Getting started with Machine Learning (ML) and Support Vector Classifiers (SVC) - A systematic step-by-step approach

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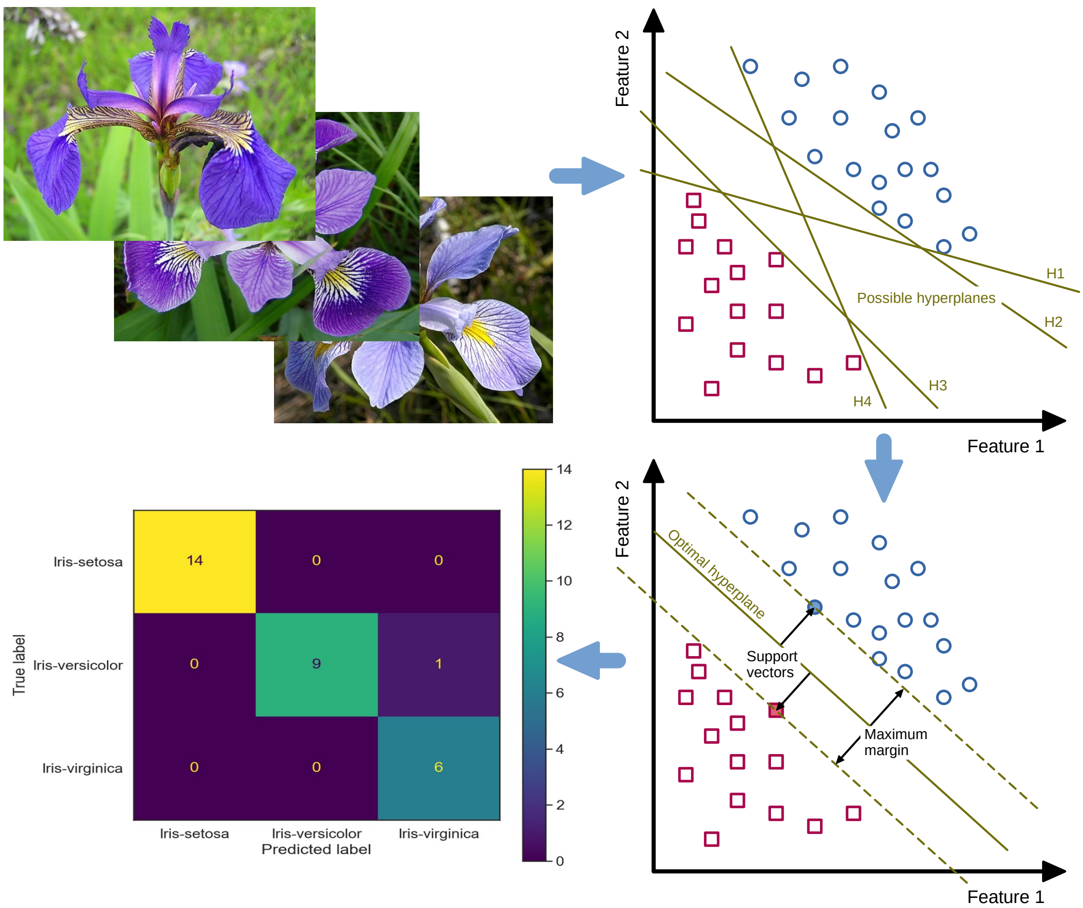

Anyone who wants to seriously deal with the hypothetical topic of our time "Artificial Intelligence (AI)" or "Machine Learning (ML)" cannot avoid dealing with the basic ML algorithms, corresponding software tools, libraries and programming systems. However, someone who opens the door for the first time to this equally very exciting as well as arbitrarily complex and, at first glance, confusing world will very quickly be overwhelmed. Here, it is a good idea to consult introductory and systematic tutorials. Therefore, this Getting Started tutorial systematically demonstrates the typical ML work process step-by-step using the very powerful and performant "Support Vector Classifier (SVC)" and the widely known and very beginner-friendly "Iris Dataset". Furthermore, the selection of the "correct" SVC kernel and its parameters are described and their effect on the classification result is shown.

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1 Introduction

1.1 English introduction

In the **digitised work environment**, there is an increasing demand for **Work equipment** to be able to adapt independently and in a task-related manner to changing work situations. This **situational adaptivity** can often only be realised through the use of **Artificial Intelligence (AI)** or **Machine**

Learning (ML), depending on the degree of flexibility. Examples of such AI applications in the world of work can range from comparatively simple **voice assistance systems** (similar, for example, to Siri or Alexa from the private sphere) to partially or even **fully autonomous systems**. Such fully autonomous systems are, for example, autonomously driving logistics vehicles in larger industrial plants (so-called **driverless transport systems**).

In addition to the many very interesting advantages in terms of economic efficiency, workload reduction, etc., such fully autonomous systems are characterised by a very high level of technical complexity. This concerns both their **operating functions** (e.g. autonomous navigation through complex industrial environments with shared use of the roadways by other human-controlled vehicles) and their **safety functions** (e.g. evaluation of complex, interconnected, mostly imaging safety sensors for monitoring the driving space).

Very high demands are placed on such autonomous systems and the AI algorithms used for them with regard to **functional safety**. However, when assessing their safety, one quickly comes up against clear limits with regard to the **transparency** and **explainability** of the decisions made by AI as well as limits to the **recognition rates** and thus their **reliability**. In particular, the detection rates achievable by AI even under the most convenient conditions very often do not meet the requirements for realising higher safety levels (e.g. Performance Level d (PLd) according to ISO 13849).

An appropriate assessment or even **testing** with regard to the required functional safety according to uniform and ideally standardised criteria has many implications for the future orientation of technical **occupational safety and health (OSH)** in Germany and in Europe. In addition to the currently still very difficult algorithmic evaluability, a significant aspect is that the previous clear separation between **placing on the market law** (see e.g. Machinery Directive) and **occupational health and safety law** (see European Occupational Health and Safety Framework Directive and German Ordinance on Occupational Safety and Health) can no longer be continued in this way. The reason for this is that the **safety-relevant properties** of the autonomous systems will change due to new or **adapted behaviours** learned during operation.

For these reasons, those involved in technical occupational safety and health who will be involved in the testing of work equipment in the future should deal with AI and ML algorithms in depth as early as possible. This is the only way to ensure that the rapid development of adaptive systems capable of learning can be accompanied by OSH and its testing institutes in a constructive, critical and technically appropriate manner. If this is not done, the OSH system will be ruthlessly circumvented or undermined by the economic interests of globally operating software giants. This would have the consequence that serious or fatal occupational accidents are likely to occur due to inadequately designed AI-based work systems.

Anyone seeking a serious technical entrance into the world of **Artificial Intelligence (AI)** or **Machine Learning (ML)** will not be able to avoid dealing with the basic ML algorithms, corresponding software tools, libraries and programming systems.

However, someone who opens the door for the first time to this equally very exciting as well as arbitrarily complex and, at first glance, confusing world will very quickly be overwhelmed. Here, it is a good idea to consult introductory and systematic tutorials.

The aim of this Getting Started tutorial is to systematically demonstrate the typical ML working process step-by-step based on the example of the very powerful and performant **Support Vector Classifier (SVC)**.

This tutorial will be presented as part of a workshop at the DGUV symposium **Artificial Intelligence**, probably in November 2022 in Dresden. The workshop addresses interested ML novices in the technical occupational safety and health of the social accident insurance institutions.

For the target audience in the workshop, the SVC algorithm was intentionally chosen to show that there are many other very powerful and performant ML algorithms apart from the **deep neural networks** that are very present in the media. On the other hand, a necessary and comprehensible introduction to neural networks and the the technical background to perceptrons, activation functions etc. for newcomers would not be possible within the time frame given for the workshop.

Furthermore, this tutorial does *not* address the generation or acquisition of ML-ready datasets. Reason for this is that a newcomer to ML will (or should) first try to familiarize himself with ML algorithms, tools, libraries and programming systems. Only then it makes sense to explore one's own environment with respect to ML-suitable applications and to acquire suitable datasets from them.

Therefore, this tutorial demonstrates the usage of selected ML tools in the form of Python libraries as well as the systematic approach to the widely known and very beginner-friendly **Iris dataset**. According to the literature, the Support Vector Classifier is particularly well suited for the classification of the iris dataset in terms of recognition rate and performance. Alternatively, decision tree-based ML algorithms such as the **Random Forests Classifier** could be used.

After the classification of the iris dataset by the SVC initially with standard parameters, the selection of the "correct" SVC kernel with its setting parameters is furthermore described and the effect on the classification result is shown.

1.2 German introduction

Von den **Arbeitsmitteln** in der **digitalisierten Arbeitswelt** wird immer stärker gefordert, dass sie sich selbstständig und aufgabenbezogen an sich ändernde Arbeitssituationen anpassen können. Diese **situative Adaptivität** kann je nach Stärke des Flexibilisierungsgrades oft nur durch Anwendung von **Artificial Intelligence (AI)** oder **Machine Learning (ML)** realisiert werden.

