Data Science Track: Course 17

Machine Learning with the Experts: School Budgets

Chap 1: Exploring the raw data

In [1]:
```
# Import plotting modules
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
plt.style.use('ggplot')
```

Exploring the data

In [4]:
```
# A column for each possible value

df = pd.DataFrame({'Eyes':['Brown','Brown','Blue','Blue'],
                   'Hair':['Curly','Straight','Wavy','Straight']},
                  index=['Jamal','Luisa','Jenny','Max'])
df
```

Out[4]:

	Eyes	Hair
Jamal	Brown	Curly
Luisa	Brown	Straight
Jenny	Blue	Wavy
Max	Blue	Straight

In [6]:
```
df_dummies = pd.get_dummies(df)
df_dummies
```

Out[6]:

	Eyes_Blue	Eyes_Brown	Hair_Curly	Hair_Straight	Hair_Wavy
Jamal	0	1	1	0	0
Luisa	0	1	0	1	0
Jenny	1	0	0	0	1
Max	1	0	0	1	0

In [7]:
```
# Load and preview the data
sample_df = pd.read_csv('datasets/drivendata/sample_data.csv')
sample_df.head()
```

Out[7]:

	label	numeric	text	with_missing
0	a	-4.167578	bar	-4.084883
1	b	-0.562668	NaN	2.043464
2	a	-21.361961	NaN	-33.315334
3	a	16.402708	foo bar	30.884604
4	a	-17.934356	foo	-27.488405

In [9]:
```
# Summarize the data
sample_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 4 columns):
label           5 non-null object
numeric         5 non-null float64
text            3 non-null object
with_missing    5 non-null float64
dtypes: float64(2), object(2)
memory usage: 240.0+ bytes
```

In [10]:
```
sample_df.describe()
```

Out[10]:

	numeric	with_missing
count	5.000000	5.000000
mean	-5.524771	-6.392111
std	15.100440	25.670748
min	-21.361961	-33.315334
25%	-17.934356	-27.488405
50%	-4.167578	-4.084883
75%	-0.562668	2.043464
max	16.402708	30.884604

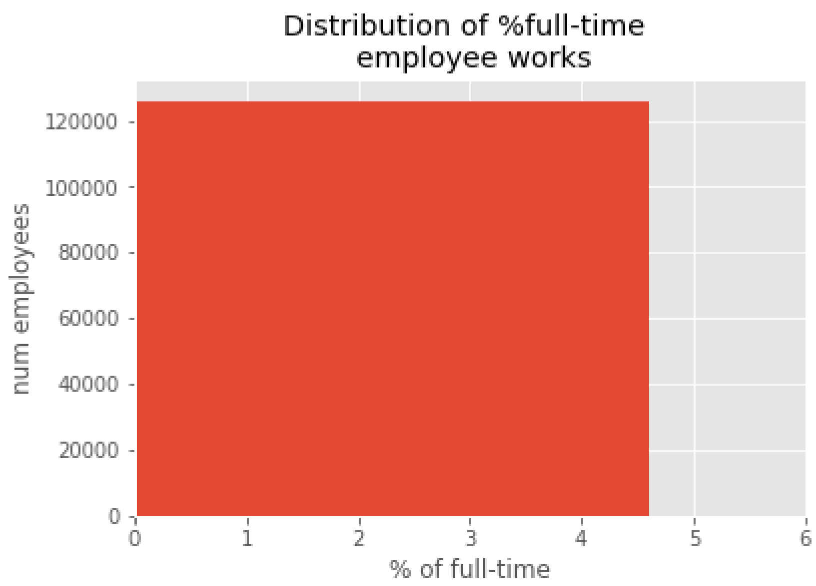
In [12]:
```
# EXERCISES
```

In [13]:
```
# Loading the data
df = pd.read_csv('datasets/drivendata/TrainingData.csv',index_col=0)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 400277 entries, 134338 to 415831
Data columns (total 25 columns):
Function                  400277 non-null object
Use                       400277 non-null object
Sharing                   400277 non-null object
Reporting                 400277 non-null object
Student_Type              400277 non-null object
Position_Type             400277 non-null object
Object_Type               400277 non-null object
Pre_K                     400277 non-null object
Operating_Status          400277 non-null object
Object_Description        375493 non-null object
Text_2                    88217 non-null object
SubFund_Description       306855 non-null object
Job_Title_Description     292743 non-null object
Text_3                    179964 non-null object
Text_4                    53746 non-null object
Sub_Object_Description    91603 non-null object
Location_Description      162054 non-null object
FTE                       126071 non-null float64
Function_Description      342195 non-null object
Facility_or_Department    53886 non-null object
Position_Extra            264764 non-null object
Total                     395722 non-null float64
Program_Description       304660 non-null object
Fund_Description          202877 non-null object
Text_1                    292285 non-null object
dtypes: float64(2), object(23)
memory usage: 79.4+ MB
```

In [16]:
```
# Summarizing the data

# Print the summary statistics
print(df.describe())

# Import matplotlib.pyplot as plt
import matplotlib.pyplot as plt

# Create the histogram
plt.hist(df['FTE'].dropna())

# Add title and labels
plt.title('Distribution of %full-time \n employee works')
plt.xlabel('% of full-time')
plt.ylabel('num employees')
plt.xlim([0,6])

# Display the histogram
plt.show()
```

```
                 FTE         Total
count  126071.000000  3.957220e+05
mean        0.426794  1.310586e+04
std         0.573576  3.682254e+05
min        -0.087551 -8.746631e+07
25%         0.000792  7.379770e+01
50%         0.130927  4.612300e+02
75%         1.000000  3.652662e+03
max        46.800000  1.297000e+08
```



Looking at the datatypes

In [18]:
```
sample_df['label'].head()
```

Out[18]:
```
0    a
1    b
2    a
3    a
4    a
Name: label, dtype: object
```

Why encode labels as categories?

```
- ML algorithms work on numbers, not strings
- Strings can be slow compared to numbers (take more space)
```

In [19]:
```
# Encode labels as categories (sample data)

sample_df.label.head(2)
```

Out[19]:
```
0    a
1    b
Name: label, dtype: object
```

In [20]:
```
sample_df.label = sample_df.label.astype('category')
sample_df.label.head(2)
```

Out[20]:
```
0    a
1    b
Name: label, dtype: category
Categories (2, object): [a, b]
```

In [22]:
```
# Dummy variable encoding

dummies = pd.get_dummies(sample_df[['label']], prefix_sep='_')
dummies.head(2)
```

Out[22]:

	label_a	label_b
0	1	0
1	0	1

In [24]:
```
# Lambda functions

square = lambda x: x*x
square(2)
```

Out[24]: 4

In [25]:
```
# Encode labels as categories

categorize_label = lambda x: x.astype('category')
sample_df[['label']] = sample_df[['label']].apply(categorize_label,axis=0)
sample_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 4 columns):
label           5 non-null category
numeric         5 non-null float64
text            3 non-null object
with_missing    5 non-null float64
dtypes: category(1), float64(2), object(1)
memory usage: 301.0+ bytes
```

In [ ]:
```
# EXERCISES
```

In [27]:
```
# Exploring datatypes in pandas
df.dtypes.value_counts()
```

Out[27]:
```
object     23
float64     2
dtype: int64
```

In [28]:
```
# Encode the labels as categorical variables
LABELS = ['Function','Use','Sharing','Reporting','Student_Type',
          'Position_Type','Object_Type','Pre_K','Operating_Status']
```

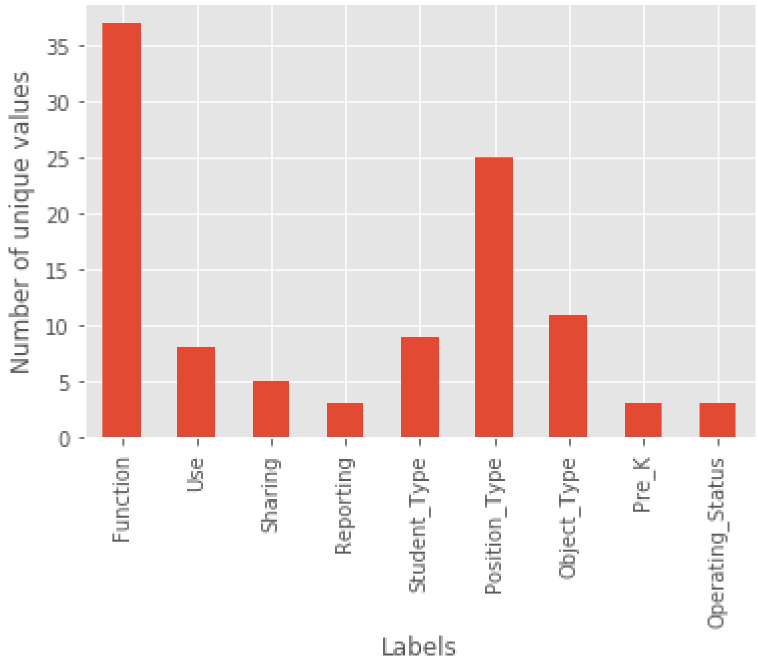
In [29]:
```
df[LABELS].dtypes
```

Out[29]:
```
Function            object
Use                 object
Sharing             object
Reporting           object
Student_Type        object
Position_Type       object
Object_Type         object
Pre_K               object
Operating_Status    object
dtype: object
```

