Supervised_Learning_Classification_Project

January 16, 2021

1 Classification of Dementia - Supervised Learning Project

[1]:
```
# Load packages:
import pandas as pd
import numpy as np

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import StratifiedShuffleSplit, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score,␣
↪recall_score, roc_auc_score

import seaborn as sns
import matplotlib.pyplot as plt

from IPython.display import set_matplotlib_formats
%matplotlib inline
set_matplotlib_formats('pdf', 'svg')
```

1.1 Data Summary

In this classification project, I am using demographics data from the Oasis Study to predict a diagnosis of dementia:
* *OASIS, Longitudinal: Principal Investigators: D. Marcus, R, Buckner, J. Csernansky, J. Morris; P50 AG05681, P01 AG03991, P01 AG026276, R01 AG021910, P20 MH071616, U24 RR021382*
* Marcus, DS, Fotenos, AF, Csernansky, JG, Morris, JC, Buckner, RL, 2010. Journal of Cognitive Neuroscience, 22, 2677-2684. doi: 10.1162/jocn.2009.21407

This dataset contains longitudinal data for 150 adults age 60 to 96. The target varible is whether the individual has dementia or not ('Group'). Other relevant features include:
* Gender (M/F)
* Age
* Years of Education (EDUC)
* Socioeconomic status (SES)
* Mini Mental State Examination (MMSE)

* Clinical Dementia Rating (CDR)
* Normalized Whole Brain Volume (nWBV)

Note that the data contains > 1 visit per subject, but I am just analzing data for the first visit here.

[2]:
```python
data = pd.read_csv('oasis_longitudinal.csv')
data.head()
```

[2]:
```
  Subject ID         MRI ID        Group  Visit  MR Delay M/F Hand  Age  EDUC  \
0  OAS2_0001  OAS2_0001_MR1  Nondemented      1         0   M    R   87    14
1  OAS2_0001  OAS2_0001_MR2  Nondemented      2       457   M    R   88    14
2  OAS2_0002  OAS2_0002_MR1     Demented      1         0   M    R   75    12
3  OAS2_0002  OAS2_0002_MR2     Demented      2       560   M    R   76    12
4  OAS2_0002  OAS2_0002_MR3     Demented      3      1895   M    R   80    12

   SES  MMSE  CDR  eTIV   nWBV    ASF
0  2.0  27.0  0.0  1987  0.696  0.883
1  2.0  30.0  0.0  2004  0.681  0.876
2  NaN  23.0  0.5  1678  0.736  1.046
3  NaN  28.0  0.5  1738  0.713  1.010
4  NaN  22.0  0.5  1698  0.701  1.034
```

Check for any duplicates:

[3]:
```python
data.duplicated().sum()
```

[3]:
```
0
```

[4]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 373 entries, 0 to 372
Data columns (total 15 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Subject ID  373 non-null    object
 1   MRI ID      373 non-null    object
 2   Group       373 non-null    object
 3   Visit       373 non-null    int64
 4   MR Delay    373 non-null    int64
 5   M/F         373 non-null    object
 6   Hand        373 non-null    object
 7   Age         373 non-null    int64
 8   EDUC        373 non-null    int64
 9   SES         354 non-null    float64
 10  MMSE        371 non-null    float64
 11  CDR         373 non-null    float64
 12  eTIV        373 non-null    int64
```

```
 13  nWBV         373 non-null    float64
 14  ASF          373 non-null    float64
dtypes: float64(5), int64(5), object(5)
memory usage: 43.8+ KB
```

[5]:
```
data.describe()
```

[5]:
```
            Visit     MR Delay         Age        EDUC         SES  \
count  373.000000   373.000000  373.000000  373.000000  354.000000
mean     1.882038   595.104558   77.013405   14.597855    2.460452
std      0.922843   635.485118    7.640957    2.876339    1.134005
min      1.000000     0.000000   60.000000    6.000000    1.000000
25%      1.000000     0.000000   71.000000   12.000000    2.000000
50%      2.000000   552.000000   77.000000   15.000000    2.000000
75%      2.000000   873.000000   82.000000   16.000000    3.000000
max      5.000000  2639.000000   98.000000   23.000000    5.000000