Als Beispiele für solche KI-Anwendungen in der Arbeitswelt können vergleichsweise einfache **Sprachassistenzsysteme** (ähnlich z. B. Siri oder Alexa aus dem privaten Umfeld) bis hin zu teil- oder gar **vollautonomen Systemen** genannt werden. Solche vollautonomen Systemen sind beispielsweise autonom fahrende Logistikfahrzeuge in größeren Industrieanlagen (sog. **fahrerlosen Transportsystemen**).

Neben den vielen sehr interessanten Vorteilen bzgl. Wirtschaftlichkeit, Arbeitserleichterung usw. kennzeichnet solche vollautonomen Systeme eine sehr hohe technische Komplexität. Diese betrifft sowohl ihre **Betriebsfunktionen** (z. B. autonome Navigation durch komplexe industrielle Umgebungen bei gemeinsamer Nutzung der Fahrwege durch andere menschlich gesteuerte Fahrzeuge) als auch seiner **Sicherheitsfunktionen** (z. B. Auswertung komplexer, miteinander verknüpfter, meist bildgebender Sicherheitssensorik zur Überwachung des Fahrraums).

An solche autonomen Systeme und die hierfür eingesetzten KI-Algorithmen werden sehr hohe Anforderungen hinsichtlich der **funktionalen Sicherheit** gestellt. Jedoch stößt man bei ihrer sicherheitstechnischen Bewertung heute noch sehr schnell an deutliche Grenzen hinsichtlich der **Transparenz** und **Erklärbarkeit** der durch KI getroffenen Entscheidungen sowie Grenzen der **Erkennnungsraten** und damit ihrer **Zuverlässigkeit**. Insbesondere erfüllen die durch KI selbst unter günstigsten Bedingungen erreichbaren Erkennnungsraten sehr oft nicht die Anforderderungen, um höhere Safety-Level (z. B. Performance Level d (PLd) nach ISO 13849) zu realisieren.

Eine hinsichtlich der geforderten funktionalen Sicherheit angemessene Bewertung oder gar **Prüfung** nach einheitlichen und idealerweise genormten Maßstäben hat viele Implikationen auf die zukünftige Ausrichtung des **technischen Arbeitsschutzes** in Deutschland und in Europa. Neben der derzeit noch sehr schwierigen algorithmischen Bewertbarkeit ist ein wesentlicher Aspekt, dass die bisherige klare Trennung zwischen **Inverkehrbringensrecht** (siehe z. B. Maschinenrichtlinie) und **betrieblichem Arbeitsschutzrecht** (siehe Arbeitschutzrahmenrichtlinie und Betriebssicherheitsverordnung) so nicht mehr aufrechterhalten werden kann. Grund hierfür ist, dass sich die **sicherheitsrelevanten Eigenschaften** der autonomen Systeme durch während des Betriebs erlernte, neue oder **angepasste Verhaltensweisen** verändern werden.

Aus diesen Gründen sollten sich insbesondere die zukünftig mit der Prüfung befassten Akteure des technischen Arbeitsschutzes möglichst frühzeitig mit den KI- bzw. ML-Algorithmen vertieft auseinandersetzen. Nur dadurch lässt sich erreichen, dass die stürmische Entwicklung lernfähiger, adaptiver Systeme durch den Arbeitsschutz und deren Prüfinstitute konstruktiv, kritisch und fachlich angemessen begleitet werden kann. Wird dies versäumt, wird das Arbeitsschutzsystem durch die wirtschaftlichen Interessen global agierender Softwaregiganten skrupellos umgangen oder ausgehebelt werden. Dies hätte die Folge, dass schwere oder tödliche Arbeitsunfälle auf Grund unzulänglich gestalteter KI-basierter Arbeitssysteme wahrscheinlich werden.

Wer einen ernsthaften fachlichen Einstieg in die Welt von **Künstlicher Intelligenz (KI)** bzw. **Machine Learning (ML)** sucht, wird nicht umhin kommen, sich mit den grundlegenden ML-Algorithmen, entsprechenden Software-Werkzeugen, Bibliotheken und Programmiersystemen auseinander zu setzen.

Wer jedoch zum ersten Mal die Tür zu dieser ebenso spannenden wie beliebig komplexen und auf den ersten Blick verwirrenden Welt öffnet, wird sehr schnell überfordert sein. Hier empfiehlt es sich, einführende und systematische Anleitungen zu Rate zu ziehen.

Ziel dieses Getting-Started-Tutorials ist es, den typischen ML-Arbeitsablauf systematisch und Schritt-für-Schritt am Beispiel des sehr leistungsfähigen **Support Vector Classifier (SVC)** zu demonstrieren.

Dieses Tutorial wird im Rahmen eines Workshops auf der DGUV-Fachtagung **Künstliche Intelligenz** voraussichtlich im November 2022 in Dresden vorgestellt. Der Workshop richtet sich an interessierte ML-Neulinge im technischen Arbeitsschutz der gesetzlichen Unfallversicherungsträger.

Für die Zielgruppe des Workshops wurde der SVC-Algorithmus bewusst gewählt, um zu zeigen, dass es neben den **tiefen neuronalen Netzen**, die in den Medien sehr präsent sind, noch viele andere sehr leistungsfähige ML-Algorithmen gibt. Andererseits wäre eine notwendige und verständliche Einführung in neuronale Netze und die technischen Hintergründe zu Perzeptronen, Aktivierungsfunktionen etc. für Neulinge in dem für den Workshop vorgegebenen Zeitrahmen nicht möglich gewesen.

Außerdem befasst sich dieses Tutorial *nicht* mit der Erzeugung oder Akquisition von ML-tauglichen Datensätzen. Der Grund dafür ist, dass ein ML-Neuling zunächst versuchen wird (oder sollte), sich mit den ML-Algorithmen, Werkzeugen, Bibliotheken und Programmiersystemen vertraut zu machen. Erst dann ist es sinnvoll, die eigene Umgebung auf ML-taugliche Anwendungen hin zu untersuchen und daraus geeignete Datensätze zu gewinnen.

Daher demonstriert dieses Tutorial die Verwendung ausgewählter ML-Tools in Form von Python-Bibliotheken sowie die systematische Herangehensweise an den weithin bekannten und sehr einsteigerfreundlichen **Iris-Datensatz**. Laut Fachliteratur ist für die Klassifikation des Iris-Datensatzes der Support Vector Classifier hinsichtlich Erkennungsrate als auch Performanz besonders gut geeignet. Alternativ könnten auch entscheidungsbaum-basierte ML-Algorithmen wie z. B. der **Random-forests-Klassifikator** eingesetzt werden.

Nach der Klassifikation des Iris-Datensatzes durch den SVC zunächst mit Standard-Parametern wird darüber hinaus die Auswahl des "richtigen" SVC-Kernels mit seinen Einstellparametern beschrieben und die Auswirkung auf das Klassifikationsergebnis wird gezeigt.

1.3 Steps of the systematic ML process

The following steps of the systematic ML process are covered in the next main sections:

- STEP 0: Get the dataset
- STEP 1: Exploring the dataset
- STEP 2: Prepare the dataset
- STEP 3: Classify by support vector classifier - SVC
- STEP 4: Evaluate the classification results - metrics
- STEP 5: Select SVC kernel and vary parameters

2 Load globally used libraries and set plot parameters

[1]:
```
import time

from IPython.display import HTML

import pandas as pd
import matplotlib.pyplot as plt
from sklearn import svm, metrics
import seaborn as sns
%matplotlib inline
```

3 STEP 0: Get the dataset

Since this is intended to be an introduction to the world of machine learning (ML), this step does NOT deal with the design of an application suitable for ML and the acquisition of valid measurement data.

In order to get to know the typical work steps and ML tools, the use of **well-known and well-researched data sets** is clearly **recommended**.

In the further course, the famous Iris flower data sets will be used. It can be downloaded on Iris Flower Dataset | Kaggle. Furthermore, the dataset is included in Python in the machine learning package Scikit-learn, so that users can access it without having to find a special source for it.

[3]:
```
# import some data to play with
irisdata_df = pd.read_csv('./datasets/IRIS_flower_dataset_kaggle.csv')
```

4 STEP 1: Exploring the dataset

4.1 Goals of exploration

The objectives of the exploration of the dataset are as follows:

1. Clarify the **origins history**:
   - Where did the data come from? => Contact persons and licensing permissions?
   - Who obtained the data and with which (measurement) methods? => Did systematic errors occur during the acquisition?
   - What were they originally intended for? => Can they be used for my application?
2. Overview of the internal **structure and organisation** of the data:
   - Which columns are there? => With which methods can they be read in (e.g. import of CSV files)?
   - What do they contain for (physical) measured variables? => Which technical or physical correlations exist?
   - Which data formats or types are there? => Do they have to be converted?
   - In which value ranges do the measurement data vary? => Are normalizations necessary?
3. Identify **anomalies** in the data sets:
   - Do the data have **gaps** or **duplicates**? => Does the data set needs to be cleaned?
   - Are there obvious erroneous entries or measurement outliers? => Does (statistical) filtering have to be carried out?
4. Avoidance of **tendencies due to bias**:
   - Are all possible classes included in the dataset and equally distributed? => Does the data set need to be enriched with additional data for balance?
5. Find a first rough **idea of which correlations** could be in the data set

4.2 Clarify the origins history

> The ***Iris* flower data sets** is a multivariate data set introduced by the British statistician and biologist *Ronald Fisher* in his paper “The use of multiple measurements in taxonomic problems as an example of linear discriminant analysis” (1936). It is sometimes called *Anderson’s Iris data set* because Edgar Anderson collected the data to quantify the morphologic variation of Iris flowers of three related species (source: Iris flower data set).