In [30]:
```
# Define the lambda function: categorize_label
categorize_label = lambda x: x.astype('category')

# Convert df[LABELS] to a categorical type
df[LABELS] = df[LABELS].apply(categorize_label,axis=0)

# Print the converted dtypes
print(df[LABELS].dtypes)
```

```
Function            category
Use                 category
Sharing             category
Reporting           category
Student_Type        category
Position_Type       category
Object_Type         category
Pre_K               category
Operating_Status    category
dtype: object
```

In [31]:
```python
# Counting unique labels

# Import matplotlib.pyplot
import matplotlib.pyplot as plt

# Calculate number of unique values for each label: num_unique_labels
num_unique_labels = df[LABELS].apply(lambda x: pd.Series.nunique(x))

# Plot number of unique values for each label
num_unique_labels.plot(kind='bar')

# Label the axes
plt.xlabel('Labels')
plt.ylabel('Number of unique values')

# Display the plot
plt.show()
```



How do we measure success?

Log loss binary classification

logloss(N=1) = y log(p) + (1-y) log(1-p)

In [33]:
```python
# Computing log loss with NumPy

def compute_log_loss(predicted, actual, eps=1e-14):
    """ Computes the logarithmic loss between predicted and
        actual when these are 1D arrays.

    :param predicted: The predicted probabilities as floats between 0-1
    :param actual: The actual binary labels. Either 0 or 1.
    :param eps (optional): log(0) is inf, so we need to offset our
                           predicted values slightly by eps from 0 or 1.
    """
    predicted = np.clip(predicted, eps, 1 - eps)
    loss = -1 * np.mean(actual * np.log(predicted)
                     + (1 - actual) * np.log(1 - predicted))
    return loss
```

In [34]:
```python
compute_log_loss(predicted=0.9, actual=0)
```

Out[34]: 2.3025850929940459

In [35]:
```python
compute_log_loss(predicted=0.5, actual=1)
```

Out[35]: 0.69314718055994529

In [36]:
```python
# EXERCISES
```

In [39]:
```python
# Penalizing highly confident wrong answers
print('A: {}'.format(compute_log_loss(predicted=0.85, actual=1)))
print('B: {}'.format(compute_log_loss(predicted=0.99, actual=0)))
print('C: {}'.format(compute_log_loss(predicted=0.51, actual=0)))
```

```
A: 0.16251892949777494
B: 4.605170185988091
C: 0.7133498878774648
```

In [40]:
```
# Computing log loss with NumPy
# 5 one-dimensional numeric arrays simulating different types of predictions

actual_labels = np.array([ 1.,  1.,  1.,  1.,  1.,
                          0.,  0.,  0.,  0.,  0.])
correct_confident = np.array([ 0.95,  0.95,  0.95,  0.95,  0.95,
                              0.05,  0.05,  0.05,  0.05,  0.05])
correct_not_confident = np.array([ 0.65,  0.65,  0.65,  0.65,  0.65,
                                  0.35,  0.35,  0.35,  0.35,  0.35])
wrong_not_confident = np.array([ 0.35,  0.35,  0.35,  0.35,  0.35,
                                0.65,  0.65,  0.65,  0.65,  0.65])
wrong_confident = np.array([ 0.05,  0.05,  0.05,  0.05,  0.05,
                            0.95,  0.95,  0.95,  0.95,  0.95])
```

In [41]:
```
# Compute and print log loss for 1st case
correct_confident = compute_log_loss(correct_confident, actual_labels)
print("Log loss, correct and confident: {}".format(correct_confident))

# Compute log loss for 2nd case
correct_not_confident = compute_log_loss(correct_not_confident, actual_labels)
print("Log loss, correct and not confident: {}".format(correct_not_confident))

# Compute and print log loss for 3rd case
wrong_not_confident = compute_log_loss(wrong_not_confident, actual_labels)
print("Log loss, wrong and not confident: {}".format(wrong_not_confident))

# Compute and print log loss for 4th case
wrong_confident = compute_log_loss(wrong_confident, actual_labels)
print("Log loss, wrong and confident: {}".format(wrong_confident))

# Compute and print log loss for actual labels
actual_labels = compute_log_loss(actual_labels, actual_labels)
print("Log loss, actual labels: {}".format(actual_labels))
```

```
Log loss, correct and confident: 0.05129329438755058
Log loss, correct and not confident: 0.4307829160924542
Log loss, wrong and not confident: 1.049822124498678
Log loss, wrong and confident: 2.9957322735539904
Log loss, actual labels: 9.99200722162646e-15
```

Chap 2: Creating a simple first model

In [65]:
```
# Import plotting modules
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
plt.style.use('ggplot')

from warnings import warn
from sklearn.linear_model import LogisticRegression
from sklearn.multiclass import OneVsRestClassifier
```

In this chapter:

- Build first-pass model based only on numeric data
- Multi-class logistic regression
- Format predictions and save to csv
- Compute log-loss score

It's time to build a model

multilabel_train_test_split

In [62]:
```
def multilabel_sample(y, size=1000, min_count=5, seed=None):
    """ Takes a matrix of binary labels `y` and returns
        the indices for a sample of size `size` if
        `size` > 1 or `size` * len(y) if size =< 1.
        The sample is guaranteed to have > `min_count` of
        each label.
    """
    try:
        if (np.unique(y).astype(int) != np.array([0, 1])).all():
            raise ValueError()
    except (TypeError, ValueError):
        raise ValueError('multilabel_sample only works with binary indicator matrices')

    if (y.sum(axis=0) < min_count).any():
        raise ValueError('Some classes do not have enough examples. Change min_count if necessary.')

    if size <= 1:
        size = np.floor(y.shape[0] * size)

    if y.shape[1] * min_count > size:
        msg = "Size less than number of columns * min_count, returning {} items instead of {}."
        warn(msg.format(y.shape[1] * min_count, size))
        size = y.shape[1] * min_count

    rng = np.random.RandomState(seed if seed is not None else np.random.randint(1))

    if isinstance(y, pd.DataFrame):
        choices = y.index
        y = y.values
    else:
        choices = np.arange(y.shape[0])

    sample_idxs = np.array([], dtype=choices.dtype)

    # first, guarantee > min_count of each label
    for j in range(y.shape[1]):
        label_choices = choices[y[:, j] == 1]
        label_idxs_sampled = rng.choice(label_choices, size=min_count, replace=False)
        sample_idxs = np.concatenate([label_idxs_sampled, sample_idxs])

    sample_idxs = np.unique(sample_idxs)

    # now that we have at least min_count of each, we can just random sample
    sample_count = int(size - sample_idxs.shape[0])

    # get sample_count indices from remaining choices
    remaining_choices = np.setdiff1d(choices, sample_idxs)
    remaining_sampled = rng.choice(remaining_choices,
                                   size=sample_count,
                                   replace=False)
    return np.concatenate([sample_idxs, remaining_sampled])

def multilabel_sample_dataframe(df, labels, size, min_count=5, seed=None):
    """ Takes a dataframe `df` and returns a sample of size `size` where all
        classes in the binary matrix `labels` are represented at
        least `min_count` times.
    """
    idxs = multilabel_sample(labels, size=size, min_count=min_count, seed=seed)
    return df.loc[idxs]


def multilabel_train_test_split(X, Y, size, min_count=5, seed=None):
    """ Takes a features matrix `X` and a label matrix `Y` and
        returns (X_train, X_test, Y_train, Y_test) where all
        classes in Y are represented at least `min_count` times.
    """
    index = Y.index if isinstance(Y, pd.DataFrame) else np.arange(Y.shape[0])

    test_set_idxs = multilabel_sample(Y, size=size, min_count=min_count, seed=seed)
    train_set_idxs = np.setdiff1d(index, test_set_idxs)

    test_set_mask = index.isin(test_set_idxs)
    train_set_mask = ~test_set_mask

    return (X[train_set_mask], X[test_set_mask], Y[train_set_mask], Y[test_set_mask])
```