             MMSE         CDR         eTIV        nWBV         ASF
count  371.000000  373.000000   373.000000  373.000000  373.000000
mean    27.342318    0.290885  1488.128686    0.729568    1.195461
std      3.683244    0.374557   176.139286    0.037135    0.138092
min      4.000000    0.000000  1106.000000    0.644000    0.876000
25%     27.000000    0.000000  1357.000000    0.700000    1.099000
50%     29.000000    0.000000  1470.000000    0.729000    1.194000
75%     30.000000    0.500000  1597.000000    0.756000    1.293000
max     30.000000    2.000000  2004.000000    0.837000    1.587000
```

1.1.1 Clean and visualize data:

Replace any rows with NAs with median/mean:

[6]:
```
data.isna().sum()
```

[6]:
```
Subject ID     0
MRI ID         0
Group          0
Visit          0
MR Delay       0
M/F            0
Hand           0
Age            0
EDUC           0
SES           19
MMSE           2
CDR            0
eTIV           0
nWBV           0
ASF            0
```

```
dtype: int64
```

[7]:
```
data["SES"].fillna(data["SES"].median(), inplace=True)
data["MMSE"].fillna(data["MMSE"].mean(), inplace=True)
```

Drop unsused variables:

[8]:
```
data.drop(columns=['Hand','MR Delay','eTIV','ASF', 'MRI ID'], inplace = True)
data.head()
```

[8]:

	Subject ID	Group	Visit	M/F	Age	EDUC	SES	MMSE	CDR	nWBV
0	OAS2_0001	Nondemented	1	M	87	14	2.0	27.0	0.0	0.696
1	OAS2_0001	Nondemented	2	M	88	14	2.0	30.0	0.0	0.681
2	OAS2_0002	Demented	1	M	75	12	2.0	23.0	0.5	0.736
3	OAS2_0002	Demented	2	M	76	12	2.0	28.0	0.5	0.713
4	OAS2_0002	Demented	3	M	80	12	2.0	22.0	0.5	0.701

How many unique subjects are there?

[9]:
```
nsubs = len(data['Subject ID'].unique())
print('\nFound ' + str(nsubs) + ' subjects over a total of ' + str(data.
↪shape[0]) + ' visits\n')
```