The dataset is published in Public Domain with a CC0-License.

This dataset became a typical test case for many statistical classification techniques in machine learning such as **support vector machines**.

> [..] measurements of the flowers of fifty plants each of the two species *Iris setosa* and *I. versicolor*, found **growing together in the same colony** and measured by Dr E. Anderson [..] (source: R. A. Fisher (1936). “The use of multiple measurements in taxonomic problems”. Annals of Eugenics)

> [..] *Iris virginica*, differs from the two other samples in **not being taken from the same natural colony** [..] (source: ibidem)

4.3 Overview of the internal structure and organisation of the data

The data set consists of 50 samples from each of three species of Iris (*Iris setosa*, *Iris virginica* and *Iris versicolor*), so there are 150 total samples. Four features were measured from each sample: the length and the width of the sepals and petals, in centimetres.
Here is a principle illustration of a flower with sepal and petal:

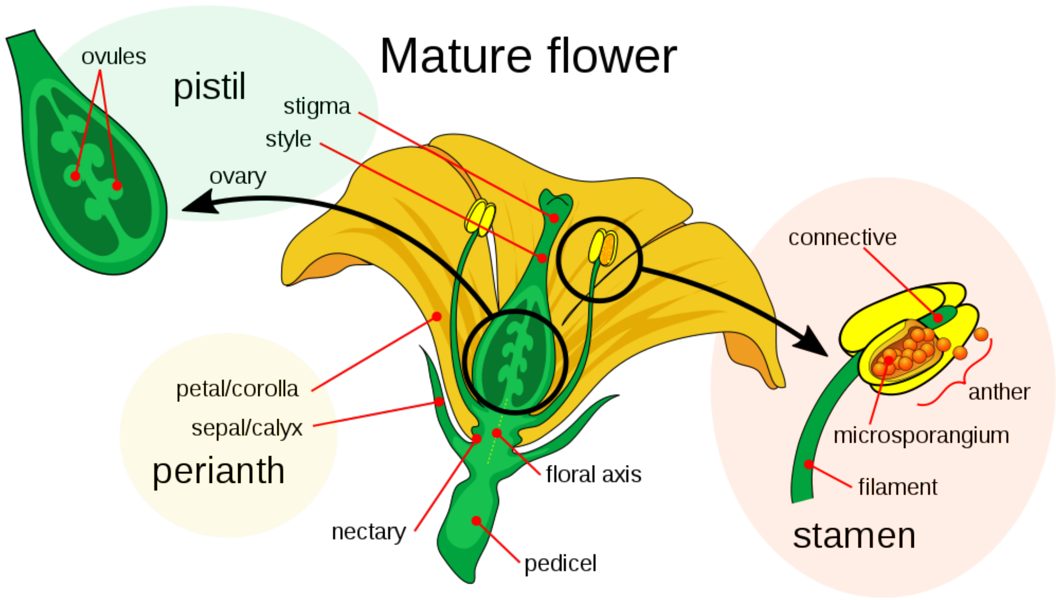

Figure 1: Principle illustration of a flower with sepal and petal (source: Mature_flower_diagram.svg, license: public domain)

Here are pictures of the three different Iris species (*Iris setosa*, *Iris virginica* and *Iris versicolor*). Given the dimensions of the flower, it will be possible to predict the class of the flower.

Figure 2: Left: *Iris setosa* (source: Irissetosa1.jpg, license: public domain); middle: *Iris versicolor* (source: Iris_versicolor_3.jpg, license: CC-SA 3.0); right: *Iris virginica* (source: Iris_virginica.jpg, license: CC-SA 2.0)

4.3.1 Inspect structure of dataframe

Print first or last 5 rows of dataframe:

[4]:
```
irisdata_df.head()
```

[4]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

[5]:

```
irisdata_df.tail()
```

[5]:

	sepal_length	sepal_width	petal_length	petal_width	species
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

While printing a dataframe - only an abbreviated view of the dataframe is shown :(
Default setting in the pandas library makes it to display only 5 lines from head and from tail.

[6]:

```
irisdata_df
```

[6]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
..	…	…	…	…	…
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

[150 rows x 5 columns]

To print all rows of a dataframe, the option `display.max_rows` has to set to `None` in pandas:

[7]:

```
pd.set_option('display.max_rows', None)
irisdata_df
```

[7]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
5	5.4	3.9	1.7	0.4	Iris-setosa
6	4.6	3.4	1.4	0.3	Iris-setosa
7	5.0	3.4	1.5	0.2	Iris-setosa
8	4.4	2.9	1.4	0.2	Iris-setosa
9	4.9	3.1	1.5	0.1	Iris-setosa
10	5.4	3.7	1.5	0.2	Iris-setosa
11	4.8	3.4	1.6	0.2	Iris-setosa
12	4.8	3.0	1.4	0.1	Iris-setosa
13	4.3	3.0	1.1	0.1	Iris-setosa
14	5.8	4.0	1.2	0.2	Iris-setosa
15	5.7	4.4	1.5	0.4	Iris-setosa

16	5.4	3.9	1.3	0.4	Iris-setosa
17	5.1	3.5	1.4	0.3	Iris-setosa
18	5.7	3.8	1.7	0.3	Iris-setosa
19	5.1	3.8	1.5	0.3	Iris-setosa
20	5.4	3.4	1.7	0.2	Iris-setosa
21	5.1	3.7	1.5	0.4	Iris-setosa
22	4.6	3.6	1.0	0.2	Iris-setosa
23	5.1	3.3	1.7	0.5	Iris-setosa
24	4.8	3.4	1.9	0.2	Iris-setosa
25	5.0	3.0	1.6	0.2	Iris-setosa
26	5.0	3.4	1.6	0.4	Iris-setosa
27	5.2	3.5	1.5	0.2	Iris-setosa
28	5.2	3.4	1.4	0.2	Iris-setosa
29	4.7	3.2	1.6	0.2	Iris-setosa
30	4.8	3.1	1.6	0.2	Iris-setosa
31	5.4	3.4	1.5	0.4	Iris-setosa
32	5.2	4.1	1.5	0.1	Iris-setosa
33	5.5	4.2	1.4	0.2	Iris-setosa
34	4.9	3.1	1.5	0.1	Iris-setosa
35	5.0	3.2	1.2	0.2	Iris-setosa
36	5.5	3.5	1.3	0.2	Iris-setosa
37	4.9	3.1	1.5	0.1	Iris-setosa
38	4.4	3.0	1.3	0.2	Iris-setosa
39	5.1	3.4	1.5	0.2	Iris-setosa
40	5.0	3.5	1.3	0.3	Iris-setosa
41	4.5	2.3	1.3	0.3	Iris-setosa
42	4.4	3.2	1.3	0.2	Iris-setosa
43	5.0	3.5	1.6	0.6	Iris-setosa
44	5.1	3.8	1.9	0.4	Iris-setosa
45	4.8	3.0	1.4	0.3	Iris-setosa
46	5.1	3.8	1.6	0.2	Iris-setosa
47	4.6	3.2	1.4	0.2	Iris-setosa
48	5.3	3.7	1.5	0.2	Iris-setosa
49	5.0	3.3	1.4	0.2	Iris-setosa
50	7.0	3.2	4.7	1.4	Iris-versicolor
51	6.4	3.2	4.5	1.5	Iris-versicolor
52	6.9	3.1	4.9	1.5	Iris-versicolor
53	5.5	2.3	4.0	1.3	Iris-versicolor
54	6.5	2.8	4.6	1.5	Iris-versicolor
55	5.7	2.8	4.5	1.3	Iris-versicolor
56	6.3	3.3	4.7	1.6	Iris-versicolor
57	4.9	2.4	3.3	1.0	Iris-versicolor
58	6.6	2.9	4.6	1.3	Iris-versicolor
59	5.2	2.7	3.9	1.4	Iris-versicolor
60	5.0	2.0	3.5	1.0	Iris-versicolor
61	5.9	3.0	4.2	1.5	Iris-versicolor
62	6.0	2.2	4.0	1.0	Iris-versicolor
63	6.1	2.9	4.7	1.4	Iris-versicolor
64	5.6	2.9	3.6	1.3	Iris-versicolor
65	6.7	3.1	4.4	1.4	Iris-versicolor
66	5.6	3.0	4.5	1.5	Iris-versicolor
67	5.8	2.7	4.1	1.0	Iris-versicolor
68	6.2	2.2	4.5	1.5	Iris-versicolor
69	5.6	2.5	3.9	1.1	Iris-versicolor
70	5.9	3.2	4.8	1.8	Iris-versicolor
71	6.1	2.8	4.0	1.3	Iris-versicolor
72	6.3	2.5	4.9	1.5	Iris-versicolor