In [63]:
```
# Splitting the multi-class dataset

NUMERIC_COLUMNS = ['FTE','Total']
LABELS = ['Function','Use','Sharing','Reporting','Student_Type',
          'Position_Type','Object_Type','Pre_K','Operating_Status']
data_to_train = df[NUMERIC_COLUMNS].fillna(-1000)
labels_to_use = pd.get_dummies(df[LABELS])
```

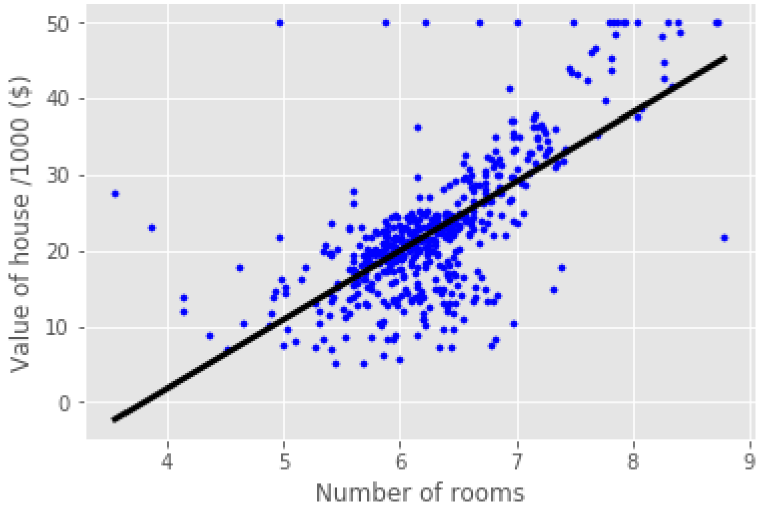
In [64]:
```
X_train, X_test, y_train, y_test = multilabel_train_test_split(
    data_to_train, labels_to_use,size=0.2, seed=123)
```

In [66]:
```
# Training the model

clf = OneVsRestClassifier(LogisticRegression())
clf.fit(X_train, y_train)
```

Out[66]:
```
OneVsRestClassifier(estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False),
          n_jobs=1)
```

In [67]:
```
# EXERCISES
```

In [272]:
```
# Setting up a train-test split in scikit-learn
```

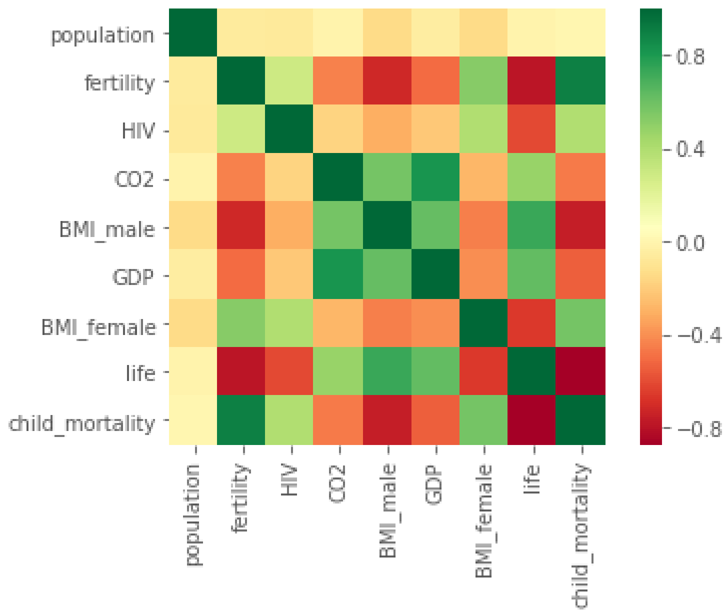


In [273]:
```
# EXERCISES
```

In [276]:
```
# Importing data for supervised learning
# Gapminder Countries GDP data

# Read the CSV file into a DataFrame: df
df = pd.read_csv('datasets/gm_2008_region.csv')

# Create arrays for features and target variable
y = df['life'].values
X = df['fertility'].values

# Print the dimensions of X and y before reshaping
print("Dimensions of y before reshaping: {}".format(y.shape))
print("Dimensions of X before reshaping: {}".format(X.shape))

# Reshape X and y
y = y.reshape(-1,1)
X = X.reshape(-1,1)

# Print the dimensions of X and y after reshaping
print("Dimensions of y after reshaping: {}".format(y.shape))
print("Dimensions of X after reshaping: {}".format(X.shape))
```

```
Dimensions of y before reshaping: (139,)
Dimensions of X before reshaping: (139,)
Dimensions of y after reshaping: (139, 1)
Dimensions of X after reshaping: (139, 1)
```

In [280]:
```
# Exploring the Gapminder data

sns.heatmap(df.corr(), square=True, cmap='RdYlGn')
plt.show()
```



Making predictions

In [282]:
```
# Linear regression on all features

X_train, X_test, y_train, y_test = \
train_test_split(X, y,test_size = 0.3, random_state=42)

reg_all = linear_model.LinearRegression()
reg_all.fit(X_train, y_train)

y_pred = reg_all.predict(X_test)
reg_all.score(X_test, y_test)
```

Out[282]: 0.729898736090749 84

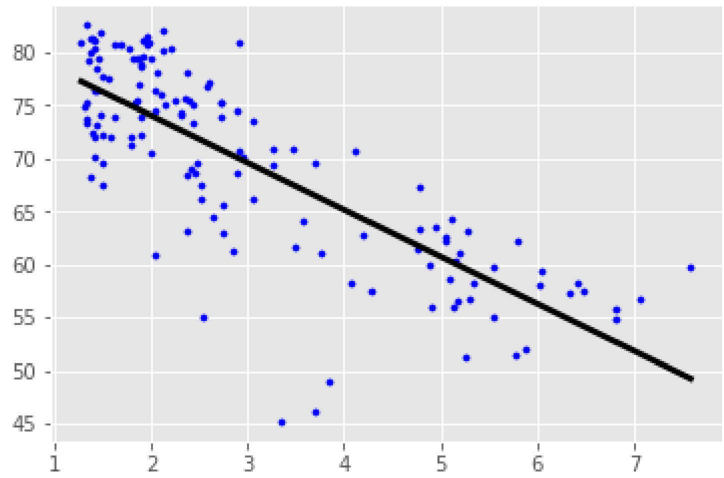
In [285]:
```
# EXERCISE
```

In [299]:
```
# Fit & predict for regression

# Read the CSV file into a DataFrame: df
df = pd.read_csv('datasets/gm_2008_region.csv')

# Create arrays for features and target variable
y = df['life'].values.reshape(-1,1)
X_fertility = df['fertility'].values.reshape(-1,1)
```

In [304]:
```
plt.scatter(X_fertility,y,c='blue',s=10);
```

In [305]:
```
# Import LinearRegression
from sklearn.linear_model import LinearRegression

# Create the regressor: reg
reg = LinearRegression()

# Create the prediction space
prediction_space = np.linspace(min(X_fertility), max(X_fertility)).reshape(-1,1)

# Fit the model to the data
reg.fit(X_fertility,y)

# Compute predictions over the prediction space: y_pred
y_pred = reg.predict(prediction_space)

# Print R^2
print(reg.score(X_fertility, y))

# Plot regression line
plt.plot(prediction_space, y_pred, color='black', linewidth=3)
plt.show()
```

```
0.619244216774
```



In [306]:
```
# Train/test split for regression

# Import necessary modules
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split

# Create training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state=42)

# Create the regressor: reg_all
reg_all = LinearRegression()

# Fit the regressor to the training data
reg_all.fit(X_train,y_train)

# Predict on the test data: y_pred
y_pred = reg_all.predict(X_test)

# Compute and print R^2 and RMSE
print("R^2: {}".format(reg_all.score(X_test, y_test)))
rmse = np.sqrt(mean_squared_error(y_test,y_pred))
print("Root Mean Squared Error: {}".format(rmse))
```

```
R^2: 0.7298987360907498
Root Mean Squared Error: 4.194027914110239
```

A very brief introduction to NLP

In [322]:
```
from sklearn.model_selection import cross_val_score

reg = linear_model.LinearRegression()
cv_results = cross_val_score(reg, X, y, cv=5)
print(cv_results)
np.mean(cv_results)
```

```
[ 0.71001079  0.75007717  0.55271526  0.547501    0.52410561]
```

Out[322]:
```
0.61688196444251187
```

In [325]:
```
# EXERCISE
```

In [326]:
```
# 5-fold cross-validation

# Import the necessary modules
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score

# Create a linear regression object: reg
reg = LinearRegression()

# Compute 5-fold cross-validation scores: cv_scores
cv_scores = cross_val_score(reg,X,y,cv=5)

# Print the 5-fold cross-validation scores
print(cv_scores)

print("Average 5-Fold CV Score: {}".format(np.mean(cv_scores)))
```

```
[ 0.71001079  0.75007717  0.55271526  0.547501    0.52410561]
Average 5-Fold CV Score: 0.6168819644425119
```

Representing text numerically

Ridge regression takes the sum of the squared values of the coefficients multiplied by some alpha, this is also known as the L2 regularization.

