Lecture2. Data Structures in Python for Data analysis

Good morning!
Доброе утро!
早上好!

我们会成功

We will succeed !

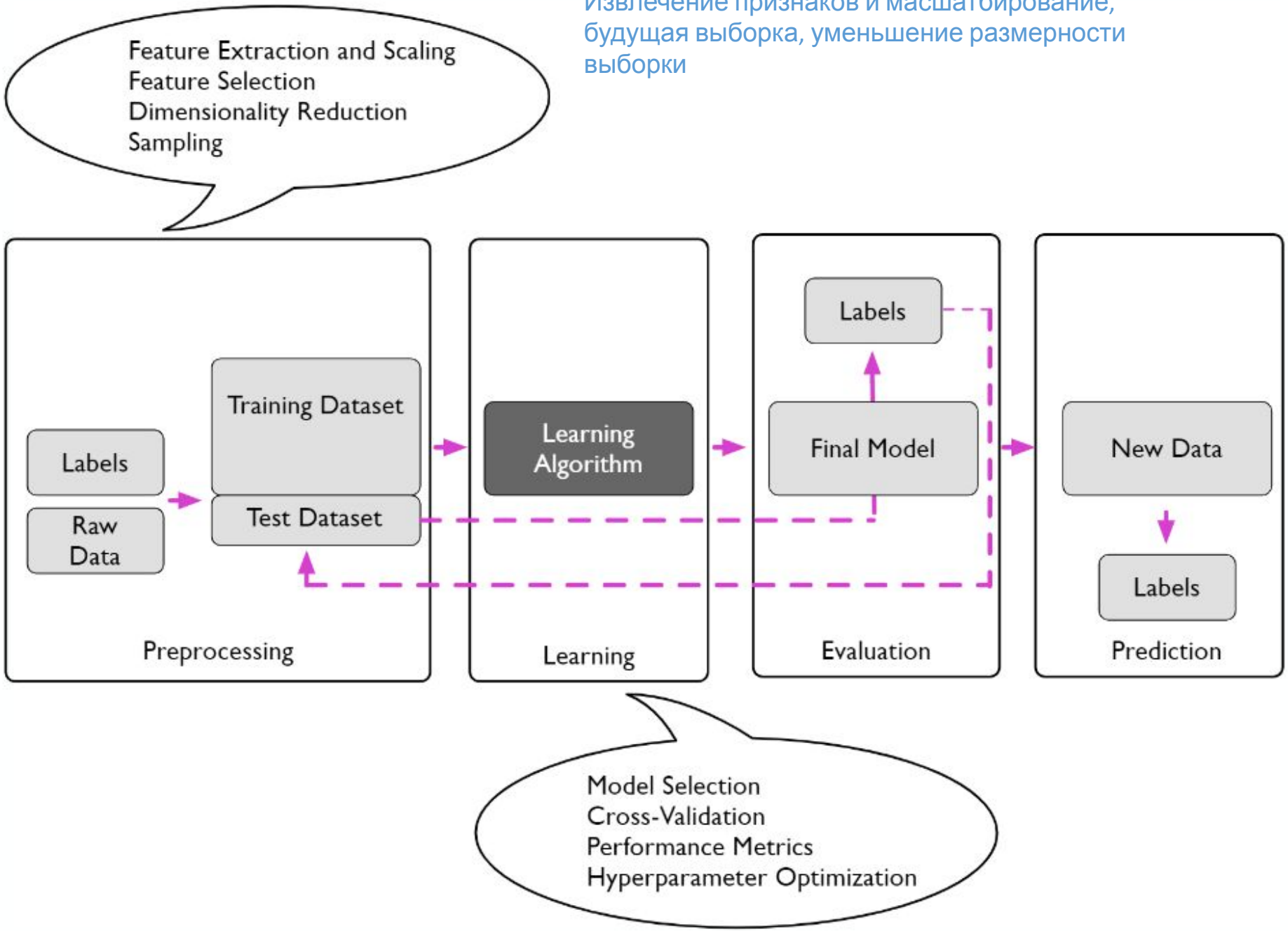
У нас все получится [U nas vse poluchitsya] !

Без булдырабыз!

☺️

Lecture3.
Data preproccessing and machine learning with Scikit-learn

Извлечение признаков и масштабирование, будущая выборка, уменьшение размерности выборки



Training set and testing set

- Machine learning is about learning some properties of a data set and then testing those properties against another data set.
- A common practice in machine learning is to evaluate an algorithm by splitting a data set into two.

- We call one of those sets the **training set**, on which we learn some properties; we call the other set the **testing set**, on which we test the learned properties.

