

Preprocessing data

SUPERVISED LEARNING WITH SCIKIT-LEARN



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Dealing with categorical features

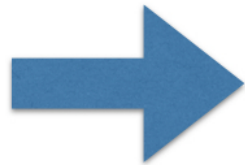
- Scikit-learn will not accept categorical features by default
- Need to encode categorical features numerically
- Convert to 'dummy variables'
 - 0: Observation was NOT that category
 - 1: Observation was that category

Dummy variables

Origin
US
Europe
Asia

Dummy variables

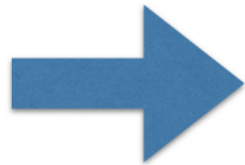
Origin
US
Europe
Asia



origin_Asia	origin_Europe	origin_US
0	0	1
0	1	0
1	0	0

Dummy variables

Origin
US
Europe
Asia



origin_Asia	origin_US
0	1
0	0
1	0

Dealing with categorical features in Python

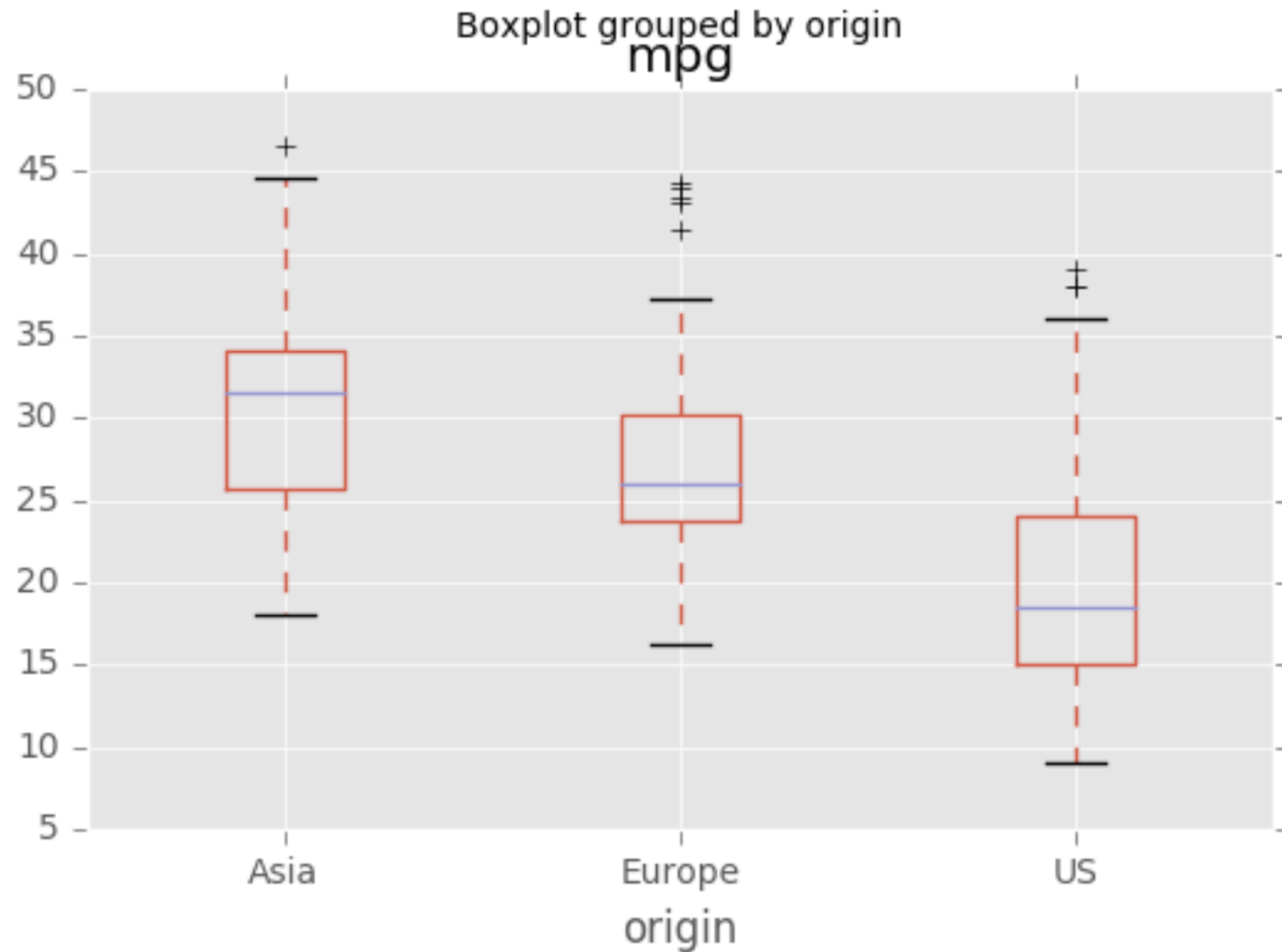
- scikit-learn: `OneHotEncoder()`
- pandas: `get_dummies()`

Automobile dataset

- mpg: Target Variable
- Origin: Categorical Feature

	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

EDA w/ categorical feature



Encoding dummy variables

```
import pandas as pd
df = pd.read_csv('auto.csv')
df_origin = pd.get_dummies(df)
print(df_origin.head())
```

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

   origin_US
0          1
1          1
2          0
3          1
4          0
```

Encoding dummy variables

```
df_origin = df_origin.drop('origin_Asia', axis=1)
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

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)
```

```
0.719064519022
```

Let's practice!

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Handling missing data

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Hugo Bowne-Anderson
Data Scientist, DataCamp

PIMA Indians dataset

```
df = pd.read_csv('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  
None
```

PIMA Indians dataset

```
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
```

Dropping missing data

```
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
```


Dropping missing data

```
df = df.dropna()  
df.shape
```

```
(393, 9)
```

Imputing missing data

- Making an educated guess about the missing values
- Example: Using the mean of the non-missing entries

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

Imputing within a pipeline

```
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)
```

Imputing within a pipeline

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

```
0.75324675324675328
```

Let's practice!

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Centering and scaling

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Hugo Bowne-Anderson
Data Scientist, DataCamp

Why scale your data?