In [328]:
```
# Ridge regression in scikit-learn

from sklearn.linear_model import Ridge
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state=42)
ridge = Ridge(alpha=0.1, normalize=True)
ridge.fit(X_train, y_train)
ridge_pred = ridge.predict(X_test)
ridge.score(X_test, y_test)
```

Out[328]: 0.74001557383978234

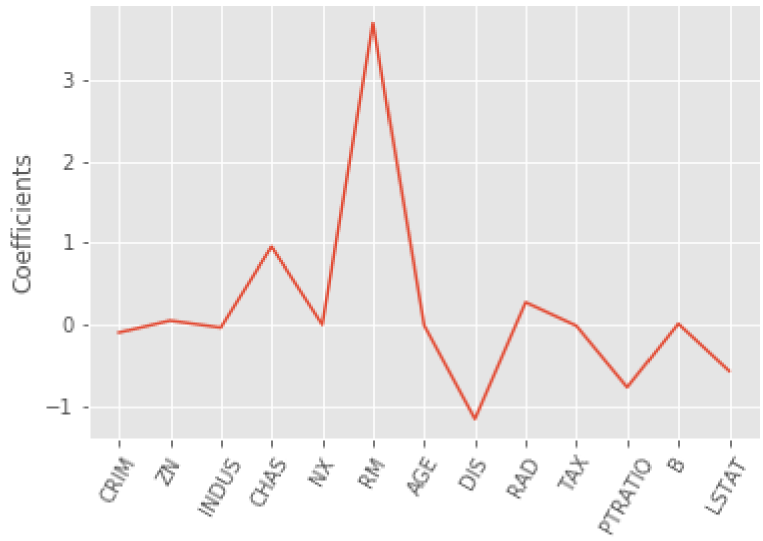
Lasso regression performs regularization by adding to the loss function a penalty term of the absolute value of each coefficient multiplied by some alpha. This is also known as L1 regularization because the regularization term is the L1 norm of the coefficients.

In [329]:
```
# Lasso regression in scikit-learn

from sklearn.linear_model import Lasso
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state=42)
lasso = Lasso(alpha=0.1, normalize=True)
lasso.fit(X_train, y_train)
lasso_pred = lasso.predict(X_test)
lasso.score(X_test, y_test)
```

Out[329]: 0.73913024600881294

In [334]:
```
# Lasso for feature selection in scikit-learn

X = boston.drop('MEDV', axis=1).values
y = boston['MEDV'].values
```

In [339]:
```
from sklearn.linear_model import Lasso

names = boston.drop('MEDV', axis=1).columns
lasso = Lasso(alpha=0.1)
lasso_coef = lasso.fit(X, y).coef_

_ = plt.plot(range(len(names)), lasso_coef)
_ = plt.xticks(range(len(names)), names, rotation=60)
_ = plt.ylabel('Coefficients')
plt.show()
```



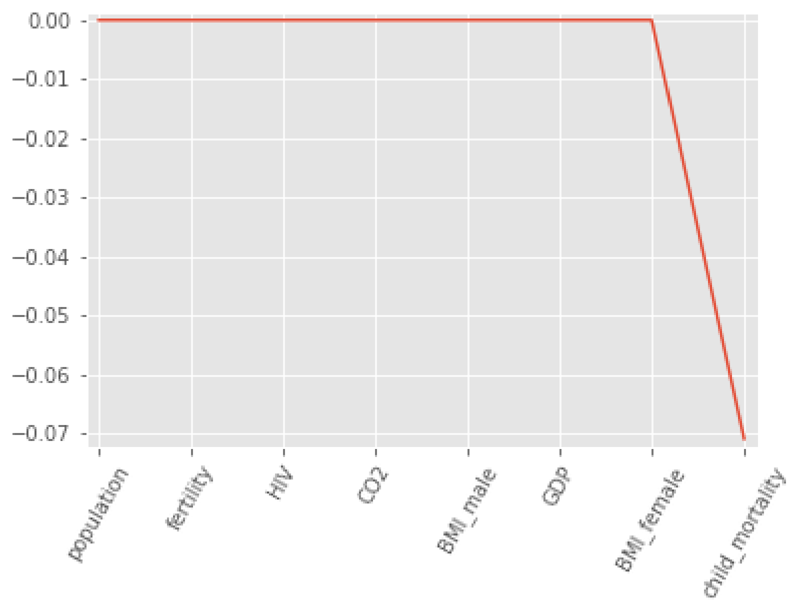
In [343]:
```
# EXERCISES
```

In [369]:
```
# Regularization I: Lasso

df_columns = df.drop(['life','Region'],axis=1).columns
X = df.drop(['life','Region'],axis=1).values
y = df['life'].values
df_columns
```

Out[369]:
```
Index(['population', 'fertility', 'HIV', 'CO2', 'BMI_male', 'GDP',
       'BMI_female', 'child_mortality'],
      dtype='object')
```

In [371]:
```
from sklearn.linear_model import Lasso

# Instantiate a lasso regressor: lasso
lasso = Lasso(alpha=0.4,normalize=True)

# Fit the regressor to the data
lasso.fit(X,y)

# Compute and print the coefficients
lasso_coef = lasso.coef_
print(lasso_coef)

# Plot the coefficients
plt.plot(range(len(df_columns)), lasso_coef)
plt.xticks(range(len(df_columns)), df_columns.values, rotation=60)
plt.margins(0.02)
plt.show()
```

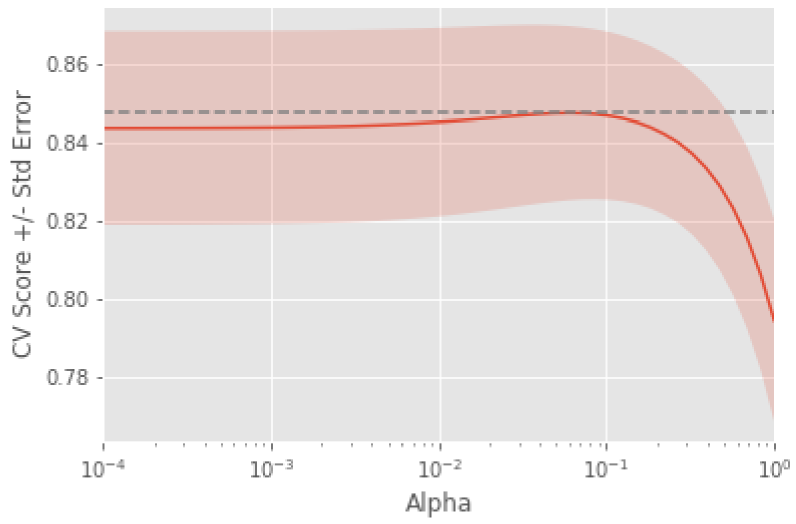
```
[-0.          -0.          -0.           0.           0.           0.          -0.
 -0.07087587]
```



In [385]:
```
# Regularization II: Ridge
# fitting ridge regression models over a range of different alphas, and plot cross-validated R^2 scores for each.
```

In [386]:
```
# function to visualize the scores and standard deviations
def display_plot(cv_scores, cv_scores_std):
    fig = plt.figure()
    ax = fig.add_subplot(1,1,1)
    ax.plot(alpha_space, cv_scores)

    std_error = cv_scores_std / np.sqrt(10)

    ax.fill_between(alpha_space, cv_scores + std_error, cv_scores - std_error, alpha=0.2)
    ax.set_ylabel('CV Score +/- Std Error')
    ax.set_xlabel('Alpha')
    ax.axhline(np.max(cv_scores), linestyle='--', color='.5')
    ax.set_xlim([alpha_space[0], alpha_space[-1]])
    ax.set_xscale('log')
    plt.show()
```

In [387]:
```
# Import necessary modules
from sklearn.linear_model import Ridge
from sklearn.model_selection import cross_val_score

# Setup the array of alphas and lists to store scores
alpha_space = np.logspace(-4, 0, 50)
ridge_scores = []
ridge_scores_std = []

# Create a ridge regressor: ridge
ridge = Ridge(normalize=True)

# Compute scores over range of alphas
for alpha in alpha_space:

    # Specify the alpha value to use: ridge.alpha
    ridge.alpha = alpha

    # Perform 10-fold CV: ridge_cv_scores
    ridge_cv_scores = cross_val_score(ridge,X,y,cv=10)

    # Append the mean of ridge_cv_scores to ridge_scores
    ridge_scores.append(np.mean(ridge_cv_scores))

    # Append the std of ridge_cv_scores to ridge_scores_std
    ridge_scores_std.append(np.std(ridge_cv_scores))

# Display the plot
display_plot(ridge_scores, ridge_scores_std)
```



Notice how the cross-validation scores change with different alphas. Which alpha should you pick? How can you fine-tune your model?