Reading a Dataset

The Iris Dataset

Iris-Setosa

Iris-Versicolor

Iris-Virginica

Fisher, R.A. "The use of multiple measurements in taxonomic problems" Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to Mathematical Statistics" (John Wiley, NY, 1950).

Data Description :

Attribute Information:
1. sepal length in cm
2. sepal width in cm
3. petal length in cm
4. petal width in cm

Class:
-- Iris Setosa
-- Iris Versicolour
-- Iris Virginica

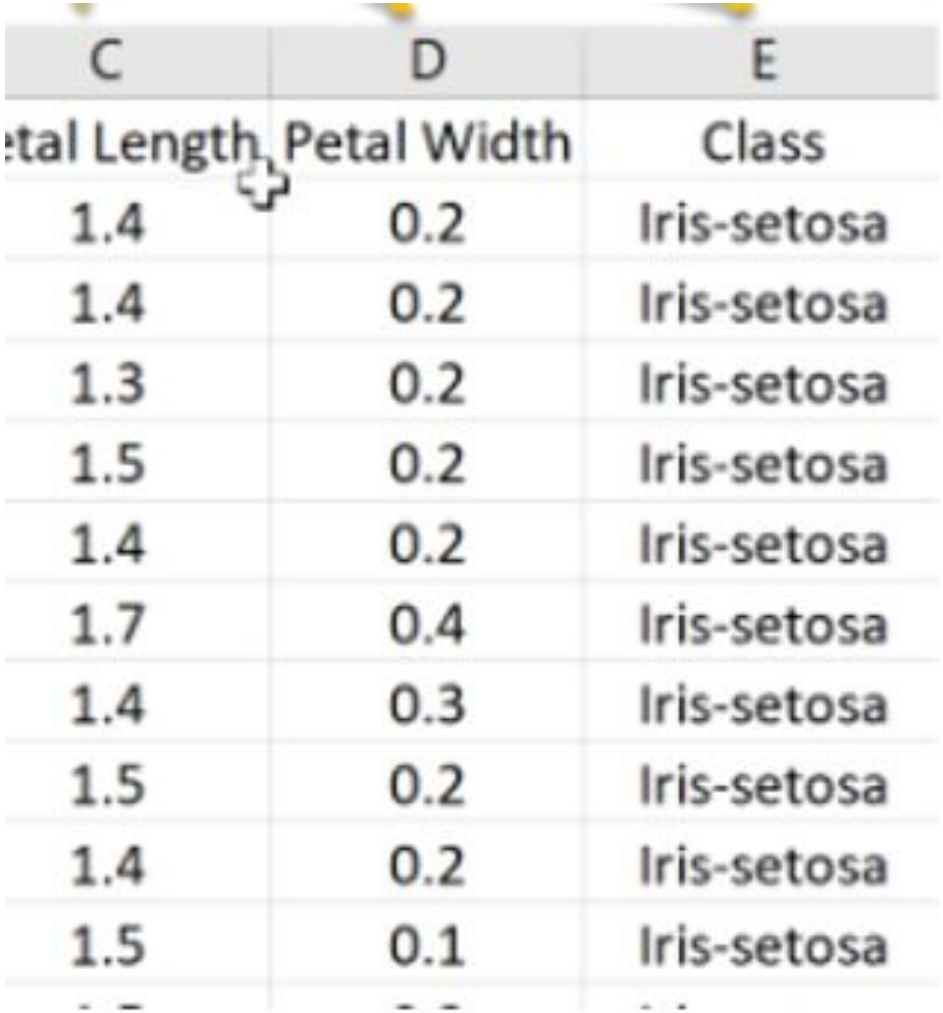
- A basic table is a two-dimensional grid of data, in which the rows represent individual elements of the dataset, and the columns represent quantities related to each of these elements.
- For example, consider the Iris dataset

	A	B	C	D	E
1	Sepal Length	Sepal Width	Petal Length	Petal Width	Class
2	5.1	3.5	1.4	0.2	Iris-setosa
3	4.9	3	1.4	0.2	Iris-setosa
4	4.7	3.2	1.3	0.2	Iris-setosa
5	4.6	3.1	1.5	0.2	Iris-setosa
6	5	3.6	1.4	0.2	Iris-setosa
7	5.4	3.9	1.7	0.4	Iris-setosa
8	4.6	3.4	1.4	0.3	Iris-setosa
9	5	3.4	1.5	0.2	Iris-setosa
10	4.4	2.9	1.4	0.2	Iris-setosa
11	4.9	3.1	1.5	0.1	Iris-setosa

Here each row of the data refers to a single observed flower, and the number of rows is the total number of flowers in the dataset. In general, we will refer to the rows of the matrix as *samples*, and the number of rows as n_samples.
The samples (i.e., rows) always refer to the individual objects described by the dataset. For example, the sample might be a flower, a person, a document, an image, a sound file, a video, an astronomical object, or anything else you can describe with a set of quantitative measurements.

