CALIFORNIA HOUSING PRICES

A Data Science Project by Pulkit Mehta

LIBRARIES

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib as mpl
from sklearn.linear_model import LinearRegression
import warnings
warnings.simplefilter("ignore")
```

EDA

DATA LOAD

In [2]:
```
data=pd.read_csv("housing.csv")
```

In [3]:
```
data.head()
```

Out[3]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

In [4]:
```
data.total_bedrooms.mean()
```

Out[4]:
```
537.8705525375618
```

DATA INFO

In [5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
longitude             20640 non-null float64
latitude              20640 non-null float64
housing_median_age    20640 non-null float64
total_rooms           20640 non-null float64
total_bedrooms        20433 non-null float64
population            20640 non-null float64
households            20640 non-null float64
median_income         20640 non-null float64
median_house_value    20640 non-null float64
ocean_proximity       20640 non-null object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

In [6]:
```
data.describe()
```

Out[6]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	3.870671	206855.816909
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	1.899822	115395.615874
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	0.499900	14999.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	2.563400	119600.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	3.534800	179700.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	4.743250	264725.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	15.000100	500001.000000

In [7]:
```
data.columns
```

Out[7]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value', 'ocean_proximity'],
      dtype='object')
```

CHECK AND FILLING MISSING VALUES

In [8]:
```
def check_counts():
    plt.figure(figsize=(10,5))
    plt.title("Missing Values")
    for col in data.columns:
        print(data[col].isnull().value_counts())
        plt.barh(col,data[col].isnull().value_counts())
    plt.yticks(range(10),data.columns)
    plt.ylabel("Features")
    plt.xlabel("Samples Count")
    plt.xlim(20000,20700)
    plt.show()
```

In [9]:
```
check_counts()
```

```
False    20640
Name: longitude, dtype: int64
False    20640
Name: latitude, dtype: int64
False    20640
Name: housing_median_age, dtype: int64
False    20640
Name: total_rooms, dtype: int64
False    20433
True       207
Name: total_bedrooms, dtype: int64
False    20640
Name: population, dtype: int64
False    20640
Name: households, dtype: int64
False    20640
Name: median_income, dtype: int64
False    20640
Name: median_house_value, dtype: int64
False    20640
Name: ocean_proximity, dtype: int64
```

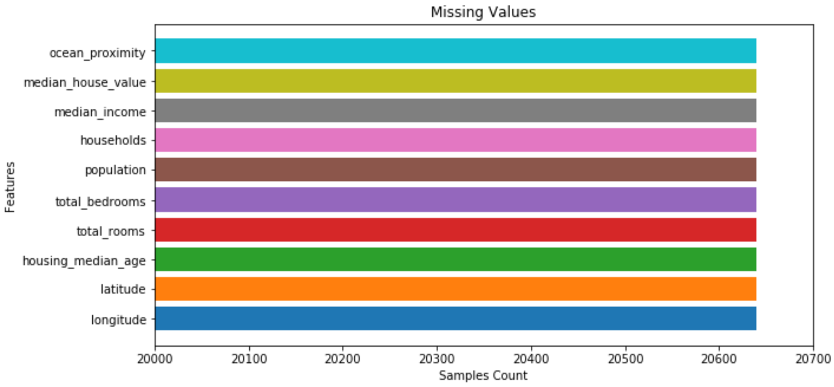
In [10]:
```
data.total_bedrooms=data.total_bedrooms.fillna(data.total_bedrooms.mean())
```

In [11]:
```
data.total_bedrooms.isnull().value_counts()
```

Out[11]:
```
False    20640
Name: total_bedrooms, dtype: int64
```

In [12]:
```
check_counts()
```

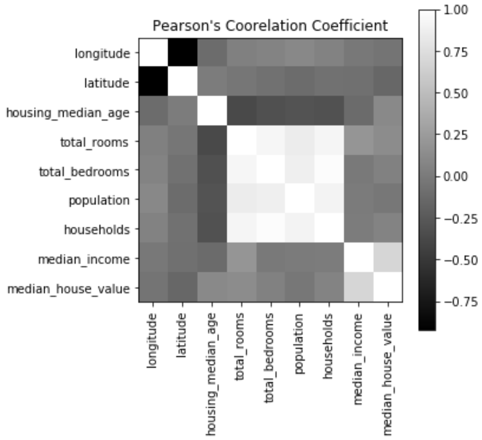
```
False    20640
Name: longitude, dtype: int64
False    20640
Name: latitude, dtype: int64
False    20640
Name: housing_median_age, dtype: int64
False    20640
Name: total_rooms, dtype: int64
False    20640
Name: total_bedrooms, dtype: int64
False    20640
Name: population, dtype: int64
False    20640
Name: households, dtype: int64
False    20640
Name: median_income, dtype: int64
False    20640
Name: median_house_value, dtype: int64
False    20640
Name: ocean_proximity, dtype: int64
```



DATA VISUALIZATIONS

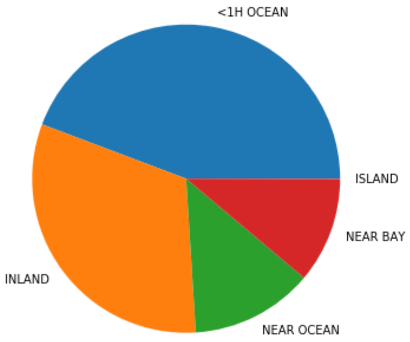
1. COORELATED FEATURES

In [13]:
```
plt.figure(figsize=(5,5))
plt.title("Pearson's Coorelation Coefficient")
plt.imshow(data.corr().values, cmap='gray')
plt.colorbar()
plt.xticks((range(9)),data.columns,rotation=90)
plt.yticks((range(9)),data.columns)
plt.show()
```



2. OCEAN PROXIMITY PIE REPRESENTATION

In [14]:
```
plt.figure(figsize=(6,6))
plt.pie(data.ocean_proximity.value_counts().values, labels=data.ocean_proximity.value_counts().keys())
plt.show()
```



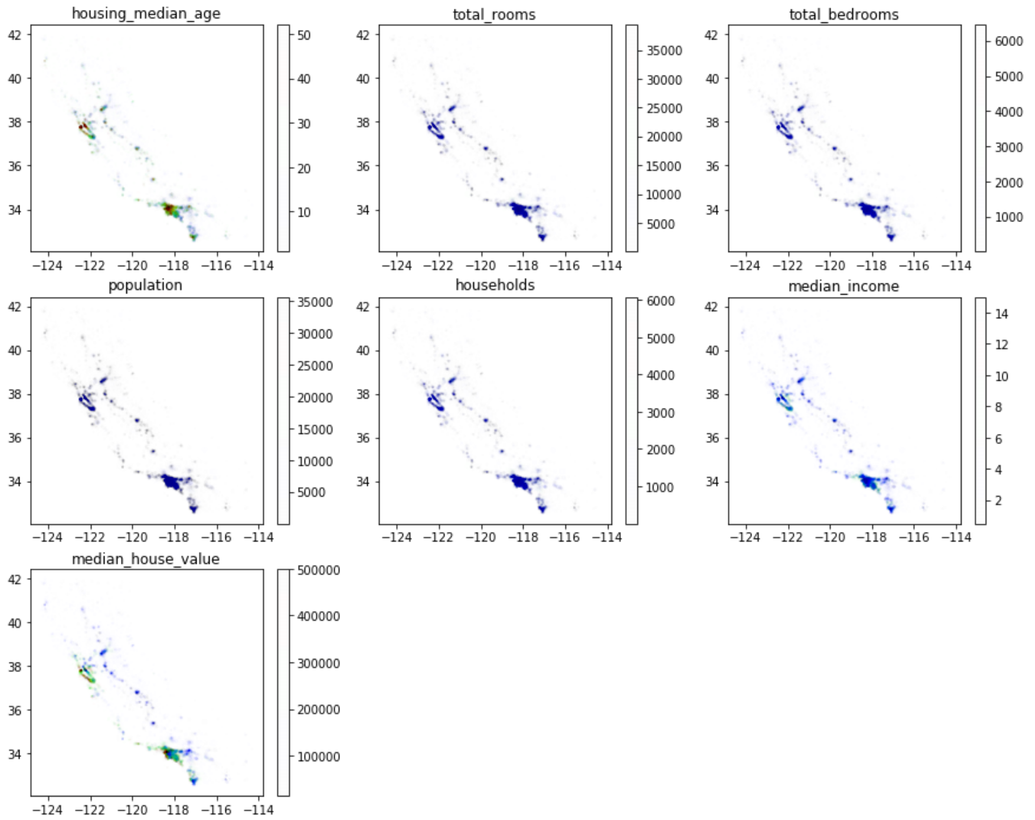
3. DATA VISUALISATION ON LAT-LONG

In [15]:
```
def area_dist(var,density):
    plt.scatter(data.longitude.values,data.latitude.values,c=var,s=data.population.values/500,
                cmap=plt.get_cmap('jet'),alpha=density)
    plt.colorbar()
```