Chap 3: Improving your model

In [391]:
```
# Import plotting modules
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
from sklearn import datasets
plt.style.use('ggplot')
```

Pipelines, feature & text preprocessing

In [398]:
```
# Confusion matrix in scikit-learn

df = pd.read_csv('datasets/house-votes-84.csv',header=None)
df.columns = ['party','infants','water','budget','physician',
              'salvador','religious','satellite','aid','missile',
              'immigration','synfuels','education','superfund',
              'crime','duty_free_exports','eaa_rsa']
df.replace({'n':0,'y':1,'?':0},inplace=True)
```

In [399]:
```
y = df['party'].values
X = df.drop('party', axis=1).values
```

In [400]:
```
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix

knn = KNeighborsClassifier(n_neighbors=8)
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.4, random_state=42)

knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
```

In [401]:
```
print(confusion_matrix(y_test, y_pred))

print(classification_report(y_test, y_pred))
```

```
[[108   7]
 [  6  53]]
             precision    recall  f1-score   support

   democrat       0.95      0.94      0.94       115
 republican       0.88      0.90      0.89        59

avg / total       0.93      0.93      0.93       174
```

In [411]:
```
# EXERCISES
```

In [412]:
```
# Metrics for classification
# computing a confusion matrix and generating a classification report

df = pd.read_csv('datasets/diabetes.csv')
y = df['diabetes'].values
X = df.drop('diabetes',axis=1).values
```

In [413]:
```
# Import necessary modules
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix

# Create training and test set
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.4,random_state=42)

# Instantiate a k-NN classifier: knn
knn = KNeighborsClassifier(n_neighbors=6)

# Fit the classifier to the training data
knn.fit(X_train,y_train)

# Predict the labels of the test data: y_pred
y_pred = knn.predict(X_test)

# Generate the confusion matrix and classification report
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

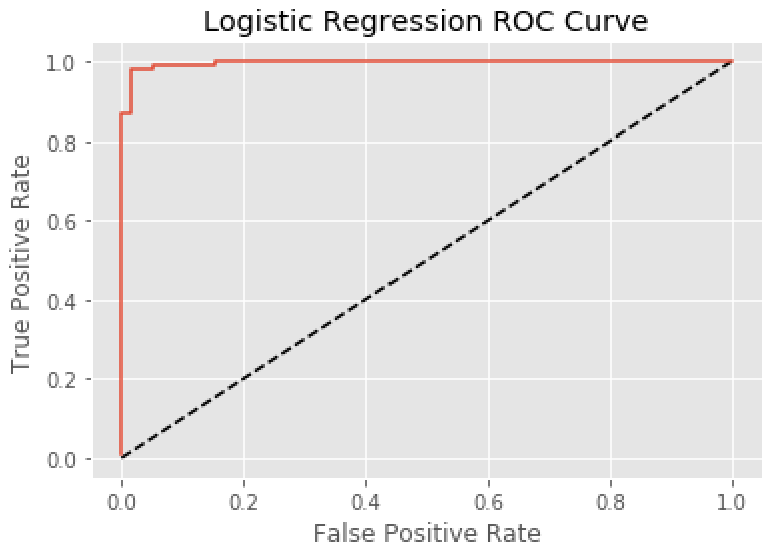
```
[[176  30]
 [ 56  46]]
             precision    recall  f1-score   support

          0       0.76      0.85      0.80       206
          1       0.61      0.45      0.52       102

avg / total       0.71      0.72      0.71       308
```

Text features and feature unions

In [429]:
```
# Logistic regression in scikit-learn

df = pd.read_csv('datasets/house-votes-84.csv',header=None)
df.columns = ['party','infants','water','budget','physician',
              'salvador','religious','satellite','aid','missile',
              'immigration','synfuels','education','superfund',
              'crime','duty_free_exports','eaa_rsa']
df.replace({'n':0,'y':1,'?':0},inplace=True)

y = df['party'].map({'republican':0,'democrat':1}).values
X = df.drop('party', axis=1).values
```

In [430]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

logreg = LogisticRegression()
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.4, random_state=42)

logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
```

In [431]:
```
# Plotting the ROC curve

from sklearn.metrics import roc_curve

y_pred_prob = logreg.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)

plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr, label='Logistic Regression')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression ROC Curve')
plt.show();
```



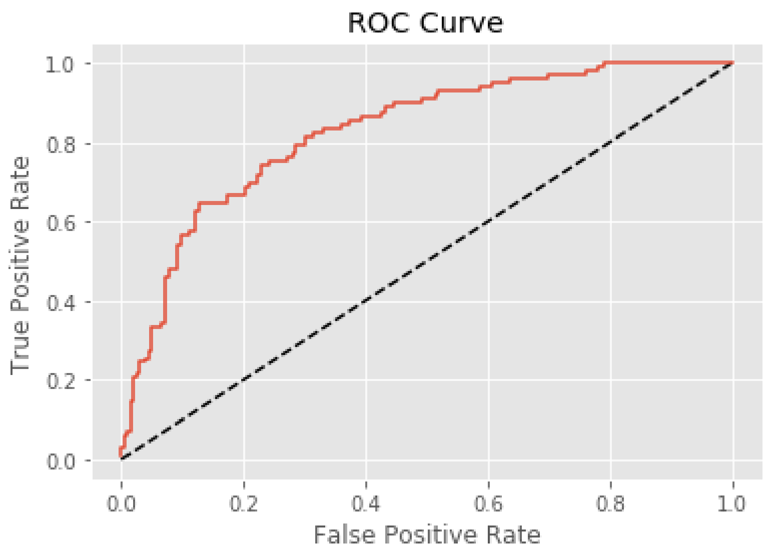
In [443]:
```
# EXERCISES
```

In [444]:
```
# Building a logistic regression model

df = pd.read_csv('datasets/diabetes.csv')
y = df['diabetes'].values
X = df.drop('diabetes',axis=1).values
```

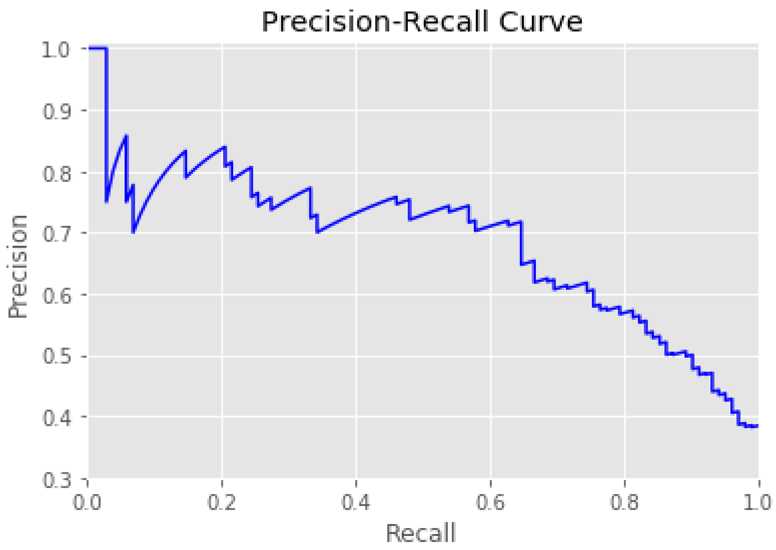
In [445]:
```
# Import the necessary modules
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report

# Create training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.4, random_state=42)

# Create the classifier: logreg
logreg = LogisticRegression()

# Fit the classifier to the training data
logreg.fit(X_train,y_train)

# Predict the labels of the test set: y_pred
y_pred = logreg.predict(X_test)

# Compute and print the confusion matrix and classification report
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[[174  32]
 [ 36  66]]
             precision    recall  f1-score   support

          0       0.83      0.84      0.84       206
          1       0.67      0.65      0.66       102

avg / total       0.78      0.78      0.78       308
```

In [447]:
```
# Plotting an ROC curve

# Import necessary modules
from sklearn.metrics import roc_curve

# Compute predicted probabilities: y_pred_prob
y_pred_prob = logreg.predict_proba(X_test)[:,1]

# Generate ROC curve values: fpr, tpr, thresholds
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)

# Plot ROC curve
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.show()
```