73	6.1	2.8	4.7	1.2	Iris-versicolor
74	6.4	2.9	4.3	1.3	Iris-versicolor
75	6.6	3.0	4.4	1.4	Iris-versicolor
76	6.8	2.8	4.8	1.4	Iris-versicolor
77	6.7	3.0	5.0	1.7	Iris-versicolor
78	6.0	2.9	4.5	1.5	Iris-versicolor
79	5.7	2.6	3.5	1.0	Iris-versicolor
80	5.5	2.4	3.8	1.1	Iris-versicolor
81	5.5	2.4	3.7	1.0	Iris-versicolor
82	5.8	2.7	3.9	1.2	Iris-versicolor
83	6.0	2.7	5.1	1.6	Iris-versicolor
84	5.4	3.0	4.5	1.5	Iris-versicolor
85	6.0	3.4	4.5	1.6	Iris-versicolor
86	6.7	3.1	4.7	1.5	Iris-versicolor
87	6.3	2.3	4.4	1.3	Iris-versicolor
88	5.6	3.0	4.1	1.3	Iris-versicolor
89	5.5	2.5	4.0	1.3	Iris-versicolor
90	5.5	2.6	4.4	1.2	Iris-versicolor
91	6.1	3.0	4.6	1.4	Iris-versicolor
92	5.8	2.6	4.0	1.2	Iris-versicolor
93	5.0	2.3	3.3	1.0	Iris-versicolor
94	5.6	2.7	4.2	1.3	Iris-versicolor
95	5.7	3.0	4.2	1.2	Iris-versicolor
96	5.7	2.9	4.2	1.3	Iris-versicolor
97	6.2	2.9	4.3	1.3	Iris-versicolor
98	5.1	2.5	3.0	1.1	Iris-versicolor
99	5.7	2.8	4.1	1.3	Iris-versicolor
100	6.3	3.3	6.0	2.5	Iris-virginica
101	5.8	2.7	5.1	1.9	Iris-virginica
102	7.1	3.0	5.9	2.1	Iris-virginica
103	6.3	2.9	5.6	1.8	Iris-virginica
104	6.5	3.0	5.8	2.2	Iris-virginica
105	7.6	3.0	6.6	2.1	Iris-virginica
106	4.9	2.5	4.5	1.7	Iris-virginica
107	7.3	2.9	6.3	1.8	Iris-virginica
108	6.7	2.5	5.8	1.8	Iris-virginica
109	7.2	3.6	6.1	2.5	Iris-virginica
110	6.5	3.2	5.1	2.0	Iris-virginica
111	6.4	2.7	5.3	1.9	Iris-virginica
112	6.8	3.0	5.5	2.1	Iris-virginica
113	5.7	2.5	5.0	2.0	Iris-virginica
114	5.8	2.8	5.1	2.4	Iris-virginica
115	6.4	3.2	5.3	2.3	Iris-virginica
116	6.5	3.0	5.5	1.8	Iris-virginica
117	7.7	3.8	6.7	2.2	Iris-virginica
118	7.7	2.6	6.9	2.3	Iris-virginica
119	6.0	2.2	5.0	1.5	Iris-virginica
120	6.9	3.2	5.7	2.3	Iris-virginica
121	5.6	2.8	4.9	2.0	Iris-virginica
122	7.7	2.8	6.7	2.0	Iris-virginica
123	6.3	2.7	4.9	1.8	Iris-virginica
124	6.7	3.3	5.7	2.1	Iris-virginica
125	7.2	3.2	6.0	1.8	Iris-virginica
126	6.2	2.8	4.8	1.8	Iris-virginica
127	6.1	3.0	4.9	1.8	Iris-virginica
128	6.4	2.8	5.6	2.1	Iris-virginica
129	7.2	3.0	5.8	1.6	Iris-virginica

```
130           7.4          2.8           6.1          1.9  Iris-virginica
131           7.9          3.8           6.4          2.0  Iris-virginica
132           6.4          2.8           5.6          2.2  Iris-virginica
133           6.3          2.8           5.1          1.5  Iris-virginica
134           6.1          2.6           5.6          1.4  Iris-virginica
135           7.7          3.0           6.1          2.3  Iris-virginica
136           6.3          3.4           5.6          2.4  Iris-virginica
137           6.4          3.1           5.5          1.8  Iris-virginica
138           6.0          3.0           4.8          1.8  Iris-virginica
139           6.9          3.1           5.4          2.1  Iris-virginica
140           6.7          3.1           5.6          2.4  Iris-virginica
141           6.9          3.1           5.1          2.3  Iris-virginica
142           5.8          2.7           5.1          1.9  Iris-virginica
143           6.8          3.2           5.9          2.3  Iris-virginica
144           6.7          3.3           5.7          2.5  Iris-virginica
145           6.7          3.0           5.2          2.3  Iris-virginica
146           6.3          2.5           5.0          1.9  Iris-virginica
147           6.5          3.0           5.2          2.0  Iris-virginica
148           6.2          3.4           5.4          2.3  Iris-virginica
149           5.9          3.0           5.1          1.8  Iris-virginica
```

4.3.2 Get data types

[8]:
```
irisdata_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

[9]:
```
irisdata_df.describe()
```

[9]:
```
       sepal_length  sepal_width  petal_length  petal_width
count    150.000000   150.000000    150.000000   150.000000
mean       5.843333     3.054000      3.758667     1.198667
std        0.828066     0.433594      1.764420     0.763161
min        4.300000     2.000000      1.000000     0.100000
25%        5.100000     2.800000      1.600000     0.300000
50%        5.800000     3.000000      4.350000     1.300000
75%        6.400000     3.300000      5.100000     1.800000
max        7.900000     4.400000      6.900000     2.500000
```

4.3.3 Get data ranges with Boxplots

Boxplots can be used to explore the data ranges in the dataset. These also provide information about **outliers**.

[10]:
```
sns.set_context("notebook", font_scale=1.3, rc={"lines.linewidth": 2.0})
sns.set_style("whitegrid")
#sns.set_style("white")

fig, axs = plt.subplots(2, 2, figsize=(12, 10))

fn = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width']
cn = ['Iris-setosa', 'Iris-versicolor', 'Iris-virginica']
box1 = sns.boxplot(x = 'species', y = 'sepal_length',
                   data = irisdata_df, order = cn, ax = axs[0,0])
box2 = sns.boxplot(x = 'species', y = 'sepal_width',
                   data = irisdata_df, order = cn, ax = axs[0,1])
box3 = sns.boxplot(x = 'species', y = 'petal_length',
                   data = irisdata_df, order = cn, ax = axs[1,0])
box4 = sns.boxplot(x = 'species', y = 'petal_width',
                   data = irisdata_df,  order = cn, ax = axs[1,1])