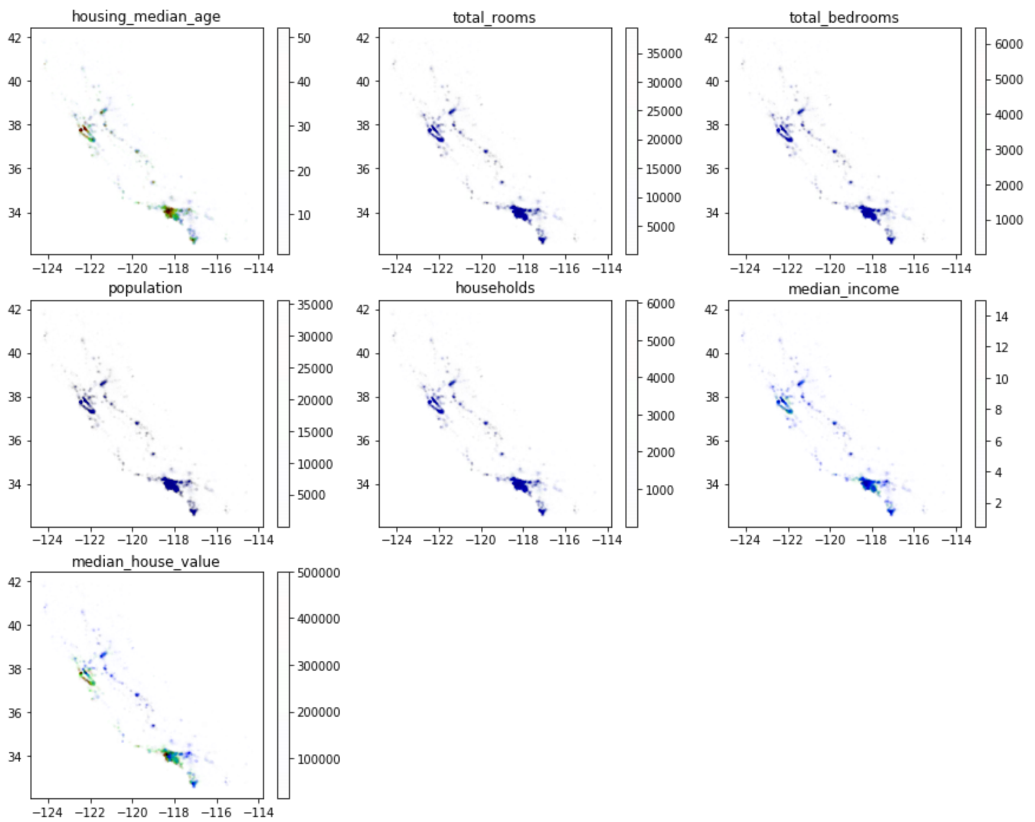
In [16]:
```
plot_vars=['housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value']
def plot_dist(density):
    print("Density:",density)
    density=density
    plt.figure(figsize=(15,12))
    for col in plot_vars:
        plt.subplot(3,3,plot_vars.index(col)+1)
        plt.title(col)
        area_dist(data[col],density)
    plt.show()
```

In [17]:
```python
for d in [0.002,0.004,0.006,0.008,0.01,0.1,0.5,1.0]:
    print("Population on Latitude-Longitude")
    plot_dist(d)
    print("----------------------------------------------------------------------------------------------------")
```

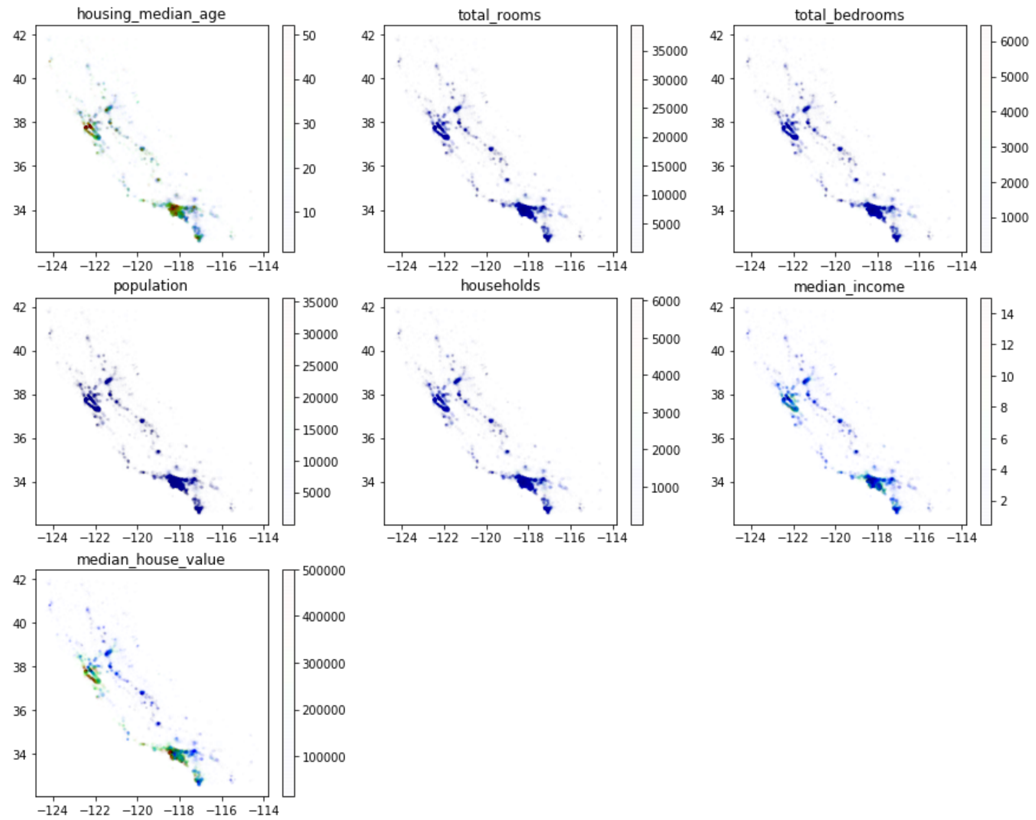
```
Population on Latitude-Longitude
Density: 0.002
```



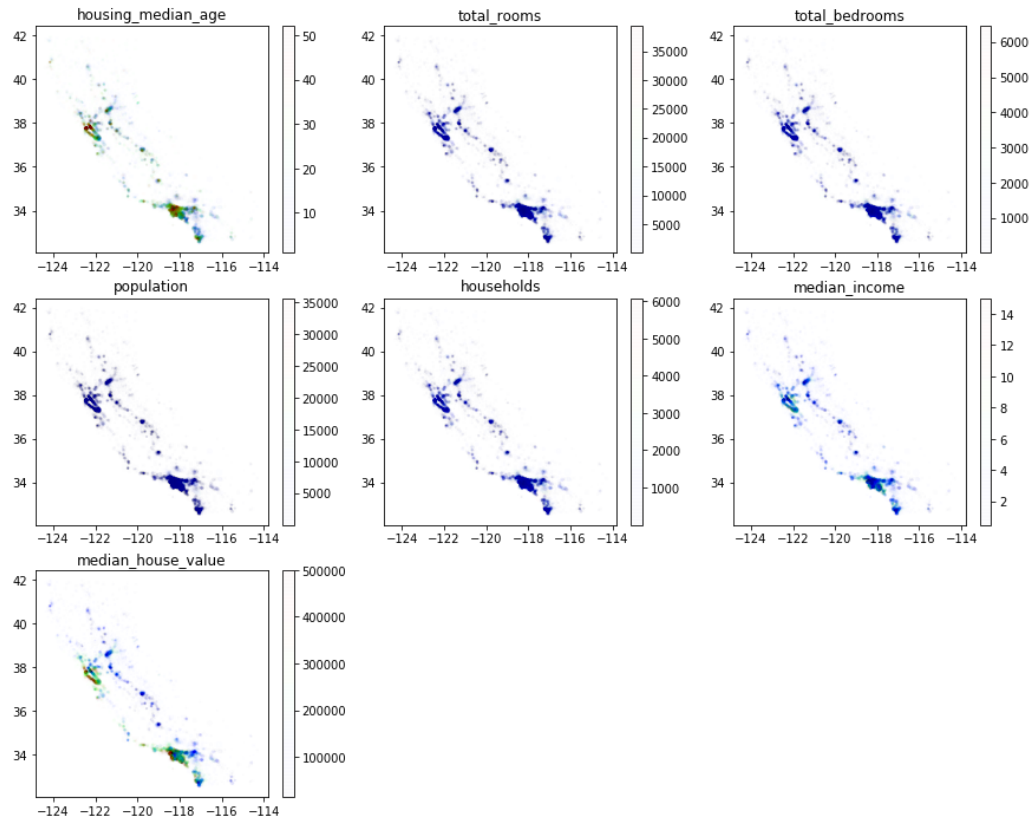

```
----------------------------------------------------------------------------------------------------
Population on Latitude-Longitude
Density: 0.004
```