```

Found 150 subjects over a total of 373 visits

```

Given that subjects have multiple visits, I'm just going to analyze the first visit for now:

[10]:
```
data_1 = data[data['Visit'] == 1].copy().reset_index(drop=True)
data_1.drop(columns='Visit', inplace=True)
data_1.shape
```

[10]: (150, 9)

How many subjects per group, and how many are male/female?

[11]:
```
data_1[['Group', 'M/F']].value_counts().to_frame().reset_index()
```

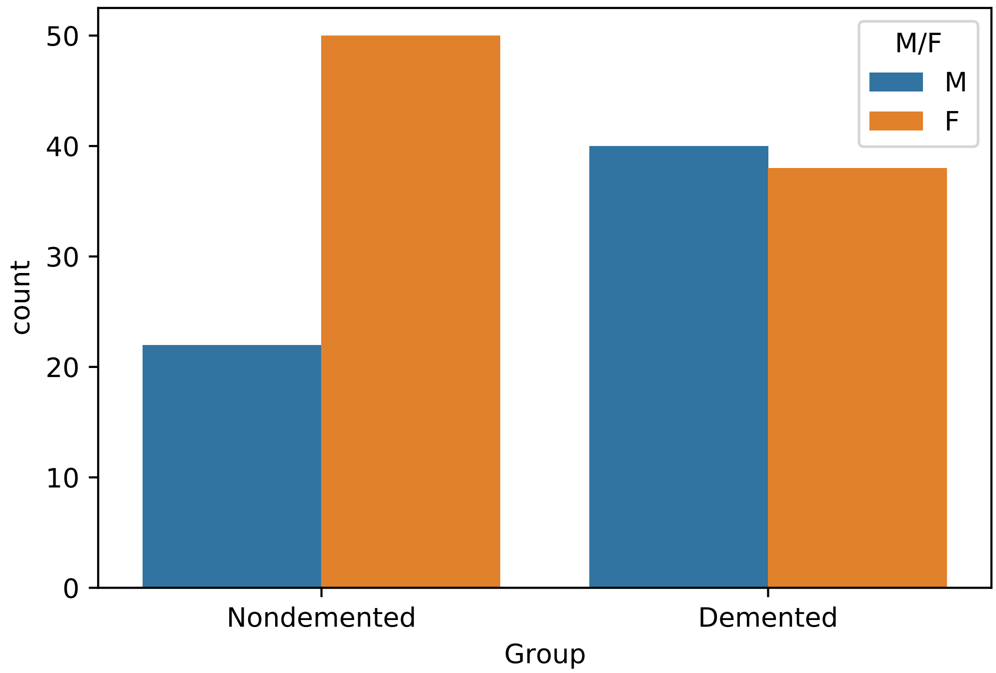
[11]:

	Group	M/F	0
0	Nondemented	F	50
1	Demented	M	36
2	Demented	F	28
3	Nondemented	M	22
4	Converted	F	10
5	Converted	M	4

Move converted to demented group:

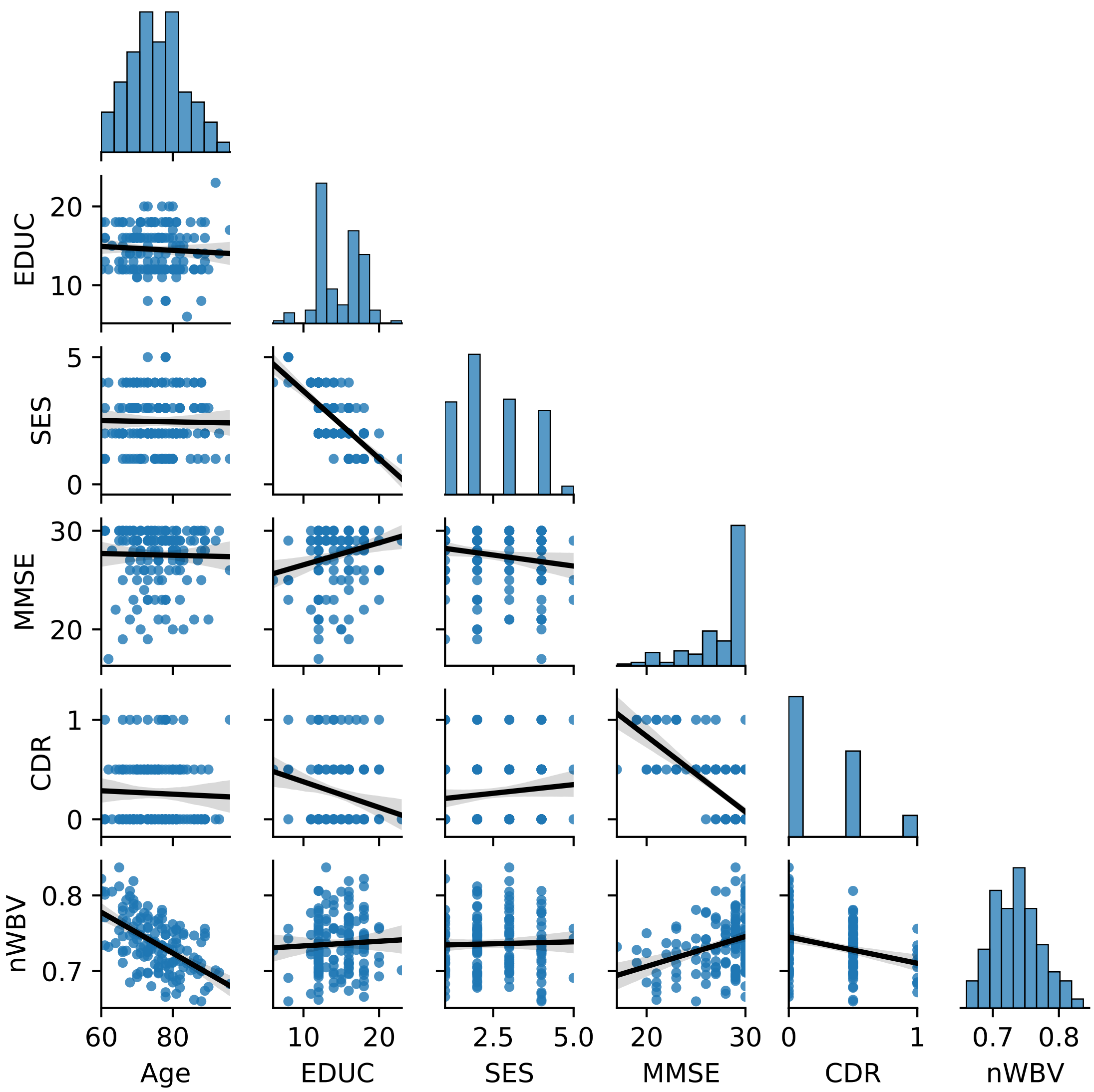
[12]:
```
data_1['Group'].replace(['Converted'], ['Demented'], inplace=True)
```

[13]:
```
# plot:
sns.countplot(data=data_1, x='Group', hue= 'M/F')
plt.show()
```