# add some spacing between subplots
fig.tight_layout(pad=2.0)

plt.show()
```

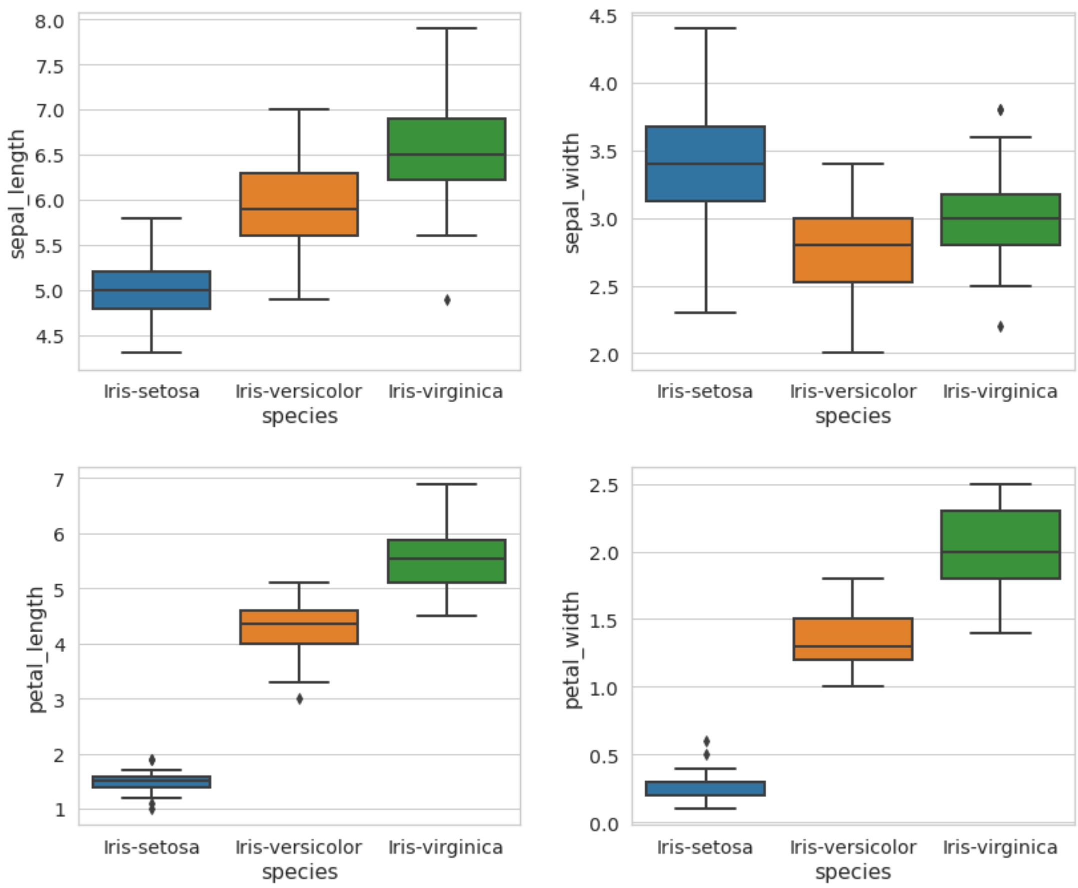

Figure 3: Boxplots used to explore the data ranges in the Iris dataset

4.4 Identify anomalies in the data sets

4.4.1 Find gaps in dataset

This section was inspired by Working with Missing Data in Pandas.

Checking for missing values using `isnull()` In order to check for missing values in Pandas DataFrame, we use the function `isnull()`. This function returns a dataframe of Boolean values which are True for **NaN values**.

[11]:
```
pd.set_option('display.max_rows', 40)
pd.set_option('display.min_rows', 30)
```

[12]:
```
irisdata_df.isnull()
```

[12]:
```
     sepal_length  sepal_width  petal_length  petal_width  species
0           False        False         False        False    False
1           False        False         False        False    False
2           False        False         False        False    False
3           False        False         False        False    False
4           False        False         False        False    False
5           False        False         False        False    False
6           False        False         False        False    False
7           False        False         False        False    False
8           False        False         False        False    False
9           False        False         False        False    False
10          False        False         False        False    False
11          False        False         False        False    False
12          False        False         False        False    False
13          False        False         False        False    False
14          False        False         False        False    False
..            …          …            …          …         …
135         False        False         False        False    False
136         False        False         False        False    False
137         False        False         False        False    False
138         False        False         False        False    False
139         False        False         False        False    False
140         False        False         False        False    False
141         False        False         False        False    False
142         False        False         False        False    False
143         False        False         False        False    False
144         False        False         False        False    False
145         False        False         False        False    False
146         False        False         False        False    False
147         False        False         False        False    False
148         False        False         False        False    False
149         False        False         False        False    False

[150 rows x 5 columns]
```

Show only the gaps:

[13]:
```
irisdata_df_gaps = irisdata_df[irisdata_df.isnull().any(axis=1)]
irisdata_df_gaps
```

[13]:
```
Empty DataFrame
Columns: [sepal_length, sepal_width, petal_length, petal_width, species]
Index: []
```

Fine - this dataset seems to be complete :)

So let's look for something else for exercise: employes.csv

[14]:
```python
# import data to dataframe from csv file
employees_df = pd.read_csv("./datasets/employees_edit.csv")

employees_df
```

[14]:
```
     First Name  Gender  Start Date Last Login Time  Salary   Bonus %  \
0       Douglas    Male    8/6/1993        12:42 PM   97308   6945.00
1        Thomas    Male   3/31/1996         6:53 AM   61933      4.17
2         Maria  Female   4/23/1993        11:17 AM  130590  11858.00
3         Jerry    Male    3/4/2005         1:00 PM  138705      9.34
4         Larry    Male   1/24/1998         4:47 PM  101004   1389.00
5        Dennis    Male   4/18/1987         1:35 AM  115163  10125.00
6          Ruby  Female   8/17/1987         4:20 PM   65476  10012.00
7           NaN  Female   7/20/2015        10:43 AM   45906  11598.00
8        Angela  Female  11/22/2005         6:29 AM   95570  18523.00
9       Frances  Female    8/8/2002         6:51 AM  139852   7524.00
10       Louise  Female   8/12/1980         9:01 AM   63241  15132.00
11        Julie  Female  10/26/1997         3:19 PM  102508  12637.00
12      Brandon    Male   12/1/1980         1:08 AM  112807  17492.00
13         Gary    Male   1/27/2008        11:40 PM  109831   5831.00
14     Kimberly  Female   1/14/1999         7:13 AM   41426  14543.00
…           …     …         …              …        …       …
989     Stephen     NaN   7/10/1983         8:10 PM   85668   1909.00
990       Donna  Female  11/26/1982         7:04 AM   82871  17999.00
991      Gloria  Female   12/8/2014         5:08 AM  136709  10331.00
992       Alice  Female   10/5/2004         9:34 AM   47638  11209.00
993      Justin     NaN   2/10/1991         4:58 PM   38344   3794.00
994       Robin  Female   7/24/1987         1:35 PM  100765  10982.00
995        Rose  Female   8/25/2002         5:12 AM  134505  11051.00
996     Anthony    Male  10/16/2011         8:35 AM  112769  11625.00
997        Tina  Female   5/15/1997         3:53 PM   56450     19.04
998      George    Male   6/21/2013         5:47 PM   98874   4479.00
999       Henry     NaN  11/23/2014         6:09 AM  132483  16655.00
1000    Phillip    Male   1/31/1984         6:30 AM   42392  19675.00
1001    Russell    Male   5/20/2013        12:39 PM   96914   1421.00
1002      Larry    Male   4/20/2013         4:45 PM   60500  11985.00
1003     Albert    Male   5/15/2012         6:24 PM  129949  10169.00

     Senior Management                  Team
0                 True             Marketing
1                 True                   NaN
2                False               Finance
3                 True               Finance
4                 True       Client Services
5                False                 Legal
6                 True               Product
7                  NaN               Finance
8                 True           Engineering
9                 True  Business Development
10                True                   NaN
11                True                 Legal
12                True       Human Resources
13               False                 Sales
14                True               Finance
```

```
...                ...                     ...
989              False                   Legal
990              False               Marketing
991               True                 Finance
992              False         Human Resources
993              False                   Legal
994               True         Client Services
995               True               Marketing
996               True                 Finance
997               True             Engineering
998               True               Marketing
999              False            Distribution
1000             False                 Finance
1001             False                 Product
1002             False    Business Development
1003              True                   Sales

[1004 rows x 8 columns]
```

Show only the gaps from this gappy dataset again:

[15]:
```
employees_df_gaps = employees_df[employees_df.isnull().any(axis=1)]
employees_df_gaps
```

[15]:
```
    First Name  Gender  Start Date Last Login Time  Salary   Bonus %  \
1       Thomas    Male   3/31/1996         6:53 AM   61933      4.17
7          NaN  Female   7/20/2015        10:43 AM   45906  11598.00
10      Louise  Female   8/12/1980         9:01 AM   63241  15132.00
20        Lois     NaN   4/22/1995         7:18 PM   64714   4934.00
22      Joshua     NaN    3/8/2012         1:58 AM   90816  18816.00
23         NaN    Male   6/14/2012         4:19 PM  125792   5042.00
25         NaN    Male   10/8/2012         1:12 AM   37076  18576.00
27       Scott     NaN   7/11/1991         6:58 PM  122367   5218.00
31       Joyce     NaN   2/20/2005         2:40 PM   88657  12752.00
32         NaN    Male   8/21/1998         2:27 PM  122340   6417.00
39         NaN    Male   1/29/2016         2:33 AM  122173   7797.00
41   Christine     NaN   6/28/2015         1:08 AM   66582  11308.00
49       Chris     NaN   1/24/1980        12:13 PM  113590   3055.00
51         NaN     NaN  12/17/2011         8:29 AM   41126  14009.00
53        Alan     NaN    3/3/2014         1:28 PM   40341  17578.00
..         ...     ...         ...             ...     ...       ...
916        Joe    Male   12/8/1998        10:28 AM  126120      1.02
927      Irene     NaN   2/28/1991        10:23 PM  135369      4.38
929        NaN  Female   8/23/2000         4:19 PM   95866  19388.00
941      Aaron     NaN   1/22/1986         7:39 PM   63126  18424.00
942       Mark     NaN    9/9/2006        12:27 PM   44836   2657.00
943      Ralph     NaN   7/28/1995         6:53 PM   70635   2147.00
949     Gerald     NaN   4/15/1989        12:44 PM   93712  17426.00
950        NaN  Female   9/15/1985         1:50 AM  133472  16941.00
951        NaN    Male   7/30/2012         3:07 PM  107351   5329.00
955        NaN  Female   9/14/2010         5:19 AM  143638   9662.00
965    Antonio     NaN   6/18/1989         9:37 PM  103050      3.05
976     Victor     NaN   7/28/2006         2:49 PM   76381  11159.00
989    Stephen     NaN   7/10/1983         8:10 PM   85668   1909.00
993     Justin     NaN   2/10/1991         4:58 PM   38344   3794.00
999      Henry     NaN  11/23/2014         6:09 AM  132483  16655.00