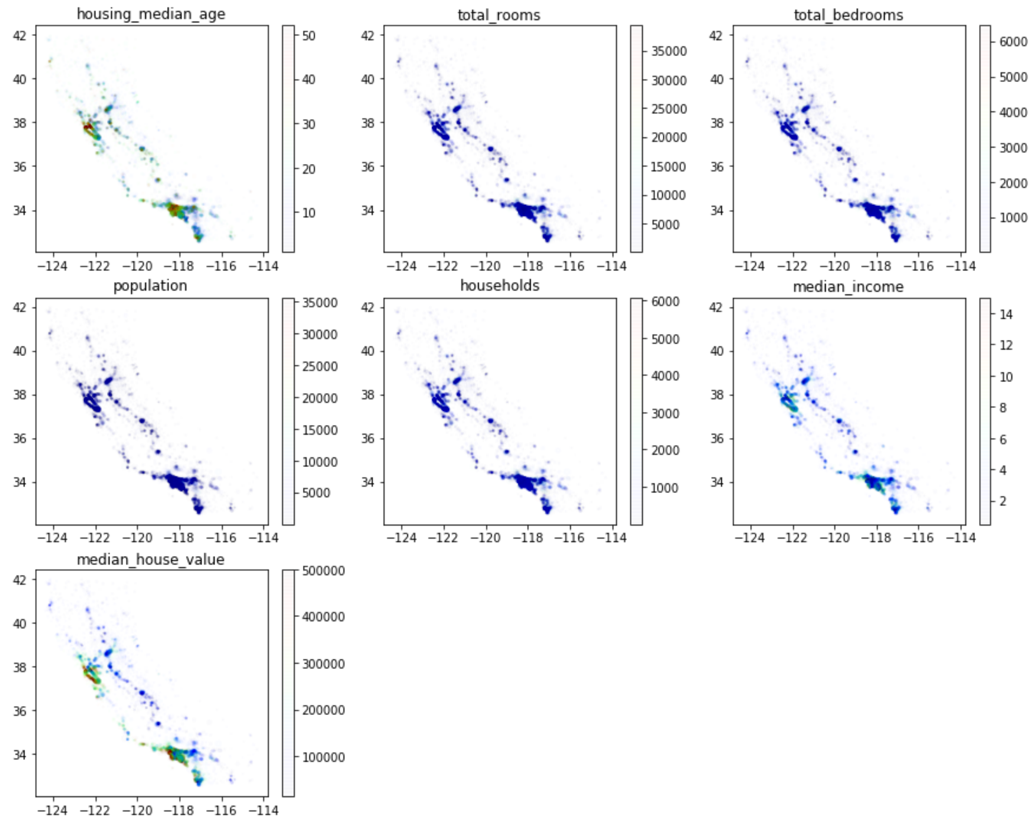

```
----------------------------------------------------------------------------------------------------
Population on Latitude-Longitude
Density: 0.006
```



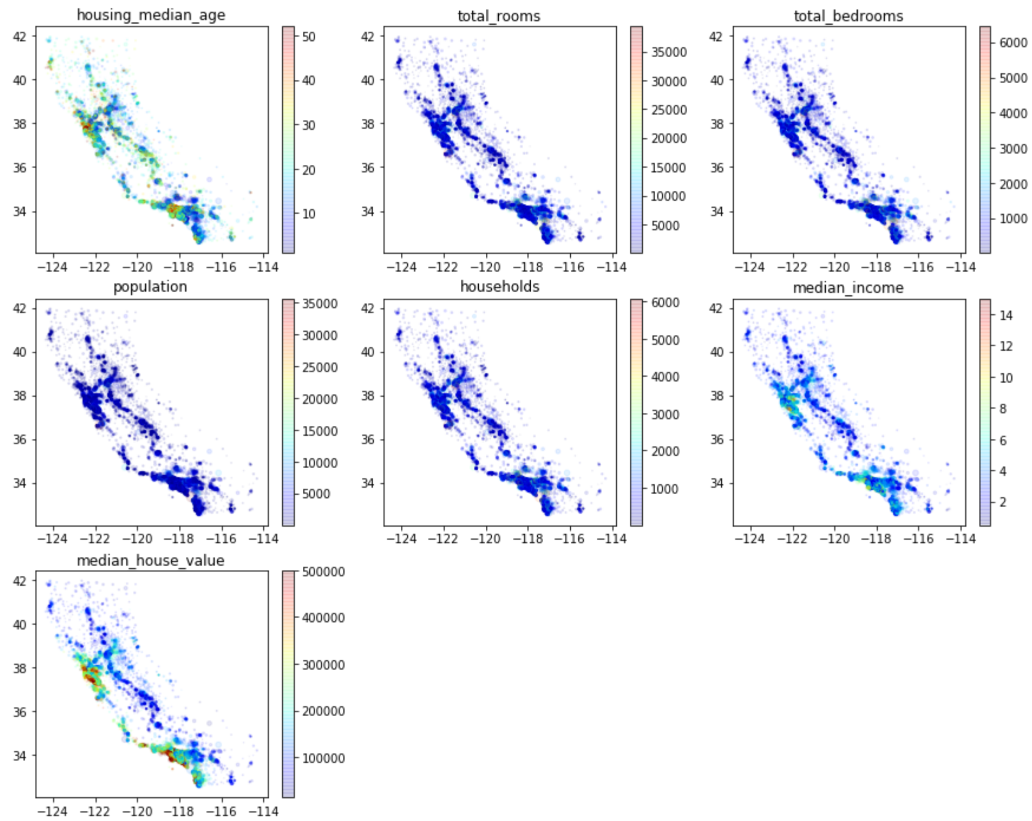

```
----------------------------------------------------------------------------------------------------
Population on Latitude-Longitude
Density: 0.008
```



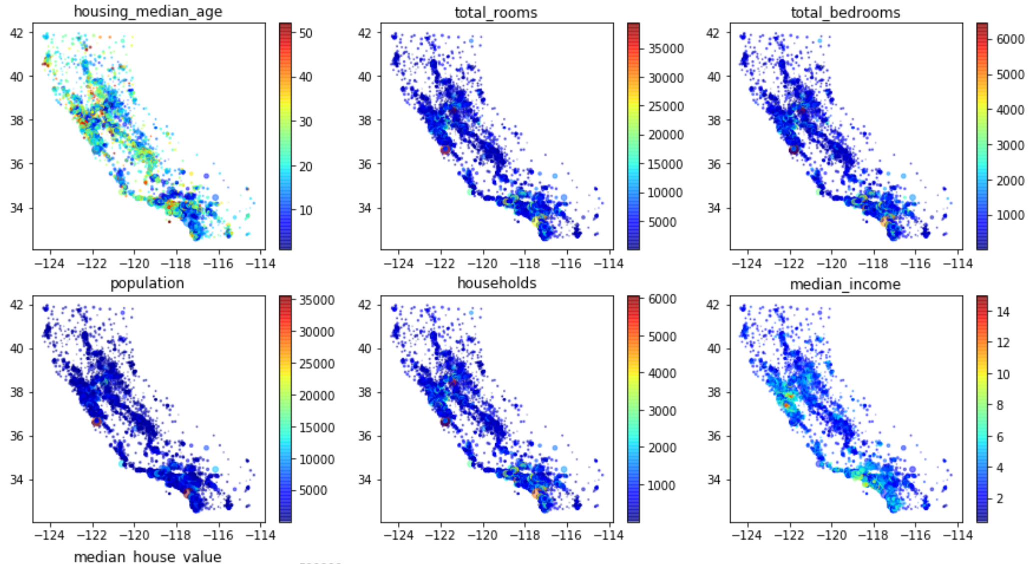

```
----------------------------------------------------------------------------------------------------
Population on Latitude-Longitude
Density: 0.01
```



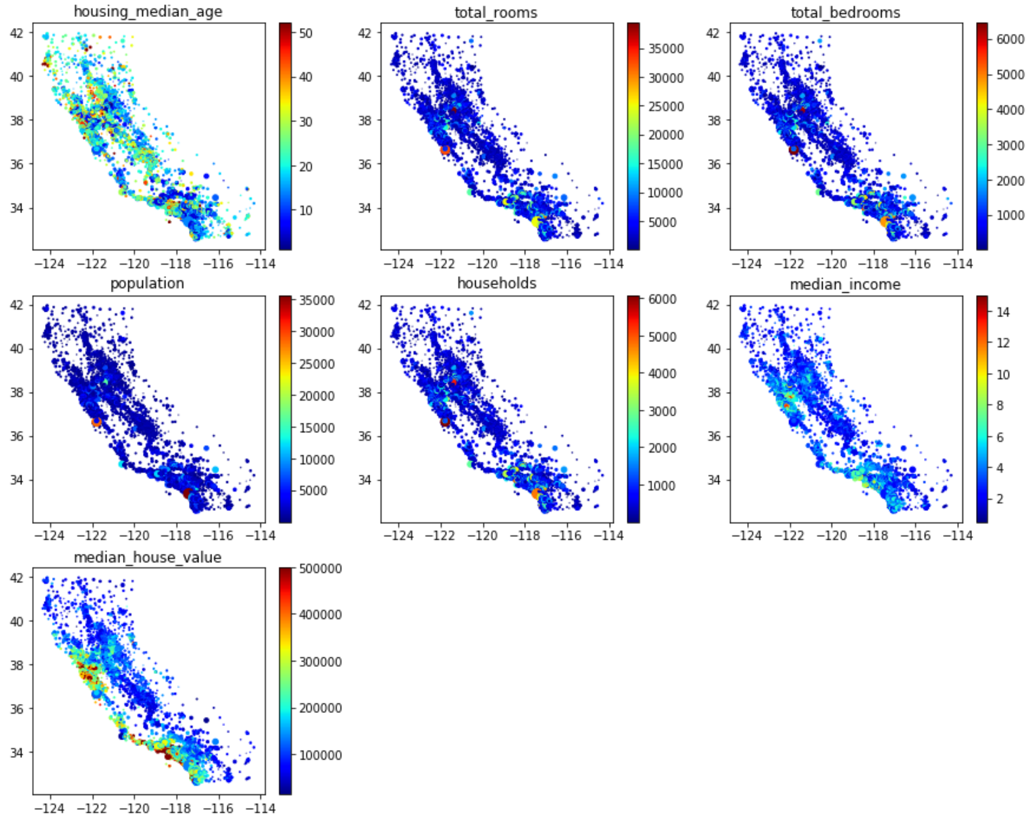

```
----------------------------------------------------------------------------------------------------
Population on Latitude-Longitude
Density: 0.1
```




```
----------------------------------------------------------------------------------------------------
Population on Latitude-Longitude
Density: 0.5
```