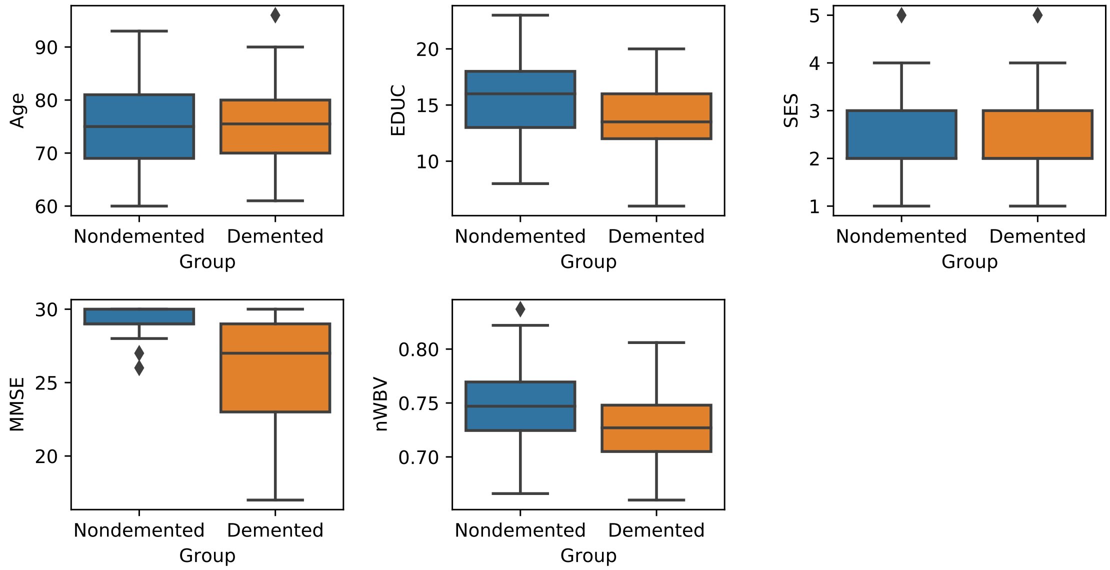
Relationships between all of my numeric variables:

[14]:
```
sns.pairplot(data_1.select_dtypes(exclude="object"),
             kind="reg", height=1, corner=True,
             plot_kws={'scatter_kws':{'s':8},
                       'line_kws':{'color':'black',
                                   'lw':2}})
plt.show()
```



[15]:
```
# Summarise continuous features per group
fig=plt.figure(figsize=(10,5))
ax1=fig.add_subplot(2,3,1)
sns.boxplot(data=data_1, x='Group', y='Age', ax=ax1)
ax1=fig.add_subplot(2,3,2)
sns.boxplot(data=data_1, x='Group', y='EDUC', ax=ax1)
ax1=fig.add_subplot(2,3,3)
sns.boxplot(data=data_1, x='Group', y='SES', ax=ax1)
ax1=fig.add_subplot(2,3,4)
sns.boxplot(data=data_1, x='Group', y='MMSE', ax=ax1)
ax1=fig.add_subplot(2,3,5)
sns.boxplot(data=data_1, x='Group', y='nWBV', ax=ax1)
```