Target array

In dataset we also work with
a *label* or *target* array, which by convention we will usually call y.
The target array is usually one dimensional, with length n_samples. The target array may have continuous numerical values, or discrete classes/labels.
The distinguishing feature of the target array is that it is usually the quantity we want to *predict from the data*: in statistical terms, it is the **dependent** variable. For example, in the preceding data we may wish to construct a model that can predict the species of flower based on the other measurements; in this case,
the species column would be considered the target array.



C	D	E
tal Length	Petal Width	Class
1.4	0.2	Iris-setosa
1.4	0.2	Iris-setosa
1.3	0.2	Iris-setosa
1.5	0.2	Iris-setosa
1.4	0.2	Iris-setosa
1.7	0.4	Iris-setosa
1.4	0.3	Iris-setosa
1.5	0.2	Iris-setosa
1.4	0.2	Iris-setosa
1.5	0.1	Iris-setosa

- **Basic Data Analysis :**
- The dataset provided has 150 rows
- **Dependent Variables** : Sepal length.Sepal Width,Petal length,Petal Width
- **Independent/Target Variable** : Class
- Missing values : None

- The dataset is divided into

Train and Test data

with 80:20 split ratio

where 80% data is training data where as 20% data is test data.

- Each training point belongs to one of N different classes.
- The goal is to construct a function which, given a new data point, will correctly predict the class to which the new point belongs.

Classification: samples belong to two or more classes and we want to learn from already labeled data how to predict the class of unlabeled data.

What is scikit-learn?

- The scikit-learn library provides an implementation of a range of algorithms for Supervised Learning and Unsupervised Learning.

You can watch the Pandas and scikit-learn features documentation on this site.

- https://pandas.pydata.org/pandas-docs/stable/

  https://scikit-learn.org/stable/documentation.html

Preprocessing Data: missing data

- Real world data is filled with missing values.
- You will often need to rid your data of these missing values in order to train a model or do meaningful analysis.
- What follows are a few ways to impute (fill) missing values in Python, for both numeric and categorical data.

idx	X1	X2
0	NaN	0.875058
1	0.763618	0.772110
2	0.617353	0.643694
3	0.738487	0.542382
4	NaN	0.071095
5	0.716237	0.685460
6	0.730759	NaN
7	NaN	0.209360
8	0.710738	0.547641
9	0.546935	NaN

Method 1: Mean or Median

- A common method of imputation with numeric features is to replace missing values with the mean of the feature's non-missing values. If the data have outliers, you may want to use the median instead. Either method is easy in Pandas:

```
df_mean_imputed = df.fillna(df.mean())
df_median_imputed = df.fillna(df.median())
```

idx	X1	X2
0	0.689161	0.875058
1	0.763618	0.772110
2	0.617353	0.643694
3	0.738487	0.542382
4	0.689161	0.071095
5	0.716237	0.685460
6	0.730759	0.543350
7	0.689161	0.209360
8	0.710738	0.547641
9	0.546935	0.543350

Imputation Method 2: Zero

- Depending on where your data are coming from, a missing value may be better represented by the number zero. Replacing missing values with zeros is accomplished similar to the above method; just replace the mean function with zero.

```
# replace missing values with the column mean

df_zero_imputed = df.fillna(0)

df_zero_imputed
```

idx	X1	X2
0	0.000000	0.875058
1	0.763618	0.772110
2	0.617353	0.643694
3	0.738487	0.542382
4	0.000000	0.071095
5	0.716237	0.685460
6	0.730759	0.000000
7	0.000000	0.209360
8	0.710738	0.547641
9	0.546935	0.000000

Imputation for Categorical Data

- For categorical features, using mean, median, or zero-imputation doesn’t make much sense. Here I’ll create an example dataset with categorical features and show two imputation methods specific to this type of data.

idx	X1	X2
0	NaN	Green
1	Red	Green
2	Blue	Red
3	Red	Blue
4	NaN	Green
5	Red	Blue
6	Green	NaN
7	NaN	Red
8	Blue	Green
9	Red	NaN

Imputation Method 1: Most Common Class

- One approach to imputing categorical features is to replace missing values with the most common class. You can do with by taking the index of the most common feature given in Pandas' value_counts function.

```
# for each column, get value counts in decreasing order and take the index (value) of most common class
df_most_common_imputed = colors.apply(lambda x: x.fillna(x.value_counts().index[0]))
```

idx	X1	X2
0	Red	Green
1	Red	Green
2	Blue	Red
3	Red	Blue
4	Red	Green
5	Red	Blue
6	Green	Green
7	Red	Red
8	Blue	Green
9	Red	Green

Imputation Method 2: “Unknown” Class

- Similar to how it’s sometimes most appropriate to impute a missing numeric feature with zeros, sometimes a categorical feature’s missing-ness itself is valuable information that should be explicitly encoded. If this is the case, most-common-class imputing would cause this information to be lost. Instead, just replace those values with a value like “Unknown” or “Missing.”