Population on Latitude-Longitude
Density: 1.0



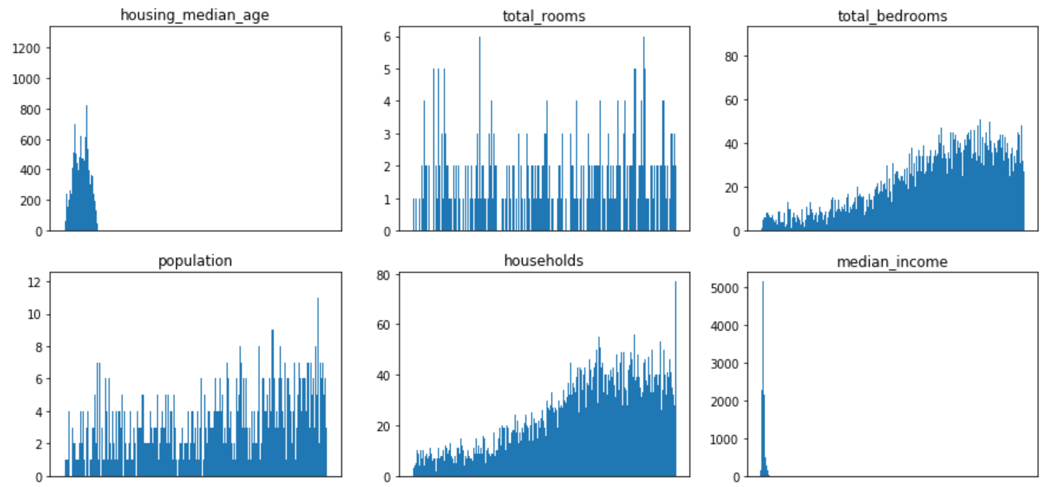
---

4. HISTOGRAMS

In [18]:
```
data.columns[2:-2]
```

Out[18]:
```
Index(['housing_median_age', 'total_rooms', 'total_bedrooms', 'population',
       'households', 'median_income'],
      dtype='object')
```

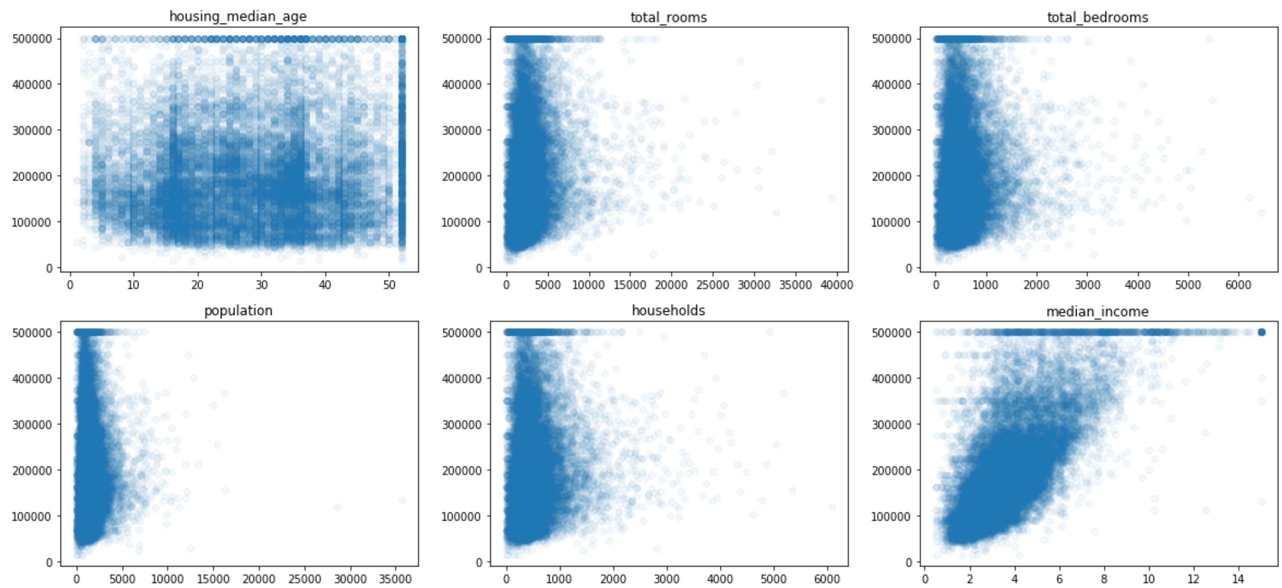
In [19]:
```
bins=400
plt.figure(figsize=(15,7))
for plot in range(1,7):
    plt.subplot(2,3,plot)
    plt.hist(data[(data.columns[2:-2].values)[plot-1]], bins=range(bins))
    plt.xticks(())
    plt.title((data.columns[2:-2].values)[plot-1])
plt.show()
```



5. MEDIAN HOUSE VALUE DISTRIBUTIONS

In [20]:
```
print("Median House Value Distribution:")
plt.figure(figsize=(20,14))
for col in plot_vars[:-1]:
    plt.subplot(3,3,(plot_vars.index(col))+1)
    plt.title(col)
    plt.scatter(data[col].values, data.median_house_value.values, alpha=0.05)
plt.show()
```

```
Median House Value Distribution:
```