```
plt.subplots_adjust(hspace=0.4,
                    wspace=0.4)
plt.show()
```



Finally, I'll need to encode my categorical features for modelling:

[16]:
```
data_1['Group'] = data_1['Group'].map({"Demented": 1, "Nondemented": 0})
data_1['M/F'] = data_1['M/F'].map({'F': 0, 'M': 1})
```

[17]:
```
data_1.head()
```

[17]:

	Subject ID	Group	M/F	Age	EDUC	SES	MMSE	CDR	nWBV
0	OAS2_0001	0	1	87	14	2.0	27.0	0.0	0.696
1	OAS2_0002	1	1	75	12	2.0	23.0	0.5	0.736
2	OAS2_0004	0	0	88	18	3.0	28.0	0.0	0.710
3	OAS2_0005	0	1	80	12	4.0	28.0	0.0	0.712
4	OAS2_0007	1	1	71	16	2.0	28.0	0.5	0.748

1.1.2 Split data into train and test samples, maintaining the balance of each target group:

[18]:
```
features = ["M/F", "Age", "EDUC", "SES", "MMSE", "nWBV"]

# Get the split indexes
strat_shuff_split = StratifiedShuffleSplit(n_splits=1,
                                           test_size=0.5,
                                           random_state=42)
```

```
# get indices
train_idx, test_idx = next(strat_shuff_split.split(data_1[features],␣
↪data_1['Group']))

# Create the dataframes
X_train = data_1.loc[train_idx, features]
y_train = data_1.loc[train_idx, 'Group']

X_test  = data_1.loc[test_idx, features]
y_test  = data_1.loc[test_idx, 'Group']
```

[19]:
```
# check balance of groups is the same
print('Train data:\n', y_train.value_counts(normalize=True),'\n')
print('Test data:\n', y_test.value_counts(normalize=True),'\n')
```

```
Train data:
 1    0.52
0    0.48
Name: Group, dtype: float64

Test data:
 1    0.52
0    0.48
Name: Group, dtype: float64
```

Scale data - not necessary for logistic regression, but otherwise it'll be needed

[20]:
```
#scaling separately for test and train data so no bleeding betwen the two
mm = MinMaxScaler()
for column in features:
    X_train[column] = mm.fit_transform(X_train[[column]])
    X_test[column] = mm.fit_transform(X_test[[column]])
```

1.2 Classification Models

I'm going to compare the performance of a simple logistic regression model, as well as k-nearest neighbors, support vector machine, and a random forest model.

Cross-validation is used for hyperparameter tuning for the last 3 models.

[21]:
```
# set up dataframe to store and compare model performance
performance = pd.DataFrame(index = ['Accuracy','Precision','Recall','AUC'],
                           columns = ['LR','KNN','SVM','RF'])
```

1.2.1 Model 1: Logistic Regression

[22]:
```
# Standard logistic regression
lr = LogisticRegression().fit(X_train, y_train)

y_pred_lr = lr.predict(X_test)
```

[23]:
```
# evaluate model performance
accuracy = accuracy_score(y_test, y_pred_lr)
precision = precision_score(y_test, y_pred_lr)
recall = recall_score(y_test, y_pred_lr)
auc = roc_auc_score(y_test, y_pred_lr)

performance['LR'] = [accuracy, precision, recall, auc]
```

1.2.2 Model 2: K-Nearest Neighbors

[24]:
```
knn = KNeighborsClassifier(weights='distance')

#create a dictionary of values for n_neighbors
param_grid = {'n_neighbors': np.arange(1,25)}
#use gridsearch to test all values for n_neighbors
knn_gs = GridSearchCV(knn, param_grid, cv=5)
#fit model
knn_gs.fit(X_train, y_train)