    Senior Management                 Team
```

```
1              True                 NaN
7               NaN             Finance
10             True                 NaN
20             True               Legal
22             True     Client Services
23              NaN                 NaN
25              NaN     Client Services
27            False               Legal
31            False             Product
32              NaN                 NaN
39              NaN     Client Services
41             True Business Development
49            False               Sales
51              NaN               Sales
53             True             Finance
..              …                   …
916           False                 NaN
927           False Business Development
929             NaN               Sales
941           False     Client Services
942           False     Client Services
943           False     Client Services
949            True        Distribution
950             NaN        Distribution
951             NaN           Marketing
955             NaN                 NaN
965           False               Legal
976            True               Sales
989           False               Legal
993           False               Legal
999           False        Distribution

[237 rows x 8 columns]
```

Fill the missing values with `fillna()` Now we are going to fill all the null (NaN) values in Gender column with *"No Gender"*.

Attention: We are doing that directly in this dataframe with `inplace = True` - we don't make a deep copy!

[16]:
```
# filling a null values using fillna()
employees_df["Gender"].fillna("No Gender", inplace = True)
employees_df
```

[16]:
```
   First Name  Gender Start Date Last Login Time  Salary   Bonus %  \
0     Douglas    Male   8/6/1993        12:42 PM   97308   6945.00
1      Thomas    Male  3/31/1996         6:53 AM   61933      4.17
2       Maria  Female  4/23/1993        11:17 AM  130590  11858.00
3       Jerry    Male   3/4/2005         1:00 PM  138705      9.34
4       Larry    Male  1/24/1998         4:47 PM  101004   1389.00
5      Dennis    Male  4/18/1987         1:35 AM  115163  10125.00
6        Ruby  Female  8/17/1987         4:20 PM   65476  10012.00
7         NaN  Female  7/20/2015        10:43 AM   45906  11598.00
8      Angela  Female 11/22/2005         6:29 AM   95570  18523.00
9     Frances  Female   8/8/2002         6:51 AM  139852   7524.00
10     Louise  Female  8/12/1980         9:01 AM   63241  15132.00
11      Julie  Female 10/26/1997         3:19 PM  102508  12637.00
```

```
12      Brandon       Male   12/1/1980         1:08 AM  112807  17492.00
13         Gary       Male   1/27/2008        11:40 PM  109831   5831.00
14     Kimberly     Female   1/14/1999         7:13 AM   41426  14543.00
…           …         …          …         …      …        …
989     Stephen  No Gender   7/10/1983         8:10 PM   85668   1909.00
990       Donna     Female  11/26/1982         7:04 AM   82871  17999.00
991      Gloria     Female   12/8/2014         5:08 AM  136709  10331.00
992       Alice     Female   10/5/2004         9:34 AM   47638  11209.00
993      Justin  No Gender   2/10/1991         4:58 PM   38344   3794.00
994       Robin     Female   7/24/1987         1:35 PM  100765  10982.00
995        Rose     Female   8/25/2002         5:12 AM  134505  11051.00
996     Anthony       Male  10/16/2011         8:35 AM  112769  11625.00
997        Tina     Female   5/15/1997         3:53 PM   56450     19.04
998      George       Male   6/21/2013         5:47 PM   98874   4479.00
999       Henry  No Gender  11/23/2014         6:09 AM  132483  16655.00
1000    Phillip       Male   1/31/1984         6:30 AM   42392  19675.00
1001    Russell       Male   5/20/2013        12:39 PM   96914   1421.00
1002      Larry       Male   4/20/2013         4:45 PM   60500  11985.00
1003     Albert       Male   5/15/2012         6:24 PM  129949  10169.00

     Senior Management                  Team
0                 True             Marketing
1                 True                   NaN
2                False               Finance
3                 True               Finance
4                 True       Client Services
5                False                 Legal
6                 True               Product
7                  NaN               Finance
8                 True           Engineering
9                 True  Business Development
10                True                   NaN
11                True                 Legal
12                True       Human Resources
13               False                 Sales
14                True               Finance
…                 …                 …
989              False                 Legal
990              False             Marketing
991               True               Finance
992              False       Human Resources
993              False                 Legal
994               True       Client Services
995               True             Marketing
996               True               Finance
997               True           Engineering
998               True             Marketing
999              False          Distribution
1000             False               Finance
1001             False               Product
1002             False  Business Development
1003              True                 Sales

[1004 rows x 8 columns]
```

Dropping missing values using `dropna()` In order to drop null values from a dataframe, we use `dropna()` function. This function drops rows or columns of datasets with NaN values in different ways.

Default is to drop rows with at least 1 null value (NaN). Giving the parameter `how = 'all'` the function drops rows with all data missing or contain null values (NaN).

[17]:
```
# making a new dataframe with dropped NaN values
employees_df_dropped = employees_df.dropna(axis = 0, how ='any')
employees_df_dropped
```

[17]:
```
     First Name     Gender  Start Date Last Login Time  Salary   Bonus %  \
0       Douglas       Male    8/6/1993        12:42 PM   97308   6945.00
2         Maria     Female   4/23/1993        11:17 AM  130590  11858.00
3         Jerry       Male    3/4/2005         1:00 PM  138705      9.34
4         Larry       Male   1/24/1998         4:47 PM  101004   1389.00
5        Dennis       Male   4/18/1987         1:35 AM  115163  10125.00
6          Ruby     Female   8/17/1987         4:20 PM   65476  10012.00
8        Angela     Female  11/22/2005         6:29 AM   95570  18523.00
9       Frances     Female    8/8/2002         6:51 AM  139852   7524.00
11        Julie     Female  10/26/1997         3:19 PM  102508  12637.00
12      Brandon       Male   12/1/1980         1:08 AM  112807  17492.00
13         Gary       Male   1/27/2008        11:40 PM  109831   5831.00
14     Kimberly     Female   1/14/1999         7:13 AM   41426  14543.00
15      Lillian     Female    6/5/2016         6:09 AM   59414   1256.00
16       Jeremy       Male   9/21/2010         5:56 AM   90370   7369.00
17        Shawn       Male   12/7/1986         7:45 PM  111737   6414.00
…           …         …           …               …        …       …
989     Stephen  No Gender   7/10/1983         8:10 PM   85668   1909.00
990       Donna     Female  11/26/1982         7:04 AM   82871  17999.00
991      Gloria     Female   12/8/2014         5:08 AM  136709  10331.00
992       Alice     Female   10/5/2004         9:34 AM   47638  11209.00
993      Justin  No Gender   2/10/1991         4:58 PM   38344   3794.00
994       Robin     Female   7/24/1987         1:35 PM  100765  10982.00
995        Rose     Female   8/25/2002         5:12 AM  134505  11051.00
996     Anthony       Male  10/16/2011         8:35 AM  112769  11625.00
997        Tina     Female   5/15/1997         3:53 PM   56450     19.04
998      George       Male   6/21/2013         5:47 PM   98874   4479.00
999       Henry  No Gender  11/23/2014         6:09 AM  132483  16655.00
1000    Phillip       Male   1/31/1984         6:30 AM   42392  19675.00
1001    Russell       Male   5/20/2013        12:39 PM   96914   1421.00
1002      Larry       Male   4/20/2013         4:45 PM   60500  11985.00
1003     Albert       Male   5/15/2012         6:24 PM  129949  10169.00

     Senior Management                  Team
0                 True             Marketing
2                False               Finance
3                 True               Finance
4                 True       Client Services
5                False                 Legal
6                 True               Product
8                 True           Engineering
9                 True  Business Development
11                True                 Legal
12                True       Human Resources
13               False                 Sales
14                True               Finance
15               False               Product
16               False       Human Resources
17               False               Product
…                    …                     …
989              False                 Legal
```

```
990               False           Marketing
991                True             Finance
992               False     Human Resources
993               False               Legal
994                True     Client Services
995                True           Marketing
996                True             Finance
997                True         Engineering
998                True           Marketing
999               False        Distribution
1000              False             Finance
1001              False             Product
1002              False  Business Development
1003               True               Sales

[903 rows x 8 columns]
```

Finally we compare the sizes of dataframes so that we learn how many rows had at least 1 Null value.

[18]:
```
print("Old data frame length:", len(employees_df))
print("New data frame length:", len(employees_df_dropped))
print("Number of rows with at least 1 NaN value: ",
      (len(employees_df)-len(employees_df_dropped)))
```