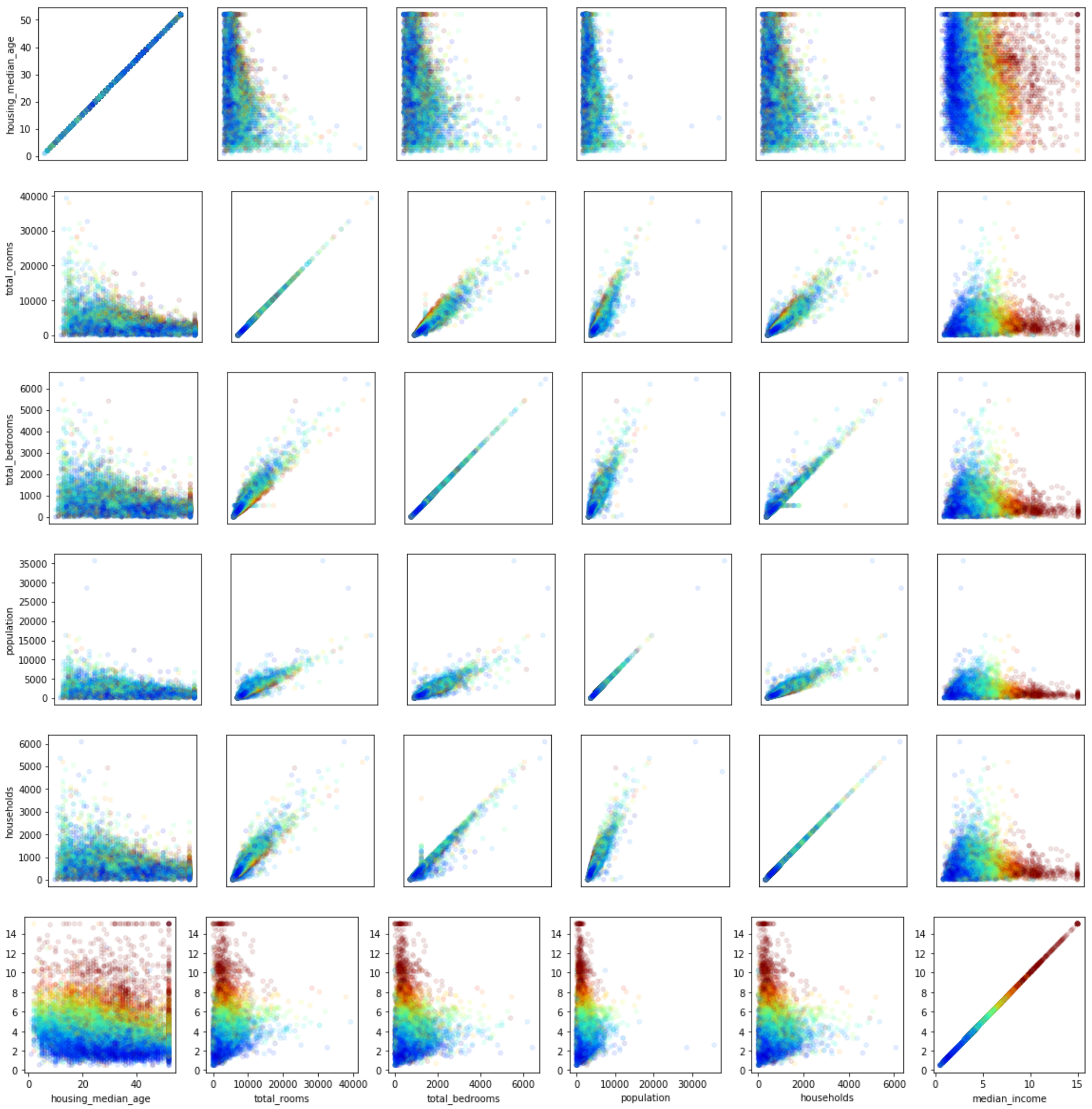


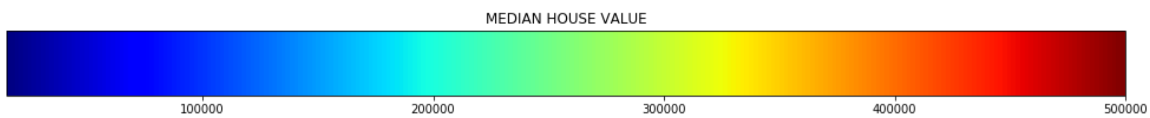
6. INTER-FEATURES PLOTS (HEATMAPPED over MEDIAN HOUSE VALUE)

In [21]:
```python
plot_vars[:-1]
```

Out[21]:
```
['housing_median_age',
 'total_rooms',
 'total_bedrooms',
 'population',
 'households',
 'median_income']
```

In [22]:
```
for col in plot_vars[:-1]:
    plt.figure(figsize=(20,3))
    plt.ylabel(col)
    for col1 in plot_vars[:-1]:
        plt.subplot(1,6,(plot_vars.index(col1))+1)
        plt.scatter(data[col1].values,data[col].values,
                    s=20,cmap=plt.get_cmap('jet'),c=data.median_house_value.values, alpha=0.1)
        if (plot_vars.index(col1))%6==0 and (plot_vars.index(col))!=5:
            plt.ylabel(col)
            plt.xticks(())
        elif (plot_vars.index(col))==5:
            plt.xlabel(col1)
        else:
            plt.xticks(())
            plt.yticks(())
    plt.show()
norm = mpl.colors.Normalize(vmin=data.median_house_value.min(), vmax=data.median_house_value.max())
fig, ax = plt.subplots(figsize=(17, 2))
plt.title("MEDIAN HOUSE VALUE")
fig.subplots_adjust(bottom=0.5)
cb1 = mpl.colorbar.ColorbarBase(ax,cmap=plt.get_cmap('jet'),
                                norm=norm,
                                orientation='horizontal')
plt.show()
```





DATA PREPRATION

In [23]:
```
data_dummies=pd.get_dummies(data)
```

In [24]:
```
data_dummies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 14 columns):
longitude                     20640 non-null float64
latitude                      20640 non-null float64
housing_median_age            20640 non-null float64
total_rooms                   20640 non-null float64
total_bedrooms                20640 non-null float64
population                    20640 non-null float64
households                    20640 non-null float64
median_income                 20640 non-null float64
median_house_value            20640 non-null float64
ocean_proximity_<1H OCEAN     20640 non-null uint8
ocean_proximity_INLAND        20640 non-null uint8
ocean_proximity_ISLAND        20640 non-null uint8
ocean_proximity_NEAR BAY      20640 non-null uint8
ocean_proximity_NEAR OCEAN    20640 non-null uint8
dtypes: float64(9), uint8(5)
memory usage: 1.5 MB
```

In [25]:
```
X=data_dummies.drop(columns='median_house_value').values
```

In [26]:
```
y=data_dummies['median_house_value'].values
```

In [27]:
```
X.shape, y.shape
```

Out[27]:
```
((20640, 13), (20640,))
```

In [28]:
```
from sklearn.model_selection import train_test_split
```

In [29]:
```
X_train,X_test, y_train, y_test= train_test_split(X,y, test_size=0.25, random_state=4)
```

In [30]:
```
X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

Out[30]:
```
((15480, 13), (15480,), (5160, 13), (5160,))
```

MODELS SELECTION

LIBRARIES

In [31]:
```
from sklearn.linear_model import LinearRegression , Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
```

PARAMETER GRIDS

In [32]:
```
param_grid_ridge= {
    'alpha': [0.001,0.01,0.1,1.0,10.0,100.0,1000]
}
param_grid_lasso= {
    'alpha': [0.001,0.01,0.1,1.0,10.0,100.0,1000]
}
param_grid_rfr={
    'n_estimators':[100]
}
param_grid_dtr={
}
```

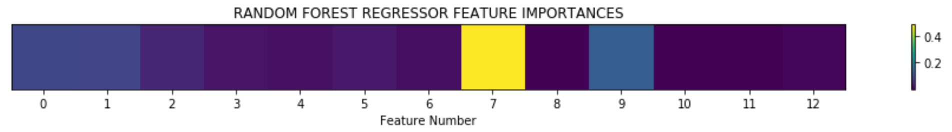
In [33]:
```
lr=LinearRegression()
grid_ridge= GridSearchCV(Ridge(), param_grid=param_grid_ridge,cv=5,n_jobs=-1)
grid_lasso= GridSearchCV(Lasso(), param_grid=param_grid_lasso,cv=5,n_jobs=-1)
grid_rfr=GridSearchCV(RandomForestRegressor(), param_grid=param_grid_rfr, cv=2, n_jobs=-1)
grid_dtr=GridSearchCV(DecisionTreeRegressor(), param_grid=param_grid_dtr, cv=2, n_jobs=-1)
```

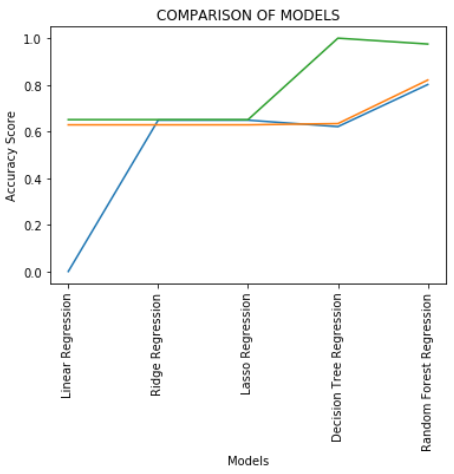
UNIVERSAL MODEL SELECTION FUNCTION

In [34]:
```
def select_model(a,b,c,d):
    models=[
        'Linear Regression',
        'Ridge Regression',
        'Lasso Regression',
        'Decision Tree Regression',
        'Random Forest Regression'
    ]
    lr.fit(a,b)
    grid_ridge.fit(a,b)
    grid_lasso.fit(a,b)
    grid_dtr.fit(a,b)
    grid_rfr.fit(a,b)
    te=[
        lr.score(c,d),
        (grid_ridge.best_estimator_.fit(a,b)).score(c,d),
        (grid_lasso.best_estimator_.fit(a,b)).score(c,d),
        (grid_dtr.best_estimator_.fit(a,b)).score(c,d),
        (grid_rfr.best_estimator_.fit(a,b)).score(c,d),
    ]
    tr=[
        lr.score(a,b),
        (grid_ridge.best_estimator_.fit(a,b)).score(a,b),
        (grid_lasso.best_estimator_.fit(a,b)).score(a,b),
        (grid_dtr.best_estimator_.fit(a,b)).score(a,b),
        (grid_rfr.best_estimator_.fit(a,b)).score(a,b),
    ]
    cv=[
        0,
        grid_ridge.best_score_,
        grid_lasso.best_score_,
        grid_dtr.best_score_,
        grid_rfr.best_score_,
    ]
    print(
         "\n================================================================================"
         "\nLinear Regression Test Score:", te[0],
         "\nLinear Regression Train Score:", tr[0],
         "\n\nRidge CV Score:", cv[1],
         "\nRidge Regression Test Score:", te[1],
         "\nRidge Regression Train Score:", tr[1],
         "\n\nLasso CV Score:", cv[2],
         "\nLasso Regression Test Score:", te[2],
         "\nLasso Regression Train Score:", tr[2],
         "\n\nDescision Tree Regression CV Score:", cv[3],
         "\nDescision Tree Regression Test Score:", te[3],
         "\nDescision Tree Regression Train Score:", tr[3],
         "\n\nRandom Forest Regression CV Score:", cv[4],
         "\nRandom Forest Regression Test Score:", te[4],
         "\nRandom Forest Regression Train Score:", tr[4],
         "\n\n\n BEST PARAMETERS USED:",
         "\n\nRidge:\n",grid_ridge.best_estimator_,
         "\n\nLasso:\n",grid_lasso.best_estimator_,
         "\n\nDescision Tree:\n",grid_dtr.best_estimator_,
         "\n\nRandom Forest:\n",grid_rfr.best_estimator_,
         "\n================================================================================\n"
    )
    plt.figure(figsize=(20,1))
    plt.title("RANDOM FOREST REGRESSOR FEATURE IMPORTANCES")
    plt.imshow((grid_rfr.best_estimator_).feature_importances_.reshape(1,-1))
    plt.colorbar()
    plt.xticks((range(a.shape[1])))
    plt.yticks(())
    plt.xlabel("Feature Number")
    plt.show()

    plt.figure()
    plt.title("COMPARISON OF MODELS")
    plt.plot(cv)
    plt.plot(te)
    plt.plot(tr)
    plt.xticks((range(5)), models, rotation=90)
    plt.xlabel("Models")
    plt.ylabel("Accuracy Score")
    plt.show()
```

In [35]:
```
select_model(X_train,y_train,X_test,y_test)
```