# what is the best value of n_neighbors?
knn_gs.best_params_
```

[24]:
```
{'n_neighbors': 14}
```

[25]:
```
y_pred_knn = knn_gs.predict(X_test)
```

[26]:
```
# evaluate model performance
accuracy = accuracy_score(y_test, y_pred_knn)
precision = precision_score(y_test, y_pred_knn)
recall = recall_score(y_test, y_pred_knn)
auc = roc_auc_score(y_test, y_pred_knn)

performance['KNN'] = [accuracy, precision, recall, auc]
```

1.2.3 Model 3: Linear Support Vector Machine

[27]:
```
LSVC = LinearSVC(penalty='l2', max_iter=1000000)

#create a dictionary of values for C
param_grid = {'C': [0.1, 1, 10, 100, 500, 1000]}
```

```
#use gridsearch to test all values for n_neighbors
svc_gs = GridSearchCV(LSVC, param_grid, cv=5)
#fit model
svc_gs.fit(X_train, y_train)

# what are the optimal hyperparameters?
svc_gs.best_params_
```

[27]: {'C': 500}

[28]:
```
y_pred_svc = svc_gs.predict(X_test)
```

[29]:
```
# evaluate model performance
accuracy = accuracy_score(y_test, y_pred_svc)
precision = precision_score(y_test, y_pred_svc)
recall = recall_score(y_test, y_pred_svc)
auc = roc_auc_score(y_test, y_pred_svc)

performance['SVM'] = [accuracy, precision, recall, auc]
```

1.2.4 Model 4: Random Forest

[30]:
```
rf = RandomForestClassifier(random_state=42,
                            warm_start=True,
                            n_jobs=-1)

# Number of trees in random forest
n_estimators = [10, 20, 30, 40, 50, 100, 150, 200, 300, 400, 600]
# Create the random grid
param_grid = {'n_estimators': n_estimators}
rf_gs = GridSearchCV(rf, param_grid, cv=5)
#fit model
rf_gs.fit(X_train, y_train)

# what are the optimal hyperparameters?
rf_gs.best_params_
```

[30]: {'n_estimators': 20}

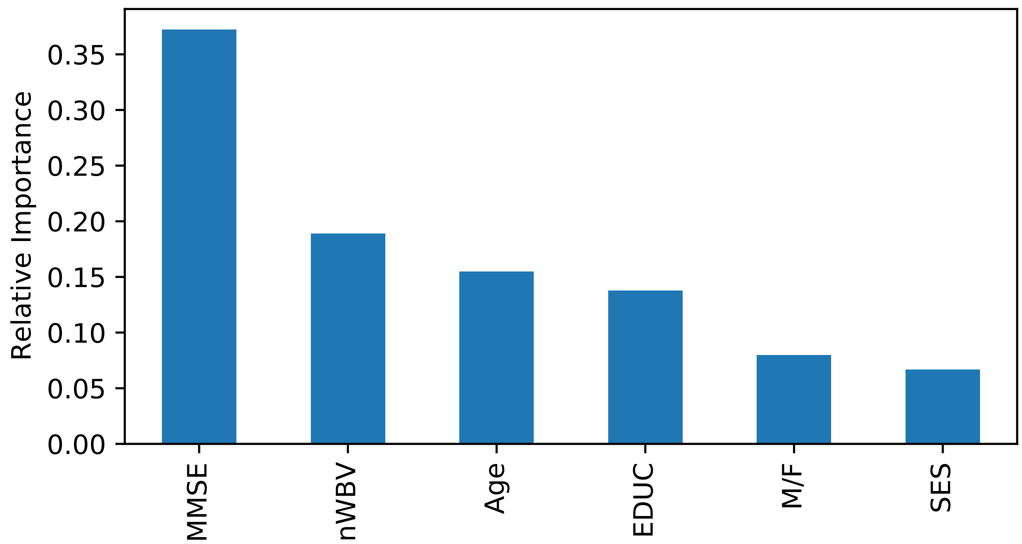
[31]:
```
y_pred_rf = rf_gs.predict(X_test)
```

[32]:
```
# evaluate model performance
accuracy = accuracy_score(y_test, y_pred_rf)
precision = precision_score(y_test, y_pred_rf)
recall = recall_score(y_test, y_pred_rf)
auc = roc_auc_score(y_test, y_pred_rf)
```