In [462]:
```
# Precision-recall Curve

from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import precision_recall_curve

pr, rc, thld = precision_recall_curve(y_test, y_pred_prob)

# Plot precision-recall curve
plt.plot(rc, pr,color='blue')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.xlim([0.0,1.0])
plt.ylim([0.3,1.01])
plt.title('Precision-Recall Curve')
plt.show()
```



Choosing a classification model

In [464]:
```
# AUC in scikit-learn

from sklearn.metrics import roc_auc_score

logreg = LogisticRegression()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=42)
logreg.fit(X_train, y_train)

y_pred_prob = logreg.predict_proba(X_test)[:,1]
roc_auc_score(y_test, y_pred_prob)
```

Out[464]: 0.82686084142394833

In [468]:
```
# AUC using cross-validation

from sklearn.model_selection import cross_val_score

cv_scores = cross_val_score(logreg, X, y, cv=5, scoring='roc_auc')
print(cv_scores)
```

```
[ 0.7987037   0.80759259  0.81944444  0.86622642  0.85056604]
```

In [469]:
```
# EXERCISES
```

In [470]:
```
# AUC computation

# Import necessary modules
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import cross_val_score

# Compute predicted probabilities: y_pred_prob
y_pred_prob = logreg.predict_proba(X_test)[:,1]

# Compute and print AUC score
print("AUC: {}".format(roc_auc_score(y_test, y_pred_prob)))

# Compute cross-validated AUC scores: cv_auc
cv_auc = cross_val_score(logreg,X,y,cv=5,scoring='roc_auc')

# Print list of AUC scores
print("AUC scores computed using 5-fold cross-validation: {}".format(cv_auc))
```

```
AUC: 0.8268608414239483
AUC scores computed using 5-fold cross-validation: [ 0.7987037   0.80759259  0.81944444  0.86622642  0.85056604]
```

In [471]:
```
# GridSearchCV in scikit-learn

from sklearn.model_selection import GridSearchCV

param_grid = {'n_neighbors': np.arange(1, 50)}
knn = KNeighborsClassifier()
knn_cv = GridSearchCV(knn, param_grid, cv=5)

knn_cv.fit(X, y)
print(knn_cv.best_params_)
print(knn_cv.best_score_)
```

```
{'n_neighbors': 14}
0.7578125
```

In [472]:
```
# EXERCISES
```

In [477]:
```
# Hyperparameter tuning with GridSearchCV

df = pd.read_csv('datasets/diabetes.csv')
y = df['diabetes']
X = df.drop('diabetes',axis=1)
```

In [480]:
```
# Import necessary modules
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression

# Setup the hyperparameter grid
c_space = np.logspace(-5, 8, 15)
param_grid = {'C': c_space}

# Instantiate a logistic regression classifier: logreg
logreg = LogisticRegression()

# Instantiate the GridSearchCV object: logreg_cv
logreg_cv = GridSearchCV(logreg, param_grid, cv=5)

# Fit it to the data
logreg_cv.fit(X,y)

# Print the tuned parameters and score
print("Tuned Logistic Regression Parameters: {}".format(logreg_cv.best_params_))
print("Best score is {}".format(logreg_cv.best_score_))
```

```
Tuned Logistic Regression Parameters: {'C': 163789.3706954068}
Best score is 0.7721354166666666
```

In [483]:
```
# Hyperparameter tuning with RandomizedSearchCV

# Import necessary modules
from scipy.stats import randint
from sklearn.model_selection import RandomizedSearchCV
from sklearn.tree import DecisionTreeClassifier

# Setup the parameters and distributions to sample from: param_dist
param_dist = {"max_depth": [3, None],
              "max_features": randint(1, 9),
              "min_samples_leaf": randint(1, 9),
              "criterion": ["gini", "entropy"]}

# Instantiate a Decision Tree classifier: tree
tree = DecisionTreeClassifier()

# Instantiate the RandomizedSearchCV object: tree_cv
tree_cv = RandomizedSearchCV(tree, param_dist, cv=5)

# Fit it to the data
tree_cv.fit(X,y)

# Print the tuned parameters and score
print("Tuned Decision Tree Parameters: {}".format(tree_cv.best_params_))
print("Best score is {}".format(tree_cv.best_score_))
```

```
Tuned Decision Tree Parameters: {'criterion': 'entropy', 'max_depth': 3, 'max_features': 8, 'min_samples_leaf': 6}
Best score is 0.7395833333333334
```

In [ ]:
```
# EXERCISES
```

In [486]:
```python
# Hold-out set in practice I: Classification

# Import necessary modules
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

# Create the hyperparameter grid
c_space = np.logspace(-5, 8, 15)
param_grid = {'C': c_space, 'penalty': ['l1', 'l2']}

# Instantiate the logistic regression classifier: logreg
logreg = LogisticRegression()

# Create train and test sets
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.4,random_state=42)

# Instantiate the GridSearchCV object: logreg_cv
logreg_cv = GridSearchCV(logreg,param_grid,cv=5)

# Fit it to the training data
logreg_cv.fit(X_train,y_train)

# Print the optimal parameters and best score
print("Tuned Logistic Regression Parameter: {}".format(logreg_cv.best_params_))
print("Tuned Logistic Regression Accuracy: {}".format(logreg_cv.best_score_))
```

```
Tuned Logistic Regression Parameter: {'C': 31.622776601683793, 'penalty': 'l2'}
Tuned Logistic Regression Accuracy: 0.7673913043478261
```

In [497]:
```python
# Hold-out set in practice II: Regression

# Gapminder Countries GDP data
# Read the CSV file into a DataFrame: df
df = pd.read_csv('datasets/gm_2008_region.csv')

# Create arrays for features and target variable
y = df['life'].values
X = df.drop(['life','Region'],axis=1).values
```

In [502]:
```python
import warnings; warnings.filterwarnings('ignore')

# Import necessary modules
from sklearn.linear_model import ElasticNet
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split

# Create train and test sets
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.4,random_state=42)

# Create the hyperparameter grid
l1_space = np.linspace(0, 1, 30)
param_grid = {'l1_ratio': l1_space}

# Instantiate the ElasticNet regressor: elastic_net
elastic_net = ElasticNet()

# Setup the GridSearchCV object: gm_cv
gm_cv = GridSearchCV(elastic_net, param_grid, cv=5)

# Fit it to the training data
gm_cv.fit(X_train,y_train)

# Predict on the test set and compute metrics
y_pred = gm_cv.predict(X_test)
r2 = gm_cv.score(X_test, y_test)
mse = mean_squared_error(y_test, y_pred)
print("Tuned ElasticNet l1 ratio: {}".format(gm_cv.best_params_))
print("Tuned ElasticNet R squared: {}".format(r2))
print("Tuned ElasticNet MSE: {}".format(mse))
```

```
Tuned ElasticNet l1 ratio: {'l1_ratio': 0.20689655172413793}
Tuned ElasticNet R squared: 0.8668305372460283
Tuned ElasticNet MSE: 10.057914133398445
```

Chap 4: Learning from the experts

In [84]:
```
# Import plotting modules
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
from sklearn import datasets
plt.style.use('ggplot')
```

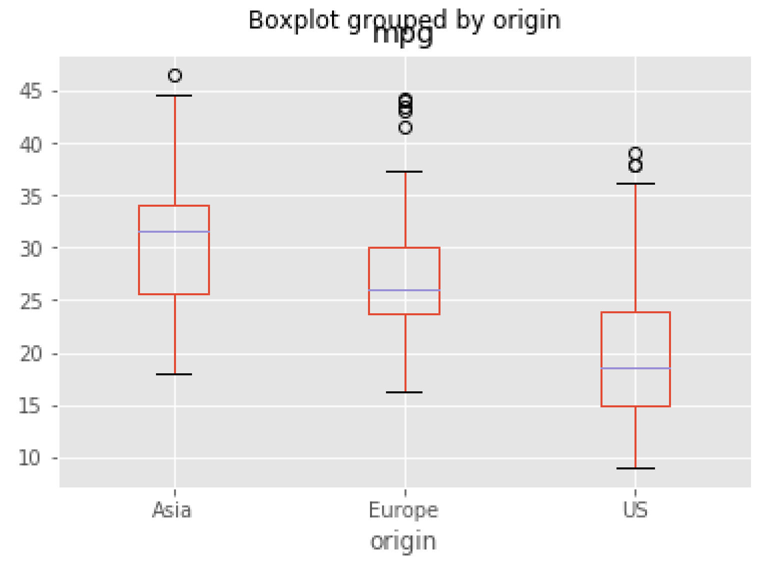
Learning from the expert: processing

In [507]:
```
df = pd.read_csv('datasets/auto.csv')
df.head()
```

Out[507]:

	mpg	displ	hp	weight	accel	origin	size
0	18.0	250.0	88	3139	14.5	US	15.0
1	9.0	304.0	193	4732	18.5	US	20.0
2	36.1	91.0	60	1800	16.4	Asia	10.0
3	18.5	250.0	98	3525	19.0	US	15.0
4	34.3	97.0	78	2188	15.8	Europe	10.0