```
=================================================================================
Linear Regression Test Score: 0.6285852376391966
Linear Regression Train Score: 0.6507474976953389

Ridge CV Score: 0.6485428497794921
Ridge Regression Test Score: 0.6285848387687865
Ridge Regression Train Score: 0.6507473345566142

Lasso CV Score: 0.6485420153767804
Lasso Regression Test Score: 0.6285844879316485
Lasso Regression Train Score: 0.6507472636660994

Descision Tree Regression CV Score: 0.6209151307001693
Descision Tree Regression Test Score: 0.6338757566556829
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.8012983280050056
Random Forest Regression Test Score: 0.8205594909365219
Random Forest Regression Train Score: 0.9748372410012166


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=0.1, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
=================================================================================
```





SCALING

In [36]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler
```

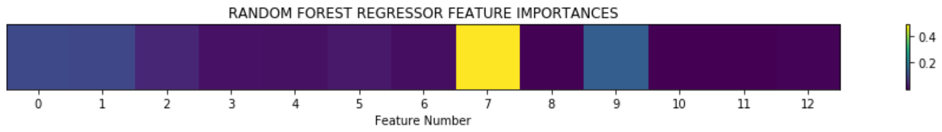
In [37]:
```
min_max= MinMaxScaler()
std = StandardScaler()
```

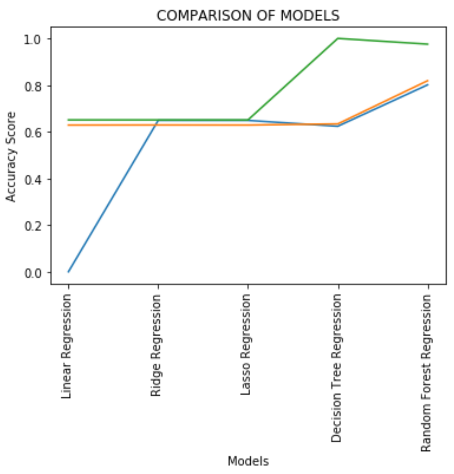
In [38]:
```
X_train_min_max= min_max.fit_transform(X_train)
X_test_min_max= min_max.transform(X_test)
X_train_std= std.fit_transform(X_train)
X_test_std= std.transform(X_test)
```

MIN MAX

In [39]:
```
select_model(X_train_min_max,y_train,X_test_min_max, y_test)
```

```
================================================================================
Linear Regression Test Score: 0.6285852376392
Linear Regression Train Score: 0.650747497695339

Ridge CV Score: 0.6487687728764551
Ridge Regression Test Score: 0.6289224570975358
Ridge Regression Train Score: 0.6506997599094235

Lasso CV Score: 0.6485602936079058
Lasso Regression Test Score: 0.6286629357886324
Lasso Regression Train Score: 0.6507456437311532

Descision Tree Regression CV Score: 0.6235562964513126
Descision Tree Regression Test Score: 0.6336578798743122
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.8010774920169474
Random Forest Regression Test Score: 0.8186593252148552
Random Forest Regression Train Score: 0.9754610954751917


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=0.1, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
================================================================================
```

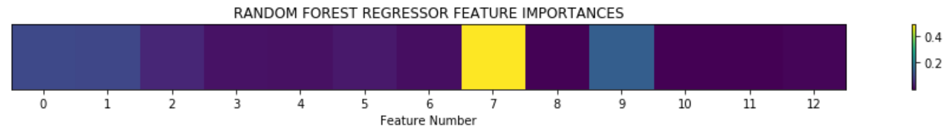


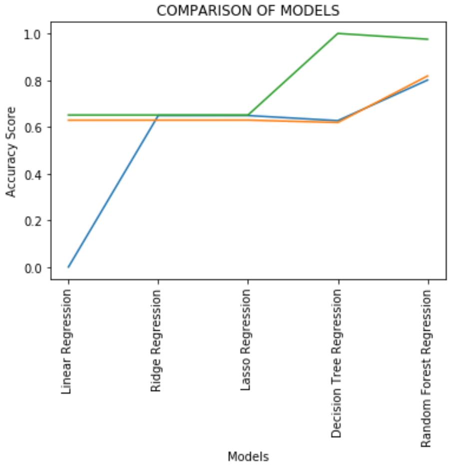


STANDARD

In [40]:
```
select_model(X_train_std,y_train,X_test_std, y_test)
```

```
================================================================================
Linear Regression Test Score: 0.6285852376391998
Linear Regression Train Score: 0.650747497695339

Ridge CV Score: 0.6485995438235158
Ridge Regression Test Score: 0.6287297455478296
Ridge Regression Train Score: 0.6507398011263401

Lasso CV Score: 0.6485502348983192
Lasso Regression Test Score: 0.6289658182053923
Lasso Regression Train Score: 0.6506625714703185

Descision Tree Regression CV Score: 0.6266299526886976
Descision Tree Regression Test Score: 0.6187747196536747
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.8005283915125816
Random Forest Regression Test Score: 0.8181321781367378
Random Forest Regression Train Score: 0.9753223744306578


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=10.0, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=100.0, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
================================================================================
```



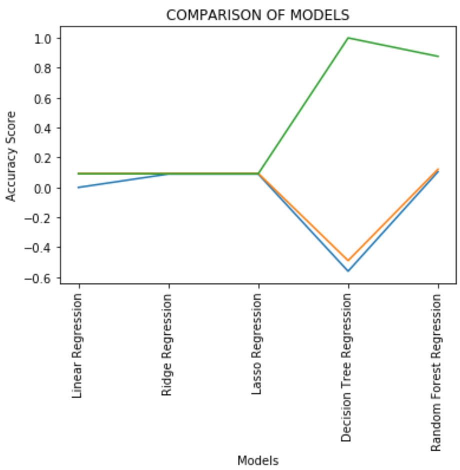


PCA

In [41]:
```
from sklearn.decomposition import PCA
```

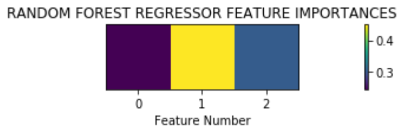
In [42]:
```
for n in range(2,11):
    print("\n\nComponents:",n)
    pca=PCA(n_components=n)
    X_train_pca=pca.fit_transform(X_train)
    X_test_pca=pca.transform(X_test)
    select_model(X_train_pca,y_train,X_test_pca,y_test)
```

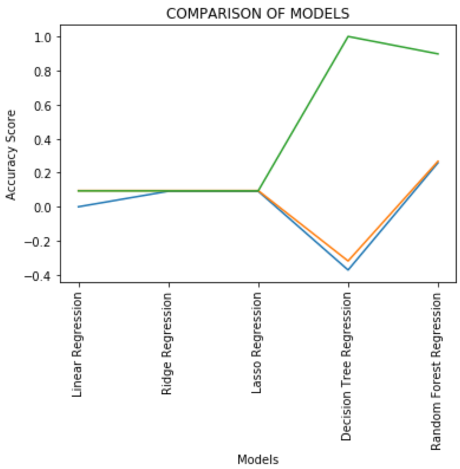
```


Components: 2

================================================================================
Linear Regression Test Score: 0.09365407312804952
Linear Regression Train Score: 0.09108290271753948

Ridge CV Score: 0.08946815301105958
Ridge Regression Test Score: 0.09365407309237428
Ridge Regression Train Score: 0.09108290271753527

Lasso CV Score: 0.08946835323768684
Lasso Regression Test Score: 0.09365404889594608
Lasso Regression Train Score: 0.09108290244383421

Descision Tree Regression CV Score: -0.5606472780157603
Descision Tree Regression Test Score: -0.48963290400021253
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.1049045904784493
Random Forest Regression Test Score: 0.12193729230930861
Random Forest Regression Train Score: 0.8766660993778383


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=1000, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=1000, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
================================================================================
```




```


Components: 3

================================================================================
Linear Regression Test Score: 0.09495554596732869
Linear Regression Train Score: 0.09338537708993744

Ridge CV Score: 0.09128465597014761
Ridge Regression Test Score: 0.0949555491694476
Ridge Regression Train Score: 0.09338537708992199
```

