Modeling Feature Subsets

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set_context('poster')
import random
from sklearn.preprocessing import StandardScaler
```

In [2]:
```
from project_helper import *
```

Separate Data Subsets

In [3]:
```
# read source data
df = pd.DataFrame.from_csv('../data/merged/all_data_2006_to_2016.csv', index_col=None)
```

In [4]:
```
# seed for consistent splits
random.seed(1636)

# all idxs
idxs = list(range(len(df)))

# shuffle and split
random.shuffle(idxs)
split = int(len(idxs)*0.7)
train_all = idxs[:split]
test_all = idxs[split:]

# idxs of outliers
outlier_idxs = list((df.MSA_abbr == 'NEW_ORLEANS_LA').nonzero()[0])
outlier_idxs += list(((df.MSA_abbr == 'MEMPHIS_TN') & (df.year == 2016)).nonzero()[0])
outlier_idxs += list(((df.MSA_abbr == 'BATON_ROUGE_LA') & (df.year == 2007)).nonzero()[0])

# cleaned idxs
train_idxs = [idx for idx in train_all if idx not in outlier_idxs]
test_idxs = [idx for idx in test_all if idx not in outlier_idxs]
```

In [5]:
```
# get labels because these don't need to change

label = 'murder_per_100_k'
y = df[label]

y_train = y.iloc[train_idxs]
y_test = y.iloc[test_idxs]

print('Train Len:\t {} \nTest Len:\t {}'.format(len(y_train),len(y_test)))
```

```
Train Len:       640
Test Len:        276
```

MSA + Year

In [6]:
```
# select only relevant features
msa_yr_cols = ['MSA_abbr','year']
x_msa_yr_df = df[msa_yr_cols]

# one-hot encoding of MSAs
x_msa_yr_dummies = pd.get_dummies(x_msa_yr_df['MSA_abbr'])

# rescale year for approx [0.1 , 1.0] to resemble MSA encoding scale
x_msa_yr_year = (x_msa_yr_df['year']-2005)/11

# combine new features
x_msa_yr = pd.concat([x_msa_yr_dummies, x_msa_yr_year], axis=1)

# train test split
x_train_msayr = x_msa_yr.iloc[train_idxs]
x_test_msayr = x_msa_yr.iloc[test_idxs]

print('Train X and y match: {}'.format(len(x_train_msayr)==len(y_train)))
print('Test  X and y match: {}'.format(len(x_test_msayr)==len(y_test)))
print('\nNumber of Predictors: {}'.format(len(x_train_msayr.columns)))
```

```
Train X and y match: True
Test  X and y match: True

Number of Predictors: 107
```

MSA + Year + Features

In [7]:
```
# drop irrelevant columns
x_features_df = df.drop(['MSA_orig', 'MSA_corr', 'MSA_abbr', 'year','murder_per_100_k'], axis=1)

# standardize, fitting only on training rows
standardizer = StandardScaler().fit(x_features_df.iloc[train_idxs])
x_features = pd.DataFrame(standardizer.transform(x_features_df), columns=x_features_df.columns)

# combine with previous MSA encodings and year
x_feats_msa_yr = pd.concat([x_features, x_msa_yr], axis=1)

# train test split
x_train_featmsayr = x_feats_msa_yr.iloc[train_idxs]
x_test_featmsayr = x_feats_msa_yr.iloc[test_idxs]

print('Train X and y match: {}'.format(len(x_train_featmsayr)==len(y_train)))
print('Test  X and y match: {}'.format(len(x_test_featmsayr)==len(y_test)))
print('\nNumber of Predictors: {}'.format(len(x_train_featmsayr.columns)))
```

```
Train X and y match: True
Test  X and y match: True

Number of Predictors: 115
```

Features + Year

In [8]:
```
# combine relevant columns from previous subsets
x_feats_yr = pd.concat([x_features, x_msa_yr_year], axis=1)

# train test split
x_train_featyr = x_feats_yr.iloc[train_idxs]
x_test_featyr = x_feats_yr.iloc[test_idxs]

print('Train X and y match: {}'.format(len(x_train_featyr)==len(y_train)))
print('Test  X and y match: {}'.format(len(x_test_featyr)==len(y_test)))
print('\nNumber of Predictors: {}'.format(len(x_train_featyr.columns)))

print('\nFEATURE NAMES:')
for name in x_train_featyr.columns:
    print(' -'+name)
```