```
performance['RF'] = [accuracy, precision, recall, auc]
```

How important are our features for predicting dementia?

[33]:
```
# feature importances:
feature_imp = pd.Series(rf_gs.best_estimator_.feature_importances_,␣
↪index=features).sort_values(ascending=False)

plt.figure(figsize=(6,3))
feature_imp.plot(kind='bar')
plt.ylabel('Relative Importance')
plt.show()
```



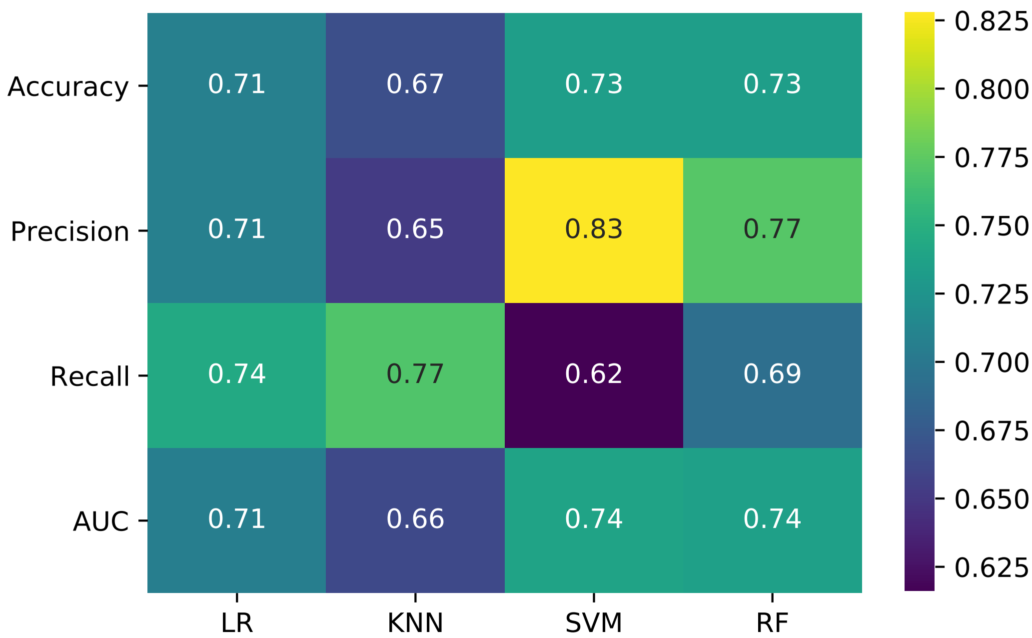
1.3 Results - Model Comparison

[34]:
```
# show performance metrics by model:
performance
```

[34]:

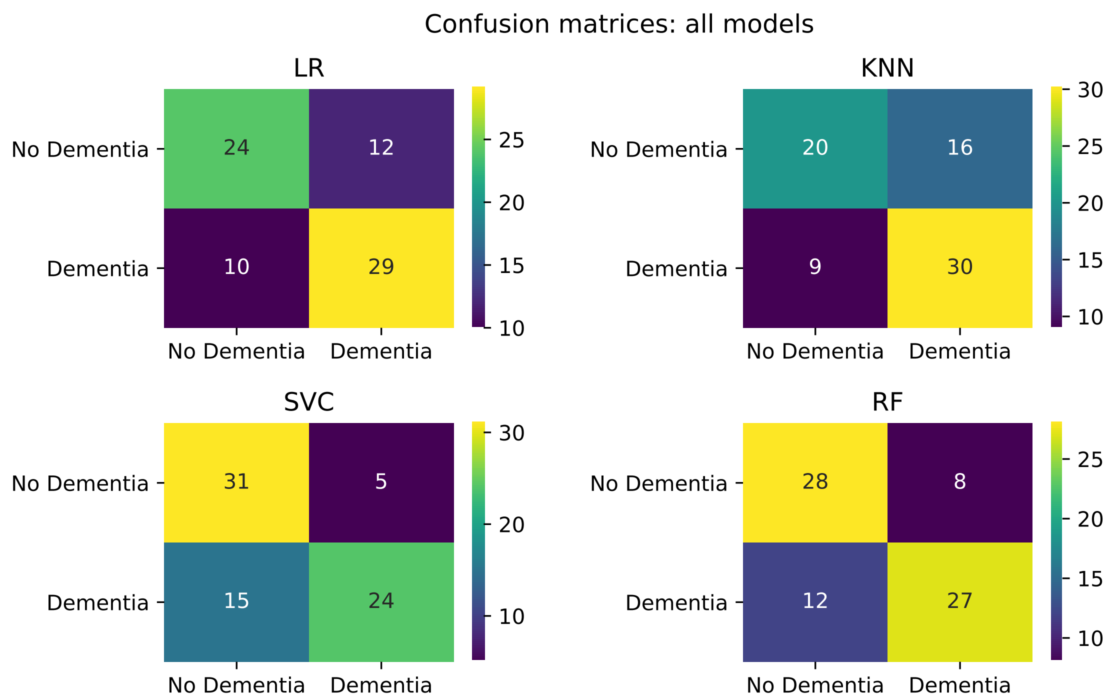
	LR	KNN	SVM	RF
Accuracy	0.706667	0.666667	0.733333	0.733333
Precision	0.707317	0.652174	0.827586	0.771429
Recall	0.743590	0.769231	0.615385	0.692308
AUC	0.705128	0.662393	0.738248	0.735043

[35]:
```
sns.heatmap(performance, annot=True,
            cmap='viridis')
plt.yticks(rotation=0)
plt.show()
```



[36]:
```
# plot confusion matrices:
fig=plt.figure(figsize=(8,5))
plt.suptitle('Confusion matrices: all models')