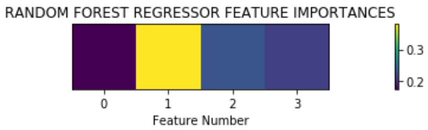
```
Lasso CV Score: 0.09128465333531527
Lasso Regression Test Score: 0.09495554596875244
Lasso Regression Train Score: 0.09338537708993744

Descision Tree Regression CV Score: -0.3713145803281776
Descision Tree Regression Test Score: -0.31835181445528327
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.2583943202894463
Random Forest Regression Test Score: 0.2671689498258898
Random Forest Regression Train Score: 0.8977682143488087


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=1000, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=0.001, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
================================================================================
```

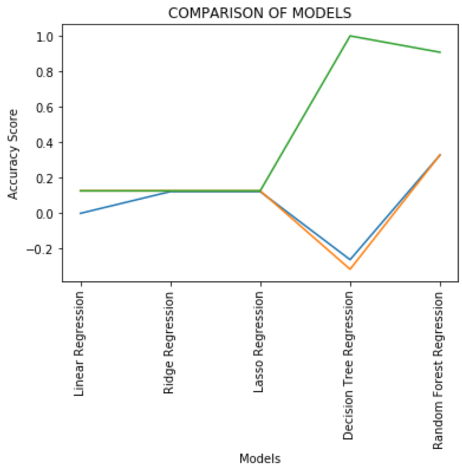





```
Components: 4

================================================================================
Linear Regression Test Score: 0.12691561629993198
Linear Regression Train Score: 0.12666711306502754

Ridge CV Score: 0.122507629802198
Ridge Regression Test Score: 0.12691559555604348
Ridge Regression Train Score: 0.1266671130538456

Lasso CV Score: 0.12250946648186048
Lasso Regression Test Score: 0.1269149124974518
Lasso Regression Train Score: 0.1266670890617526

Descision Tree Regression CV Score: -0.26137819720461
Descision Tree Regression Test Score: -0.3151267520570875
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.3283444639928056
Random Forest Regression Test Score: 0.3296319949083457
Random Forest Regression Train Score: 0.9078335878412757


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=1000, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)
```

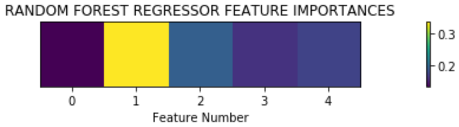
```
Lasso:
 Lasso(alpha=1000, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
================================================================================
```

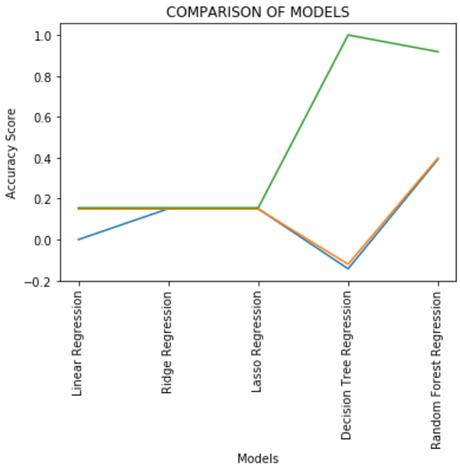




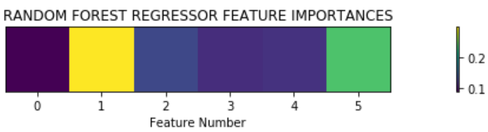

```
Components: 5

================================================================================
Linear Regression Test Score: 0.14938205601500798
Linear Regression Train Score: 0.15498296451224047

Ridge CV Score: 0.15096712580473484
Ridge Regression Test Score: 0.1493846677974936
Ridge Regression Train Score: 0.1549829582768163

Lasso CV Score: 0.15096712457449896
Lasso Regression Test Score: 0.14938205603956245
Lasso Regression Train Score: 0.15498296451224047

Descision Tree Regression CV Score: -0.14287894115659705
Descision Tree Regression Test Score: -0.12039984107792523
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.3930119612688132
Random Forest Regression Test Score: 0.3985163601506294
Random Forest Regression Train Score: 0.9181100908683213


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=1000, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=0.001, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
```

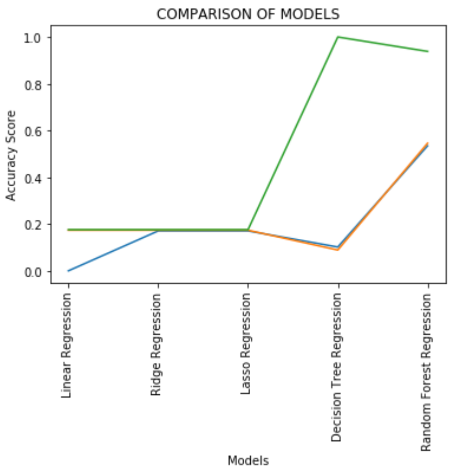
```
================================================================================
```



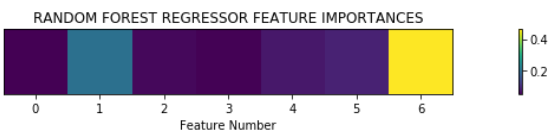


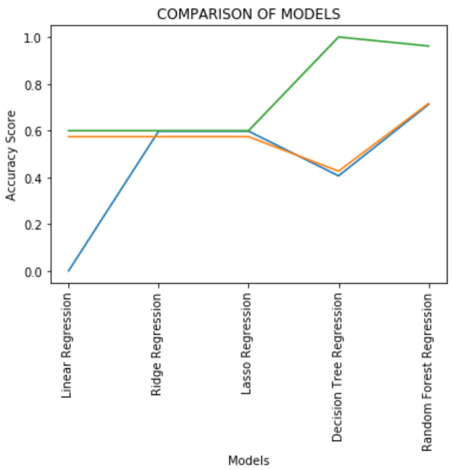

```
Components: 6

================================================================================
Linear Regression Test Score: 0.17361853165876406
Linear Regression Train Score: 0.17592236281342533

Ridge CV Score: 0.17074545674341743
Ridge Regression Test Score: 0.1735991312906192
Ridge Regression Train Score: 0.17592104992257127

Lasso CV Score: 0.1707461534258618
Lasso Regression Test Score: 0.17357843531861072
Lasso Regression Train Score: 0.17591259141704785

Descision Tree Regression CV Score: 0.10164565600902283
Descision Tree Regression Test Score: 0.08878616260239558
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.5347275867440925
Random Forest Regression Test Score: 0.54570122423686
Random Forest Regression Train Score: 0.9383637490433082


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=1000, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=1000, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
================================================================================
```



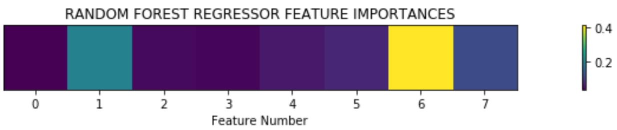


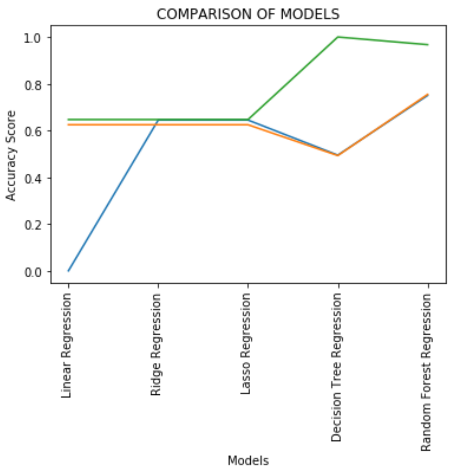

```
Components: 7

================================================================================
Linear Regression Test Score: 0.5735842550529568
Linear Regression Train Score: 0.5992625269949757

Ridge CV Score: 0.5971557968385307
Ridge Regression Test Score: 0.5735876394820036
Ridge Regression Train Score: 0.5992624991290044

Lasso CV Score: 0.5971559354157078
Lasso Regression Test Score: 0.5735943862700004
Lasso Regression Train Score: 0.5992621333104703

Descision Tree Regression CV Score: 0.406164291004788
Descision Tree Regression Test Score: 0.426353959601636
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.711503868766797
Random Forest Regression Test Score: 0.7153899232422769
Random Forest Regression Train Score: 0.961390904134224


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=10.0, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=100.0, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
================================================================================
```