In [537]:
```
# EDA w/ categorical feature
df.boxplot(column='mpg',by='origin');
plt.show()
```



In [544]:
```
# Encoding dummy variables

df_origin = pd.get_dummies(df,drop_first=True)
print(df_origin.head())
```

```
    mpg  displ   hp  weight  accel  size  origin_Europe  origin_US
0  18.0  250.0   88    3139   14.5  15.0              0          1
1   9.0  304.0  193    4732   18.5  20.0              0          1
2  36.1   91.0   60    1800   16.4  10.0              0          0
3  18.5  250.0   98    3525   19.0  15.0              0          1
4  34.3   97.0   78    2188   15.8  10.0              1          0
```

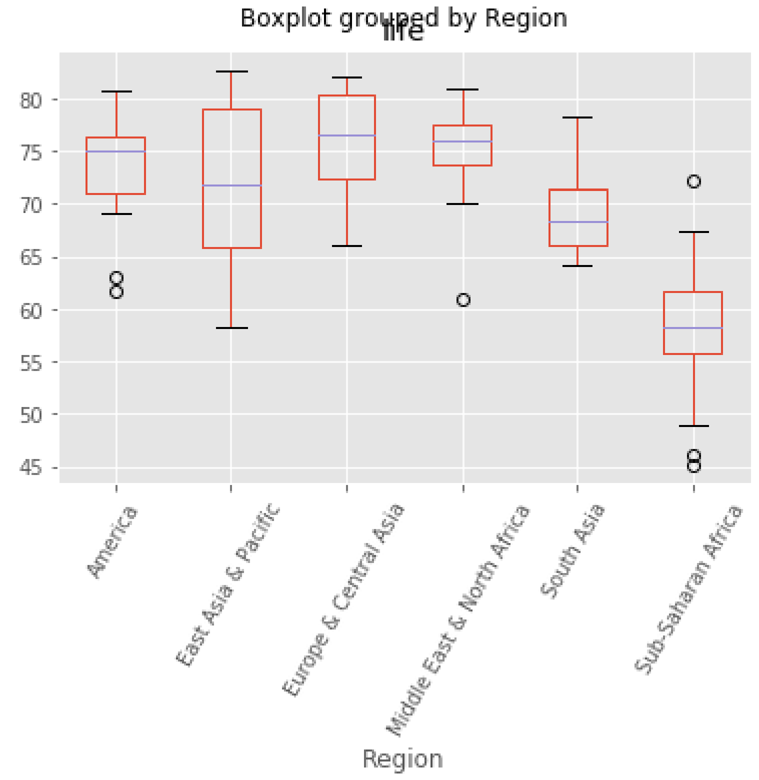
In [550]:
```
X=df_origin.drop(['origin_Europe','origin_US'],axis=1)
y=df_origin[['origin_Europe','origin_US']]
```

In [555]:
```
# Linear regression with dummy variables

from sklearn.model_selection import train_test_split
from sklearn.linear_model import Ridge

X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.3, random_state=42)

ridge = Ridge(alpha=0.5, normalize=True).fit(X_train,y_train)
ridge.score(X_test, y_test)
```

Out[555]: 0.28837060656093705

In [552]:
```
# EXERCISES
```

In [560]:
```
# Exploring categorical features

# Gapminder Countries GDP data
# Read the CSV file into a DataFrame: df
df = pd.read_csv('datasets/gm_2008_region.csv')

# Create a boxplot of life expectancy per region
df.boxplot('life', 'Region', rot=60)

# Show the plot
plt.show()
```



In [564]:
```
# Creating dummy variables

# Create dummy variables: df_region
df_region = pd.get_dummies(df)

# Print the columns of df_region
print(df_region.columns)

# Create dummy variables with drop_first=True: df_region
df_region = pd.get_dummies(df,drop_first=True)

# Print the new columns of df_region
print(df_region.columns)
```

```
Index(['population', 'fertility', 'HIV', 'CO2', 'BMI_male', 'GDP',
       'BMI_female', 'life', 'child_mortality', 'Region_America',
       'Region_East Asia & Pacific', 'Region_Europe & Central Asia',
       'Region_Middle East & North Africa', 'Region_South Asia',
       'Region_Sub-Saharan Africa'],
      dtype='object')
Index(['population', 'fertility', 'HIV', 'CO2', 'BMI_male', 'GDP',
       'BMI_female', 'life', 'child_mortality', 'Region_East Asia & Pacific',
       'Region_Europe & Central Asia', 'Region_Middle East & North Africa',
       'Region_South Asia', 'Region_Sub-Saharan Africa'],
      dtype='object')
```

In [565]:
```
# Create arrays for features and target variable
y = df_region['life']
X = df_region.drop(['life'],axis=1)
X.shape, y.shape
```

Out[565]:
```
((139, 13), (139,))
```

In [567]:
```
# Regression with categorical features

# Import necessary modules
from sklearn.linear_model import Ridge
from sklearn.model_selection import cross_val_score

# Instantiate a ridge regressor: ridge
ridge = Ridge(alpha=0.5,normalize=True)

# Perform 5-fold cross-validation: ridge_cv
ridge_cv = cross_val_score(ridge,X,y,cv=5)

# Print the cross-validated scores
print(ridge_cv)
```

```
[ 0.86808336  0.80623545  0.84004203  0.7754344   0.87503712]
```

Learning from the expert: a stats trick

In [570]:
```
# PIMA Indians dataset
df = pd.read_csv('datasets/diabetes.csv')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
pregnancies    768 non-null int64
glucose        768 non-null int64
diastolic      768 non-null int64
triceps        768 non-null int64
insulin        768 non-null int64
bmi            768 non-null float64
dpf            768 non-null float64
age            768 non-null int64
diabetes       768 non-null int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

In [571]:
```
print(df.head())
```

```
   pregnancies  glucose  diastolic  triceps  insulin   bmi    dpf  age  \
0            6      148         72       35        0  33.6  0.627   50
1            1       85         66       29        0  26.6  0.351   31
2            8      183         64        0        0  23.3  0.672   32
3            1       89         66       23       94  28.1  0.167   21
4            0      137         40       35      168  43.1  2.288   33

   diabetes
0         1
1         0
2         1
3         0
4         1
```

In [573]:
```
df.insulin.replace(0, np.nan, inplace=True)
df.triceps.replace(0, np.nan, inplace=True)
df.bmi.replace(0, np.nan, inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
pregnancies    768 non-null int64
glucose        768 non-null int64
diastolic      768 non-null int64
triceps        541 non-null float64
insulin        394 non-null float64
bmi            757 non-null float64
dpf            768 non-null float64
age            768 non-null int64
diabetes       768 non-null int64
dtypes: float64(4), int64(5)
memory usage: 54.1 KB
```

In [574]:
```
# Dropping missing data
df.dropna().shape
```

Out[574]:
```
(393, 9)
```

In [592]:
```
# Imputing missing data
y = df['diabetes']
X = df.drop('diabetes',axis=1)
```

In [593]:
```
from sklearn.preprocessing import Imputer
imp = Imputer(missing_values='NaN', strategy='mean', axis=0)
imp.fit(X)
X = imp.transform(X)
```

In [597]:
```python
# Imputing within a pipeline
# Pipeline: All steps before last must be transformers (like impute)
# Pipeline: Last step can be transformer or estimator (like classifier/regressor)

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import Imputer

imp = Imputer(missing_values='NaN', strategy='mean', axis=0)
logreg = LogisticRegression()

steps = [('imputation', imp),('logistic_regression', logreg)]
pipeline = Pipeline(steps)

X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.3, random_state=42)

pipeline.fit(X_train, y_train)
y_pred = pipeline.predict(X_test)
pipeline.score(X_test, y_test)
```

Out[597]:
```
0.76190476190476186
```

In [ ]:
```python
# EXERCISES
```

In [598]:
```python
# Dropping missing data

df = pd.read_csv('datasets/house-votes-84.csv',header=None)
df.columns = ['party','infants','water','budget','physician',
              'salvador','religious','satellite','aid','missile',
              'immigration','synfuels','education','superfund',
              'crime','duty_free_exports','eaa_rsa']
df.replace({'n':0,'y':1},inplace=True)
```

In [601]:
```python
# Convert '?' to NaN
df[df == '?'] = np.nan