```
print(df.describe())
```

```
fixed acidity  free sulfur dioxide  total sulfur dioxide  density  \
count  1599.000000          1599.000000          1599.000000  1599.000000
mean      8.319637          15.874922          46.467792    0.996747
std       1.741096          10.460157          32.895324    0.001887
min       4.600000           1.000000           6.000000    0.990070
25%       7.100000           7.000000          22.000000    0.995600
50%       7.900000          14.000000          38.000000    0.996750
75%       9.200000          21.000000          62.000000    0.997835
max      15.900000          72.000000          289.000000    1.003690

pH  sulphates  alcohol  quality
count  1599.000000  1599.000000  1599.000000  1599.000000
mean     3.311113    0.658149   10.422983    0.465291
std     0.154386    0.169507    1.065668    0.498950
min     2.740000    0.330000    8.400000    0.000000
25%     3.210000    0.550000    9.500000    0.000000
50%     3.310000    0.620000   10.200000    0.000000
75%     3.400000    0.730000   11.100000    1.000000
max     4.010000    2.000000   14.900000    1.000000
```

Why scale your data?

- Many models use some form of distance to inform them
- Features on larger scales can unduly influence the model
- Example: k-NN uses distance explicitly when making predictions
- We want features to be on a similar scale
- Normalizing (or scaling and centering)

Ways to normalize your data

- Standardization: Subtract the mean and divide by variance
- All features are centered around zero and have variance one
- Can also subtract the minimum and divide by the range
- Minimum zero and maximum one
- Can also normalize so the data ranges from -1 to +1
- See scikit-learn docs for further details

Scaling in scikit-learn

```
from sklearn.preprocessing import scale  
X_scaled = scale(X)
```

```
np.mean(X), np.std(X)
```

```
(8.13421922452, 16.7265339794)
```

```
np.mean(X_scaled), np.std(X_scaled)
```

```
(2.54662653149e-15, 1.0)
```

Scaling in a pipeline

```
from sklearn.preprocessing import StandardScaler
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)
accuracy_score(y_test, y_pred)
```

0.956

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

0.928

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)
```

Scaling and CV in a pipeline

```
print(cv.best_params_)
```

```
{'knn__n_neighbors': 41}
```

```
print(cv.score(X_test, y_test))
```

```
0.956
```

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

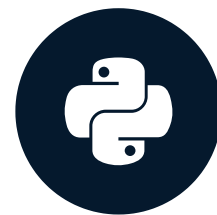
	precision	recall	f1-score	support
0	0.97	0.90	0.93	39
1	0.95	0.99	0.97	75
avg / total	0.96	0.96	0.96	114

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Final thoughts

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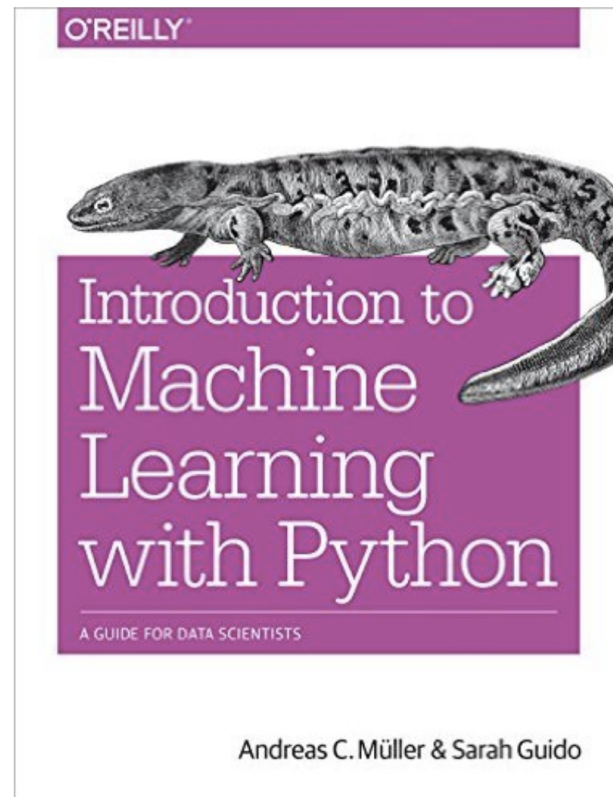
Hugo and Andy
Data Scientists

What you've learned

- Using machine learning techniques to build predictive models
- For both regression and classification problems
- With real-world data
- Underfitting and overfitting
- Test-train split
- Cross-validation
- Grid search

What you've learned

- Regularization, lasso and ridge regression
- Data preprocessing
- For more: Check out the scikit-learn documentation



Let's practice!

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