- df_unknown_imputed = colors.fillna("Unknown")

idx	X1	X2
0	Unknown	Green
1	Red	Green
2	Blue	Red
3	Red	Blue
4	Unknown	Green
5	Red	Blue
6	Green	Unknown
7	Unknown	Red
8	Blue	Green
9	Red	Unknown

Column-Specific Imputation Rules

- You can combine any of the above methods by imputing specific columns rather than the entire dataframe. Returning to the numeric example, we can mean-impute X1 and median-impute X2 by specifying the column(s) to be imputed.

```
# replace missing values with the column mean
df['X1'] = df['X1'].fillna(df['X1'].mean())
df['X2'] = df['X2'].fillna(df['X2'].median())
df
```

Preprocessing Data
If data set are strings

- We saw in our initial exploration that most of the columns in our data set are strings, but the algorithms in scikit-learn understand only numeric data. Luckily, the scikit-learn library provides us with many methods for converting string data into numerical data. One such method is the LabelEncoder() method. We will use this method to convert the categorical labels in our data set like ‘won’ and ‘loss’ into numerical labels. To visualize what we are trying to to achieve with the LabelEncoder() method let’s consider the images below.

- The image below represents a dataframe that has one column named ‘color’ and three records ‘Red’, ‘Green’ and ‘Blue’.

	Color
0	Red
1	Green
2	Blue

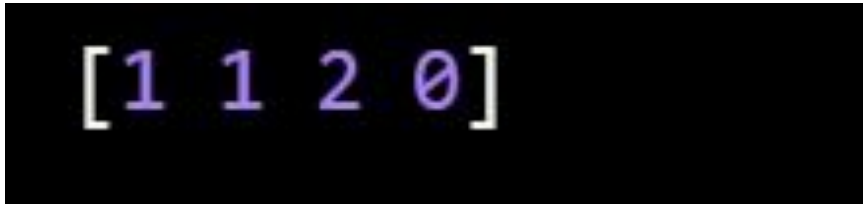
	Color
0	1
1	2
2	3

- Since the machine learning algorithms in scikit-learn understand only numeric inputs, we would like to convert the categorical labels like ‘Red, ‘Green’ and ‘Blue’ into numeric labels. When we are done converting the categorical labels in the original dataframe, we would get something like this

```
#import the necessary module
from sklearn import preprocessing
# create the Labelencoder object
le = preprocessing.LabelEncoder()

#convert the categorical columns into numeric
encoded_value = le.fit_transform(["paris", "paris", "tokyo", "amsterdam"])

print(encoded_value)
```



he LabelEncoder() method assigns the numeric values to the classes in the order of the first letter of the classes from the original list: “(a)msterdam” gets an encoding of ‘0’ , “(p)aris gets an encoding of 1” and “(t)okyo” gets an encoding of 2.

Training Set & Test Set

- A Machine Learning algorithm needs to be trained on a set of data to learn the relationships between different features and how these features affect the target variable.
- For this we need to divide the entire data set into two sets.
- One is the training set on which we are going to train our algorithm to build a model.
- The other is the testing set on which we will test our model to see how accurate its predictions are.

But before doing all this splitting, let's first separate our features and target variables.

```
data=df4[['DemAffl','DemAge','DemCluster','DemClusterGroup','DemGender','DemReg','DemTVReg','PromClass','PromSpend','PromTime']]
target = df4['TargetBuy']
data.head(2)
```

```
#import the necessary module
from sklearn.model_selection import train_test_split
#split data set into train and test setsdata_train, data_test,
target_train, target_test = train_test_split(data, target, test_size = 0.30)
```

we used the train_test_split() method to divide the data into a training set (data_train,target_train) and a test set (data_test,data_train). The first argument of the train_test_split() method are the features that we separated out in the previous section, the second argument is the target('Opportunity Result'). The third argument 'test_size' is the percentage of the data that we want to separate out as training data .

Watch subtitled video

- https://www.coursera.org/lecture/machine-learning/what-is-machine-learning-Ujm7v

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