```
Old data frame length: 1004
New data frame length: 903
Number of rows with at least 1 NaN value:  101
```

4.4.2 Find and remove duplicates in dataset

This section was inspired by: - How to Find Duplicates in Pandas DataFrame (With Examples) - How to Drop Duplicate Rows in a Pandas DataFrame

Checking for duplicate values using `duplicated()` In order to check for duplicate values in Pandas DataFrame, we use a function `duplicated()`. This function can be used in two ways: - find duplicate rows across **all columns** with `duplicateRows = df[df.duplicated()]` - find duplicate rows across **specific columns** `duplicateRows = df[df.duplicated(subset=['col1', 'col2'])]`

Find duplicate rows across **all columns**:

[19]:
```
# import (again) data to dataframe from csv file
employees_df = pd.read_csv("./datasets/employees_edit.csv")
```

[20]:
```
# find duplicate rows across all columns
duplicateRows = employees_df[employees_df.duplicated()]
duplicateRows
```

[20]:
```
    First Name  Gender  Start Date Last Login Time  Salary  Bonus %  \
112      Karen  Female  11/30/1999         7:46 AM  102488  17653.0
127      Linda  Female   5/25/2000         5:45 PM  119009  12506.0
296    Brandon     NaN   11/3/1997         8:17 PM  121333  15295.0
580   Nicholas    Male    3/1/2013         9:26 PM  101036   2826.0

    Senior Management                  Team
112              True               Product
127              True  Business Development
296             False  Business Development
```

```
580                True       Human Resources
```

[21]:
```
# argument keep='last' displays the first duplicate rows instead of the last
duplicateRows = employees_df[employees_df.duplicated(keep='last')]
duplicateRows
```

[21]:
```
    First Name  Gender  Start Date Last Login Time  Salary  Bonus %  \
55       Karen  Female  11/30/1999         7:46 AM  102488  17653.0
92       Linda  Female   5/25/2000         5:45 PM  119009  12506.0
153    Brandon     NaN   11/3/1997         8:17 PM  121333  15295.0
442   Nicholas    Male    3/1/2013         9:26 PM  101036   2826.0

    Senior Management                  Team
55               True               Product
92               True  Business Development
153             False  Business Development
442              True       Human Resources
```

Find duplicate rows across **specific columns**:

[22]:
```
# identify duplicate rows across 'First Name' and 'Last Login Time' columns
duplicateRows = employees_df[employees_df.duplicated(
                    subset=['First Name', 'Last Login Time'])]
duplicateRows
```

[22]:
```
    First Name  Gender  Start Date Last Login Time  Salary  Bonus %  \
112      Karen  Female  11/30/1999         7:46 AM  102488  17653.0
127      Linda  Female   5/25/2000         5:45 PM  119009  12506.0
296    Brandon     NaN   11/3/1997         8:17 PM  121333  15295.0
577        NaN  Female   1/13/2009         1:01 PM  118736   7421.0
580   Nicholas    Male    3/1/2013         9:26 PM  101036   2826.0
632        NaN     NaN    9/2/1988        12:49 PM  147309   1702.0
881        NaN    Male    9/5/1980         7:36 AM  114896  13823.0
929        NaN  Female   8/23/2000         4:19 PM   95866  19388.0
934      Nancy  Female   9/10/2001        11:57 PM   85213   2386.0
973      Linda  Female    2/4/2010         8:49 PM   44486  17308.0

    Senior Management                  Team
112              True               Product
127              True  Business Development
296             False  Business Development
577               NaN       Client Services
580              True       Human Resources
632               NaN          Distribution
881               NaN       Client Services
929               NaN                 Sales
934              True             Marketing
973              True           Engineering
```

[23]:
```
# argument keep='last' displays the first duplicate rows instead of the last
duplicateRows = employees_df[employees_df.duplicated(
                    subset=['First Name', 'Last Login Time'], keep='last')]
duplicateRows
```

[23]:
```
    First Name  Gender  Start Date Last Login Time  Salary   Bonus %  \
23         NaN    Male   6/14/2012         4:19 PM  125792  5042.00
37       Linda  Female  10/19/1981         8:49 PM   57427  9557.00
```

```
55       Karen  Female  11/30/1999         7:46 AM  102488  17653.00
66       Nancy  Female  12/15/2012        11:57 PM  125250   2672.00
92       Linda  Female   5/25/2000         5:45 PM  119009  12506.00
153    Brandon     NaN   11/3/1997         8:17 PM  121333  15295.00
222        NaN  Female   6/17/1991        12:49 PM   71945      5.56
269        NaN    Male    2/4/2005         1:01 PM   40451  16044.00
442   Nicholas    Male    3/1/2013         9:26 PM  101036   2826.00
778        NaN  Female   6/18/2000         7:36 AM  106428  10867.00

    Senior Management                  Team
23                NaN                   NaN
37               True       Client Services
55               True               Product
66               True  Business Development
92               True  Business Development
153             False  Business Development
222               NaN             Marketing
269               NaN          Distribution
442              True       Human Resources
778               NaN                   NaN
```

Dropping duplicate values using `drop_duplicates()` In order to drop duplicate values from a dataframe, we use `drop_duplicates()` function.

This function can be used in two ways: - remove duplicate rows across **all columns** with `df.drop_duplicates()` - find duplicate rows across **specific columns** `df.drop_duplicates(subset=['col1', 'col2'])`

Attention: We are doing that directly in this dataframe with `inplace = True` - we don't make a deep copy!

Remove duplicate rows across **all columns**:

[24]:
```
# remove duplicate rows across all columns
employees_df.drop_duplicates(inplace=True)
employees_df
```

[24]:
```
    First Name  Gender  Start Date Last Login Time  Salary   Bonus %  \
0      Douglas    Male    8/6/1993        12:42 PM   97308  6945.00
1       Thomas    Male   3/31/1996         6:53 AM   61933     4.17
2        Maria  Female   4/23/1993        11:17 AM  130590  11858.00
3        Jerry    Male    3/4/2005         1:00 PM  138705     9.34
4        Larry    Male   1/24/1998         4:47 PM  101004  1389.00
5       Dennis    Male   4/18/1987         1:35 AM  115163  10125.00
6         Ruby  Female   8/17/1987         4:20 PM   65476  10012.00
7          NaN  Female   7/20/2015        10:43 AM   45906  11598.00
8       Angela  Female  11/22/2005         6:29 AM   95570  18523.00
9      Frances  Female    8/8/2002         6:51 AM  139852   7524.00
10      Louise  Female   8/12/1980         9:01 AM   63241  15132.00
11       Julie  Female  10/26/1997         3:19 PM  102508  12637.00
12     Brandon    Male   12/1/1980         1:08 AM  112807  17492.00
13        Gary    Male   1/27/2008        11:40 PM  109831   5831.00
14    Kimberly  Female   1/14/1999         7:13 AM   41426  14543.00
…          …      …          …             …        …       …
989    Stephen     NaN   7/10/1983         8:10 PM   85668   1909.00
990      Donna  Female  11/26/1982         7:04 AM   82871  17999.00
991     Gloria  Female   12/8/2014         5:08 AM  136709  10331.00
992      Alice  Female   10/5/2004         9:34 AM   47638  11209.00
```

```
993       Justin     NaN   2/10/1991         4:58 PM    38344    3794.00
994        Robin  Female   7/24/1987         1:35 PM   100765   10982.00
995         Rose  Female   8/25/2002         5:12 AM   134505   11051.00
996      Anthony    Male  10/16/2011         8:35 AM   112769   11625.00
997         Tina  Female   5/15/1997         3:53 PM    56450      19.04
998       George    Male   6/21/2013         5:47 PM    98874    4479.00
999        Henry     NaN  11/23/2014         6:09 AM   132483   16655.00
1000     Phillip    Male   1/31/1984         6:30 AM    42392   19675.00
1001     Russell    Male   5/20/2013        12:39 PM    96914    1421.00
1002       Larry    Male   4/20/2013         4:45 PM    60500   11985.00
1003      Albert    Male   5/15/2012         6:24 PM   129949   10169.00

     Senior Management                  Team
0                 True             Marketing
1                 True                   NaN
2                False               Finance
3                 True               Finance
4                 True       Client Services
5                False                 Legal
6                 True               Product
7                  NaN               Finance
8                 True           Engineering
9                 True  Business Development
10                True                   NaN
11                True                 Legal
12                True       Human Resources
13               False                 Sales
14                True               Finance
…                  …                    …
989              False                 Legal
990              False             Marketing
991               True               Finance
992              False       Human Resources
993              False                 Legal
994               True       Client Services
995               True             Marketing
996               True               Finance
997               True           Engineering
998               True             Marketing
999              False          Distribution
1000             False               Finance
1001             False               Product
1002             False  Business Development
1003              True                 Sales