```
Train X and y match: True
Test  X and y match: True

Number of Predictors: 9

FEATURE NAMES:
 -now_married_except_separated
 -less_than_high_school_diploma
 -unmarried_portion_of_women_15_to_50_years_who_had_a_birth_in_past_12_months
 -households_with_food_stamp_snap_benefits
 -percentage_married-couple_family
 -percentage_female_householder_no_husband_present_family
 -poverty_all_people
 -house_median_value_(dollars)
 -year
```

Fitting The Models

In [9]:
```
from sklearn.linear_model import LinearRegression, RidgeCV, LassoCV, BayesianRidge, HuberRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.neural_network import MLPRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.svm import SVR
```

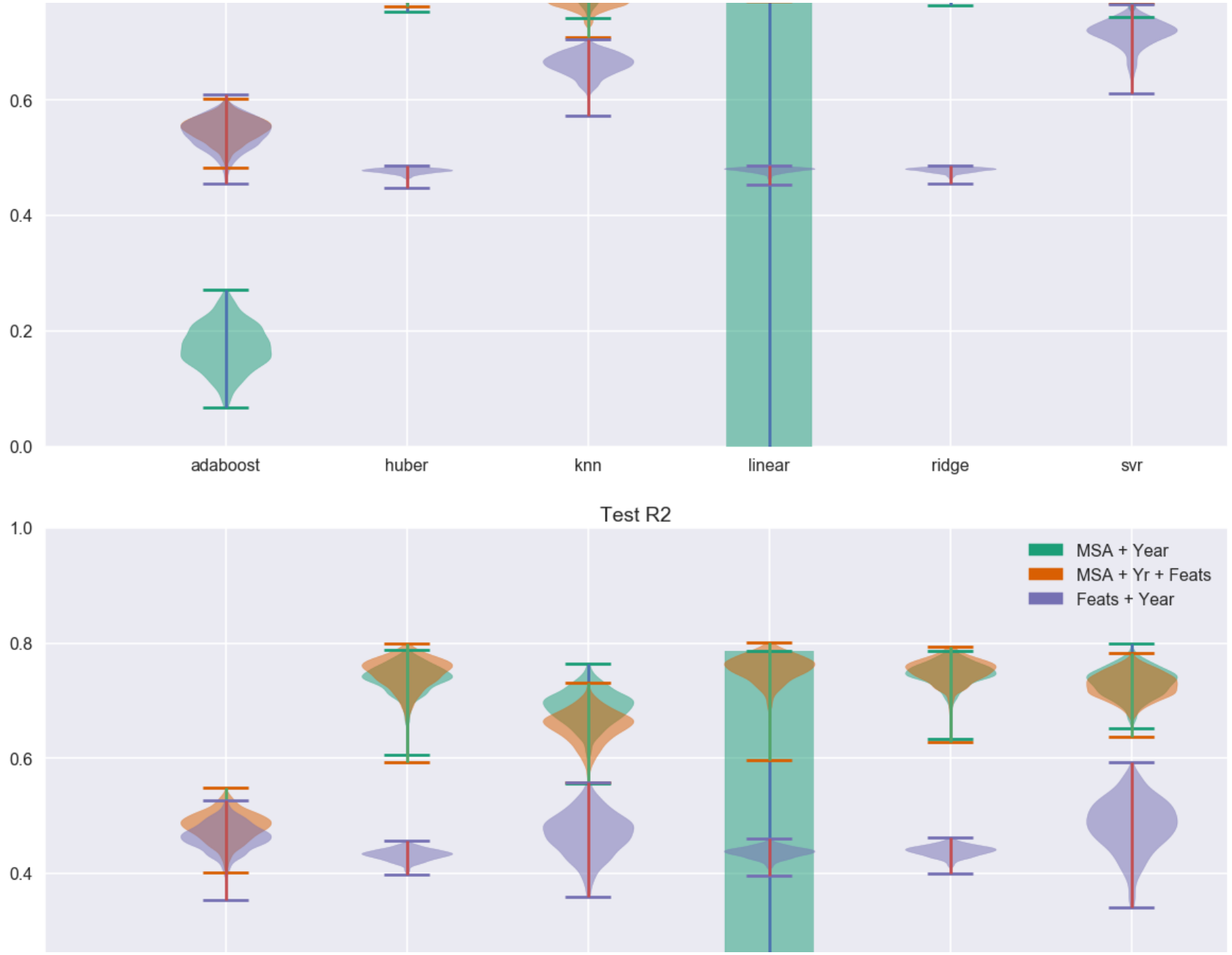
In [10]:
```
# instantiate and fit models
def make_models(x_train, y_train):
    md = dict()