# Print the number of NaNs
print(df.isnull().sum())

# Print shape of original DataFrame
print("Shape of Original DataFrame: {}".format(df.shape))

# Drop missing values and print shape of new DataFrame
df = df.dropna()

# Print shape of new DataFrame
print("Shape of DataFrame After Dropping All Rows with Missing Values: {}".format(df.shape))
```

```
party                  0
infants               12
water                 48
budget                11
physician             11
salvador              15
religious             11
satellite             14
aid                   15
missile               22
immigration            7
synfuels              21
education             31
superfund             25
crime                 17
duty_free_exports     28
eaa_rsa              104
dtype: int64
Shape of Original DataFrame: (435, 17)
Shape of DataFrame After Dropping All Rows with Missing Values: (232, 17)
```

In [602]:
```
# Imputing missing data in a ML Pipeline I

# Import the Imputer module
from sklearn.preprocessing import Imputer
from sklearn.svm import SVC

# Setup the Imputation transformer: imp
imp = Imputer(missing_values='NaN', strategy='most_frequent', axis=0)

# Instantiate the SVC classifier: clf
clf = SVC()

# Setup the pipeline with the required steps: steps
steps = [('imputation', imp),('SVM', clf)]
```

In [603]:
```
# Imputing missing data in a ML Pipeline II

# Import necessary modules
from sklearn.preprocessing import Imputer
from sklearn.pipeline import Pipeline
from sklearn.svm import SVC

# Setup the pipeline steps: steps
steps = [('imputation', Imputer(missing_values='NaN', strategy='most_frequent', axis=0)),
        ('SVM', SVC())]

# Create the pipeline: pipeline
pipeline = Pipeline(steps)

# Create training and test sets
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_state=42)

# Fit the pipeline to the train set
pipeline.fit(X_train,y_train)

# Predict the labels of the test set
y_pred = pipeline.predict(X_test)

# Compute metrics
print(classification_report(y_test, y_pred))
```

```
             precision    recall  f1-score   support

          0       0.65      1.00      0.79       151
          1       0.00      0.00      0.00        80

avg / total       0.43      0.65      0.52       231
```

Learning from the expert: a computational trick and the winning model

In [663]:
```
# Why scale your data?

df = pd.read_csv('datasets/winequality-red.csv',header=0,sep=';')
X = df.drop('quality',axis=1).values
y = df['quality'].values
df.head()
```

Out[663]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

In [664]:
```
# Scaling in scikit-learn

from sklearn.preprocessing import scale

X_scaled = scale(X)
print(np.mean(X), np.std(X))
print(np.mean(X_scaled), np.std(X_scaled))
```

```
8.13421922452 16.7265339794
2.54662653149e-15 1.0
```

In [665]:

```
# Scaling in a pipeline

from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score

steps = [('scaler', StandardScaler()),('knn', KNeighborsClassifier())]
pipeline = Pipeline(steps)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=21)

knn_scaled = pipeline.fit(X_train, y_train)
y_pred = pipeline.predict(X_test)
print(accuracy_score(y_test, y_pred))

knn_unscaled = KNeighborsClassifier().fit(X_train, y_train)
print(knn_unscaled.score(X_test, y_test))
```

```
0.615625
0.49375
```

In [673]:

```
# CV and scaling in a pipeline

steps = [('scaler', StandardScaler()),(('knn', KNeighborsClassifier()))]
pipeline = Pipeline(steps)
parameters = {'knn__n_neighbors':np.arange(1, 50)}

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=21)

cv = GridSearchCV(pipeline, param_grid=parameters)
cv.fit(X_train, y_train)
y_pred = cv.predict(X_test)
```

In [674]:

```
print(cv.best_params_)
print(cv.score(X_test, y_test))
print(classification_report(y_test, y_pred))
```

```
{'knn__n_neighbors': 1}
0.634375
             precision    recall  f1-score   support

          3       0.00      0.00      0.00         1
          4       0.18      0.12      0.15        16
          5       0.66      0.72      0.69       127
          6       0.68      0.60      0.64       131
          7       0.63      0.69      0.66        42
          8       0.25      0.33      0.29         3

avg / total       0.63      0.63      0.63       320
```

In [675]:

```
# EXERCISES
```

In [684]:

```
# Centering and scaling your data

# White wine quality dataset.
df = pd.read_csv('datasets/white-wine.csv')
y = df.quality < 5
X = df.drop('quality',axis=1).values
```

In [685]:

```
# Import scale
from sklearn.preprocessing import scale

# Scale the features: X_scaled
X_scaled = scale(X)

# Print the mean and standard deviation of the unscaled features
print("Mean of Unscaled Features: {}".format(np.mean(X)))
print("Standard Deviation of Unscaled Features: {}".format(np.std(X)))

# Print the mean and standard deviation of the scaled features
print("Mean of Scaled Features: {}".format(np.mean(X_scaled)))
print("Standard Deviation of Scaled Features: {}".format(np.std(X_scaled)))
```

```
Mean of Unscaled Features: 18.432687072460002
Standard Deviation of Unscaled Features: 41.54494764094571
Mean of Scaled Features: 2.7314972981668206e-15
Standard Deviation of Scaled Features: 0.9999999999999999
```

In [687]:
```
# Centering and scaling in a pipeline

# Import the necessary modules
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

# Setup the pipeline steps: steps
steps = [('scaler', StandardScaler()),
        ('knn', KNeighborsClassifier())]

# Create the pipeline: pipeline
pipeline = Pipeline(steps)

# Create train and test sets
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_state=42)

# Fit the pipeline to the training set: knn_scaled
knn_scaled = pipeline.fit(X_train,y_train)

# Instantiate and fit a k-NN classifier to the unscaled data
knn_unscaled = KNeighborsClassifier().fit(X_train, y_train)

# Compute and print metrics
print('Accuracy with Scaling: {}'.format(knn_scaled.score(X_test,y_test)))
print('Accuracy without Scaling: {}'.format(knn_unscaled.score(X_test,y_test)))
```

```
Accuracy with Scaling: 0.964625850340136
Accuracy without Scaling: 0.9666666666666667
```

In [689]:
```
# Bringing it all together I: Pipeline for classification

from sklearn.pipeline import Pipeline
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.grid_search import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
```

In [690]:
```
# Setup the pipeline
steps = [('scaler', StandardScaler()),
         ('SVM', SVC())]

pipeline = Pipeline(steps)

# Specify the hyperparameter space
parameters = {'SVM__C':[1, 10, 100],
              'SVM__gamma':[0.1, 0.01]}

# Create train and test sets
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=21)

# Instantiate the GridSearchCV object: cv
cv = GridSearchCV(pipeline, param_grid=parameters)

# Fit to the training set
cv.fit(X_train,y_train)

# Predict the labels of the test set: y_pred
y_pred = cv.predict(X_test)

# Compute and print metrics
print("Accuracy: {}".format(cv.score(X_test, y_test)))
print(classification_report(y_test, y_pred))
print("Tuned Model Parameters: {}".format(cv.best_params_))
```

```
Accuracy: 0.9693877551020408
             precision    recall  f1-score   support

      False       0.97      1.00      0.98       951
       True       0.43      0.10      0.17        29

avg / total       0.96      0.97      0.96       980

Tuned Model Parameters: {'SVM__C': 100, 'SVM__gamma': 0.01}
```

In [702]:
```
# Bringing it all together II: Pipeline for regression

df = pd.read_csv('datasets/gm_2008_region.csv')
y = df['life'].values
X = df.drop(['life','Region'],axis=1).values
```

In [705]:
```
# Setup the pipeline steps: steps
steps = [('imputation', Imputer(missing_values='NaN', strategy='mean', axis=0)),
         ('scaler', StandardScaler()),
         ('elasticnet', ElasticNet())]

# Create the pipeline: pipeline
pipeline = Pipeline(steps)

# Specify the hyperparameter space
parameters = {'elasticnet__l1_ratio':np.linspace(0,1,30)}

# Create train and test sets
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.4,random_state=42)

# Create the GridSearchCV object: gm_cv
gm_cv = GridSearchCV(pipeline,param_grid=parameters)

# Fit to the training set
gm_cv.fit(X_train,y_train)

# Compute and print the metrics
r2 = gm_cv.score(X_test, y_test)
print("Tuned ElasticNet Alpha: {}".format(gm_cv.best_params_))
print("Tuned ElasticNet R squared: {}".format(r2))
```

```
Tuned ElasticNet Alpha: {'elasticnet__l1_ratio': 1.0}
Tuned ElasticNet R squared: 0.8862016570888217
```

Next steps and the social impact of your work

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