shape[1]), feat_labels, rotation=90)
plt.xlim([-1, X_train.shape[1]])
plt.tight_layout()
plt.show()
```



Features are ranked in the same order as before. However, the first few features became less valuable and features such as sentence length became more valuable.

Women's Logistic Regression

In [199]:
```
LogisticRegression(penalty='l1')
lr = LogisticRegression(penalty='l1', C=0.1)
lr.fit(X_train_std, y_train)
print('Training accuracy:', lr.score(X_train_std, y_train))
print('Test accuracy:', lr.score(X_test_std, y_test))
```

```
Training accuracy: 0.697083434885
Test accuracy: 0.695392214207
```

In [201]:
```
def drop_columns_for_knn_women(df):
    df.drop('OFFGENERAL', axis=1, inplace=True)
    df.drop('ADMITYR', axis=1, inplace=True)
    df.drop('AGEADMIT', axis=1, inplace=True)
    df.drop('RACE', axis=1, inplace=True)
    df.drop('OFFDETAIL', axis=1, inplace=True)
    df.drop('PROJ_PRISREL_YEAR', axis=1, inplace=True)
    df.drop('AGERELEASE', axis=1, inplace=True)

    return df
```

In [202]:
```
female_df = drop_columns_for_knn_women(female_df)
```

In [219]:
```
%%time
X, y = female_df.iloc[:, 1:].values, female_df.iloc[:, 0].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, ra
stdsc = StandardScaler()
X_train_std = stdsc.fit_transform(X_train)
X_test_std = stdsc.transform(X_test)
knn = KNeighborsClassifier(n_neighbors=19)
sbs = SBS(knn, k_features=8)
sbs.fit(X_train_std, y_train)
```

```
CPU times: user 2.28 s, sys: 32.5 ms, total: 2.31 s
Wall time: 2.4 s
```

In [220]:
```
sbs.scores_
```

Out[220]:
```
[0.76394562876030603]
```

Overall I am a little dissapointed that my results weren't more accurate. I do think machine learning presents interesting moral questions. Such as would it be acceptable to use an algorithm like this? How should it be used? How accurate does it need to be? It turns out that many states are currently using machine learning to help make parole decisions.

More information can be found here

http://www.wsj.com/articles/SB10001424052702304626104579121251595240852
(http://www.wsj.com/articles/SB10001424052702304626104579121251595240852)

Actual software company

http://www.northpointeinc.com/products/northpointe-software-suite
(http://www.northpointeinc.com/products/northpointe-software-suite)

I think that additional data about the prisoners, as well as more accurate data would provide more accurate results. Northpointe uses a survey that they have prisoners fill out as well as some additional data.

In [ ]:

```
```