    md['linear'] = LinearRegression().fit(x_train, y_train)
    md['ridge'] = RidgeCV(cv=5).fit(x_train, y_train)
    md['huber'] = GridSearchCV(HuberRegressor(),{'epsilon': [1.0,1.2,1.4,1.6,1.8]}, n_jobs=-1).fit(x
    md['knn'] = GridSearchCV(KNeighborsRegressor(),{'n_neighbors':[5,10,20,40]}, n_jobs=-1).fit(x_tr
    md['adaboost'] = GridSearchCV(AdaBoostRegressor(), {'learning_rate':[0.1,0.3,0.6,1.0]}, n_jobs=-
    md['svr'] = GridSearchCV(SVR(), {'C':[0.01,0.1,1,10,100],'epsilon':[0.001,0.01,0.1,1,10]}, n_job

    return md
```

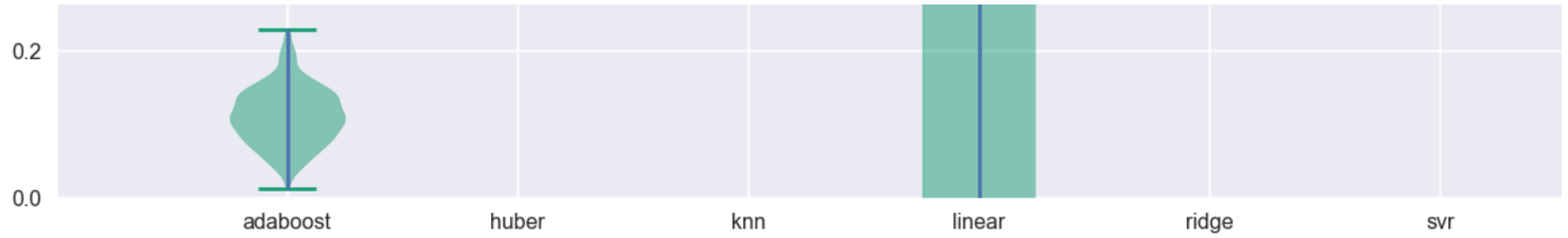
In [11]:
```
# MSA + Year
exp_1 = run_experiment(make_models, 599, x_train_msayr, y_train, x_test_msayr, y_test)
print('1: Done')

# MSA + Year + Features
exp_2 = run_experiment(make_models, 599, x_train_featmsayr, y_train, x_test_featmsayr, y_test)
print('2: Done')

# Features + Year
exp_3 = run_experiment(make_models, 599, x_train_featyr, y_train, x_test_featyr, y_test)
print('3: Done')
```

```
/Users/davidloving/anaconda3/envs/tf-gpu/lib/python3.6/site-packages/scipy/linalg/basic.py:1226:
RuntimeWarning: internal gelsd driver lwork query error, required iwork dimension not returned. T
his is likely the result of LAPACK bug 0038, fixed in LAPACK 3.2.2 (released July 21, 2010). Fall
ing back to 'gelss' driver.
  warnings.warn(mesg, RuntimeWarning)

1: Done
2: Done
3: Done
```

Accuracy Results

In [12]:
```
violin_plots([exp_1, exp_2, exp_3],
             ['Train R2','Test R2'],
             experiment_name=['MSA + Year','MSA + Yr + Feats','Feats + Year'],
             center_zero=False)
```


0.6
0.4
0.2
0.0
adaboost
huber
knn
linear
ridge
svr
Test R2
1.0
0.8
0.6
0.4
MSA + Year
MSA + Yr + Feats
Feats + Year


0.2
0.0
adaboost
huber
knn
linear
ridge
svr