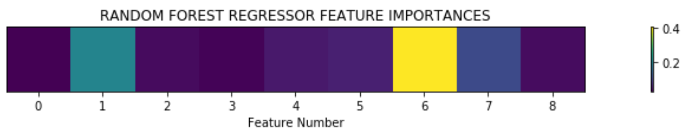


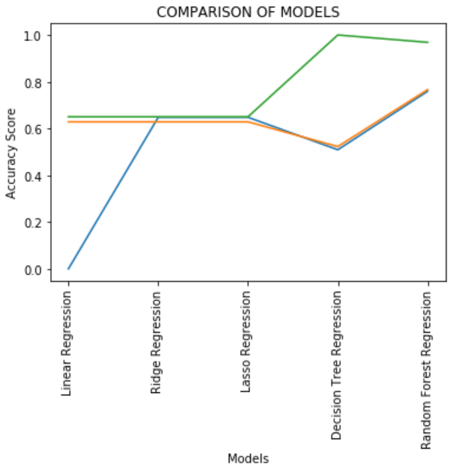

```
Components: 8

================================================================================
Linear Regression Test Score: 0.6247062506493437
Linear Regression Train Score: 0.6468952677236497

Ridge CV Score: 0.6447707042104689
Ridge Regression Test Score: 0.6247064159420825
Ridge Regression Train Score: 0.6468952661920093

Lasso CV Score: 0.6447707150472347
Lasso Regression Test Score: 0.624706787378823
Lasso Regression Train Score: 0.6468952450345142

Descision Tree Regression CV Score: 0.49469203786064003
Descision Tree Regression Test Score: 0.49279608203979
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.7497992118596561
Random Forest Regression Test Score: 0.7544531334510073
Random Forest Regression Train Score: 0.9672356109632062


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=10.0, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
================================================================================
```



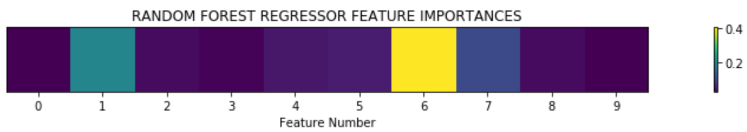


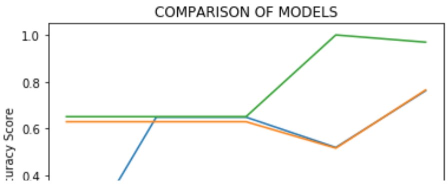

```
Components: 9

==============================================================================
Linear Regression Test Score: 0.6285343286509856
Linear Regression Train Score: 0.6500909432628564

Ridge CV Score: 0.6479681619362733
Ridge Regression Test Score: 0.6285344780102775
Ridge Regression Train Score: 0.6500909414615766

Lasso CV Score: 0.6479681431200839
Lasso Regression Test Score: 0.6285343285746018
Lasso Regression Train Score: 0.6500909432628559

Descision Tree Regression CV Score: 0.5091765669859164
Descision Tree Regression Test Score: 0.5227533708040644
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.7592225106071476
Random Forest Regression Test Score: 0.7663361273226728
Random Forest Regression Train Score: 0.9685997568202229


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=0.001, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
==============================================================================
```






```
Components: 10

================================================================================
Linear Regression Test Score: 0.62850394134139
Linear Regression Train Score: 0.6500912159563909

Ridge CV Score: 0.647939172209163
Ridge Regression Test Score: 0.6285054783241111
Ridge Regression Train Score: 0.6500910363335906

Lasso CV Score: 0.6479594726416008
Lasso Regression Test Score: 0.6285207224353819
Lasso Regression Train Score: 0.6500853152481829

Descision Tree Regression CV Score: 0.5181842669819443
Descision Tree Regression Test Score: 0.5153690665125219
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.7612301503686204
Random Forest Regression Test Score: 0.7642565556956177
Random Forest Regression Train Score: 0.9690403291561359


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=10.0, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=100.0, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
================================================================================
```

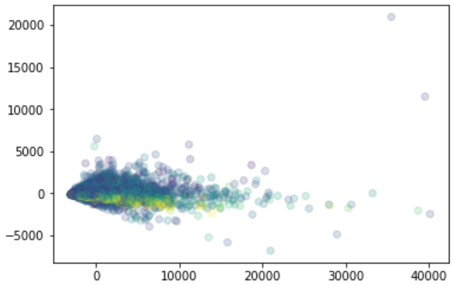




In [43]:
```
pca=PCA(n_components=2)
X_train_pca=pca.fit_transform(X_train)
X_test_pca=pca.transform(X_test)
```

In [44]:
```
plt.scatter(X_train_pca[:,0],X_train_pca[:,1],c=y_train, alpha=0.2)
```

Out[44]: <matplotlib.collections.PathCollection at 0x2139ba7c048>



POLYNOMIAL FEATURES

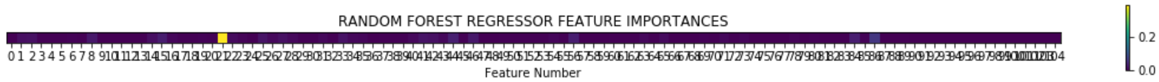
In [45]:
```
from sklearn.preprocessing import PolynomialFeatures
```

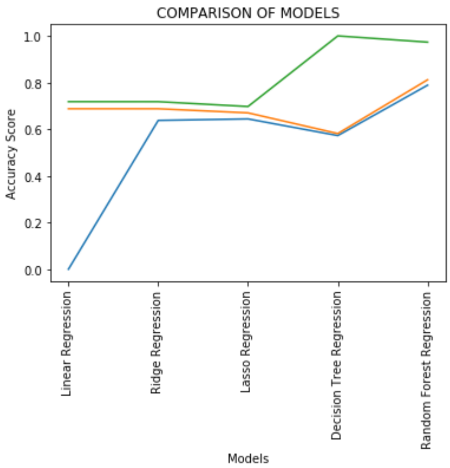
In [46]:
```
pf=PolynomialFeatures(degree=2)
```

In [47]:
```
X_train_poly= pf.fit_transform(X_train)
X_test_poly= pf.transform(X_test)
```

In [48]:
```
select_model(X_train_poly,y_train,X_test_poly,y_test)
```

```
================================================================================
Linear Regression Test Score: 0.68783170776807
Linear Regression Train Score: 0.7182431396891928

Ridge CV Score: 0.6378525649442146
Ridge Regression Test Score: 0.6877606744841716
Ridge Regression Train Score: 0.7180915021769906

Lasso CV Score: 0.644241129233054
Lasso Regression Test Score: 0.6701807603714545
Lasso Regression Train Score: 0.6974510865623134

Descision Tree Regression CV Score: 0.5727659754557035
Descision Tree Regression Test Score: 0.5815556356083702
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.7888768293565313
Random Forest Regression Test Score: 0.8119842008914537
Random Forest Regression Train Score: 0.9732810040326242


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=0.001, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=10.0, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
================================================================================
```



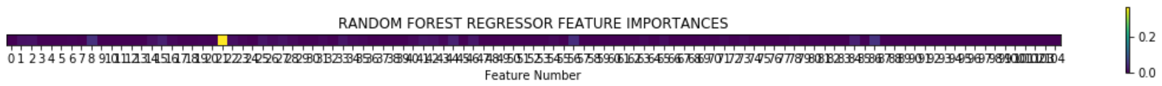


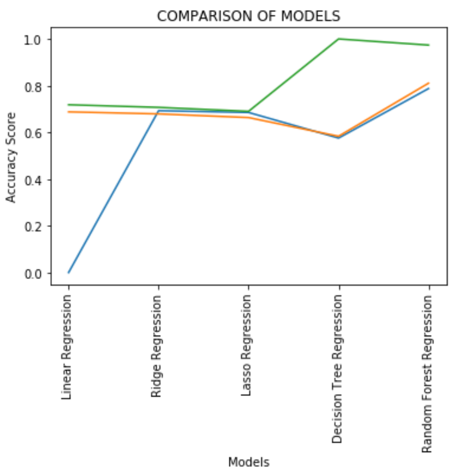
POLYNOMIAL FEATURES WITH SCALING

In [49]:
```
X_train_poly_min_max= min_max.fit_transform(X_train_poly)
X_test_poly_min_max= min_max.transform(X_test_poly)
```

In [50]:
```
select_model(X_train_poly_min_max,y_train,X_test_poly_min_max,y_test)
```

```
=================================================================================
Linear Regression Test Score: 0.6878316808306729
Linear Regression Train Score: 0.7182431477713154

Ridge CV Score: 0.6927427083618544
Ridge Regression Test Score: 0.6791061091693829
Ridge Regression Train Score: 0.7070399652280258

Lasso CV Score: 0.6852734233312834
Lasso Regression Test Score: 0.663394347654029
Lasso Regression Train Score: 0.6900297269297251

Descision Tree Regression CV Score: 0.5756057811768366
Descision Tree Regression Test Score: 0.583379180916188
Descision Tree Regression Train Score: 1.0

Random Forest Regression CV Score: 0.7876122871651469
Random Forest Regression Test Score: 0.8105387125788657
Random Forest Regression Train Score: 0.9737709144198211


 BEST PARAMETERS USED:

Ridge:
 Ridge(alpha=0.01, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)

Lasso:
 Lasso(alpha=10.0, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)

Descision Tree:
 DecisionTreeRegressor(criterion='mse', max_depth=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')

Random Forest:
 RandomForestRegressor(bootstrap=True, criterion='mse', 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=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
=================================================================================
```





END