ax1=fig.add_subplot(2,2,1)
plt.title('LR')
sns.heatmap(pd.DataFrame(confusion_matrix(y_test, y_pred_lr),
             index=["No Dementia", "Dementia"],
             columns=["No Dementia", "Dementia"]),
             annot=True, fmt='d', cmap='viridis', ax=ax1)

ax1=fig.add_subplot(2,2,2)
plt.title('KNN')
sns.heatmap(pd.DataFrame(confusion_matrix(y_test, y_pred_knn),
             index=["No Dementia", "Dementia"],
             columns=["No Dementia", "Dementia"]),
             annot=True, fmt='d', cmap='viridis', ax=ax1)

ax1=fig.add_subplot(2,2,3)
plt.title('SVC')
sns.heatmap(pd.DataFrame(confusion_matrix(y_test, y_pred_svc),
             index=["No Dementia", "Dementia"],
             columns=["No Dementia", "Dementia"]),
             annot=True, fmt='d', cmap='viridis', ax=ax1)
```

```
ax1=fig.add_subplot(2,2,4)
plt.title('RF')
sns.heatmap(pd.DataFrame(confusion_matrix(y_test, y_pred_rf),
             index=["No Dementia", "Dementia"],
             columns=["No Dementia", "Dementia"]),
             annot=True, fmt='d', cmap='viridis', ax=ax1)

plt.subplots_adjust(hspace=0.4,
                    wspace=0.6)
plt.show()
```



1.4 Key Findings

The key finding from the above classification models are that:

- MMSE is the most important feature by far for predicting dementia, following by normalized intracramial volume and age.

- Both SVM and RF models have the highest accuracy and auc scores.

- SVM and RF seems to trade-off precision and recall differently:
  - SVM produces high precision, which means that the model does not falsely label nondemented people (0) has having dementia (1) very often.

  - However, the SVM model has the worst recall (sensitivity), which means that it fails to identify people with dementia quite frequently. Despite being the worst-performing model overall, recall is actually where KNN does best.

- I think, based on a balance of performance metrics, the RF model might be the best to use.

1.5 Problems and Future Directions

The above models could be potentially improved in a number of ways, by, for example, adding polynomial terms or trying non-linear SVM. One limitation was relatively few samples (only 150 people) and few features (6 ended up being used to predict dementia). More subjects and more information about those subjects is likely to improve model performance, for example, by including more specific information from brain strctures rather than just intracranial volume, and additional cognitive assessments could provide more sensitive indicators of cognitive decline.

[ ]:
```

```