[1000 rows x 8 columns]
```

Remove duplicate rows across **specific columns**:

[25]:
```
# remove duplicate rows across 'First Name' and 'Last Login Time' columns
employees_df.drop_duplicates(
    subset=['First Name', 'Last Login Time'], keep='last', inplace=True)
employees_df
```

[25]:
```
     First Name  Gender  Start Date Last Login Time  Salary    Bonus %  \
0       Douglas    Male    8/6/1993        12:42 PM   97308    6945.00
1        Thomas    Male   3/31/1996         6:53 AM   61933       4.17
2         Maria  Female   4/23/1993        11:17 AM  130590   11858.00
```

```
3         Jerry    Male    3/4/2005         1:00 PM  138705       9.34
4         Larry    Male   1/24/1998         4:47 PM  101004    1389.00
5        Dennis    Male   4/18/1987         1:35 AM  115163   10125.00
6          Ruby  Female   8/17/1987         4:20 PM   65476   10012.00
7           NaN  Female   7/20/2015        10:43 AM   45906   11598.00
8        Angela  Female  11/22/2005         6:29 AM   95570   18523.00
9       Frances  Female    8/8/2002         6:51 AM  139852    7524.00
10       Louise  Female   8/12/1980         9:01 AM   63241   15132.00
11        Julie  Female  10/26/1997         3:19 PM  102508   12637.00
12      Brandon    Male   12/1/1980         1:08 AM  112807   17492.00
13         Gary    Male   1/27/2008        11:40 PM  109831    5831.00
14     Kimberly  Female   1/14/1999         7:13 AM   41426   14543.00
…           …      …        …            …      …        …
989     Stephen     NaN   7/10/1983         8:10 PM   85668    1909.00
990       Donna  Female  11/26/1982         7:04 AM   82871   17999.00
991      Gloria  Female   12/8/2014         5:08 AM  136709   10331.00
992       Alice  Female   10/5/2004         9:34 AM   47638   11209.00
993      Justin     NaN   2/10/1991         4:58 PM   38344    3794.00
994       Robin  Female   7/24/1987         1:35 PM  100765   10982.00
995        Rose  Female   8/25/2002         5:12 AM  134505   11051.00
996     Anthony    Male  10/16/2011         8:35 AM  112769   11625.00
997        Tina  Female   5/15/1997         3:53 PM   56450      19.04
998      George    Male   6/21/2013         5:47 PM   98874    4479.00
999       Henry     NaN  11/23/2014         6:09 AM  132483   16655.00
1000    Phillip    Male   1/31/1984         6:30 AM   42392   19675.00
1001    Russell    Male   5/20/2013        12:39 PM   96914    1421.00
1002      Larry    Male   4/20/2013         4:45 PM   60500   11985.00
1003     Albert    Male   5/15/2012         6:24 PM  129949   10169.00

     Senior Management                  Team
0                 True             Marketing
1                 True                   NaN
2                False               Finance
3                 True               Finance
4                 True       Client Services
5                False                 Legal
6                 True               Product
7                  NaN               Finance
8                 True           Engineering
9                 True  Business Development
10                True                   NaN
11                True                 Legal
12                True       Human Resources
13               False                 Sales
14                True               Finance
…                 …                    …
989              False                 Legal
990              False             Marketing
991               True               Finance
992              False       Human Resources
993              False                 Legal
994               True       Client Services
995               True             Marketing
996               True               Finance
997               True           Engineering
998               True             Marketing
999              False          Distribution
```

```
1000          False               Finance
1001          False               Product
1002          False  Business Development
1003           True                 Sales

[994 rows x 8 columns]
```

4.5 Avoidance of tendencies due to bias

The description of the Iris dataset says, that it consists of **50 samples** from **each of three species** of Iris (Iris setosa, Iris virginica and Iris versicolor), so there are **150 total samples**.

But how to prove it?

4.5.1 Count occurrences of unique values

To prove whether all possible classes included in the dataset and equally distributed, you can use the function `df.value_counts`.

Following parameters can be used for fine tuning: - `dropna=False` causes that NaN values are included - `normalize=True`: relative frequencies of the unique values are returned - `ascending=False`: sort resulting classes descending

[26]:
```
# import (again) data to dataframe from csv file
employees_df = pd.read_csv("./datasets/employees_edit.csv")
```

[27]:
```
# count unique values without missing values in a column,
# ordered descending and normalized
irisdata_df['species'].value_counts(ascending=False, dropna=False, normalize=True)
```

[27]:
```
Iris-setosa        0.333333
Iris-versicolor    0.333333
Iris-virginica     0.333333
Name: species, dtype: float64
```

[28]:
```
# count unique values and missing values in a column,
# ordered descending and not absolute values
employees_df['Team'].value_counts(ascending=False, dropna=False, normalize=False)
```

[28]:
```
Client Services         106
Business Development    103
Finance                 102
Marketing                98
Product                  96
Sales                    94
Engineering              92
Human Resources          92
Distribution             90
Legal                    88
NaN                      43
Name: Team, dtype: int64
```

4.5.2 Display Histogram

This section was inspired by: Pandas Histogram – DataFrame.hist().

Histograms represent **frequency distributions** graphically. This requires the separation of the data into classes (so-called **bins**).

These classes are represented in the histogram as rectangles of equal or variable width. The height of each rectangle then represents the (relative or absolute) **frequency density**.

[29]:
```
employees_df.hist(column=['Salary'])
plt.show()
```

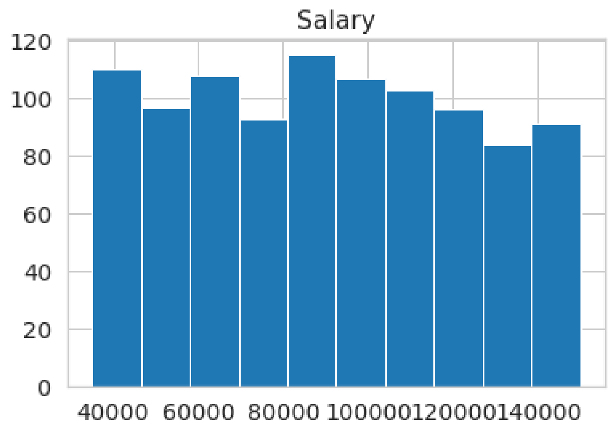

Figure 4: Histogram for frequency distribution of the salary

[30]:
```
employees_df.hist(column='Salary', by='Gender')
plt.show()
```

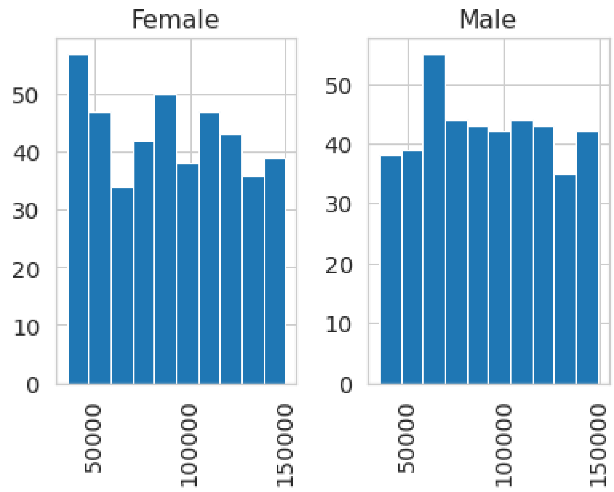

Figure 5: Histogram for the frequency distribution of the salary in comparison between men and women

4.6 First idea of correlations in data set

To get a rough idea of the **dependencies** and **correlations** in the data set, it can be helpful to visualize the whole dataset in a **correlation heatmap**. They show in a glance which variables are correlated, to what degree and in which direction.

Later, 2 particularly well correlated variables are selected from the data set and plotted in a **scatterplot**.

4.6.1 Visualise data with correlation heatmap

This section was inspired by How to Create a Seaborn Correlation Heatmap in Python?.

Correlation matrices are an **essential tool of exploratory data analysis**. Correlation heatmaps contain the same information in a visually appealing way. What more: they show in a glance which variables are correlated, to what degree, in which direction, and alerts us to potential multicollinearity problems (source: ibidem).

Simple correlation matrix Because **string values can never be correlated**, the class names (species) have to be converted first:

[187]:
```
# encoding the class column
irisdata_df_enc = irisdata_df.replace({"species":  {"Iris-setosa":0,
                                                    "Iris-versicolor":1,
                                                    "Iris-virginica":2}})

#irisdata_df_enc
```

[32]:
```
irisdata_df_enc.corr()
```

[32]:

	sepal_length	sepal_width	petal_length	petal_width	species
sepal_length	1.000000	-0.109369	0.871754	0.817954	0.782561
sepal_width	-0.109369	1.000000	-0.420516	-0.356544	-0.419446
petal_length	0.871754	-0.420516	1.000000	0.962757	0.949043
petal_width	0.817954	-0.356544	0.962757	1.000000	0.956464
species	0.782561	-0.419446	0.949043	0.956464	1.000000

Correlation heatmap Choose the color sets from color map.

[33]:
```
# increase the size of the heatmap
plt.figure(figsize=(16, 6))

# store heatmap object in a variable to easily access it
# when you want to include more features (such as title)
# set the range of values to be displayed on the colormap from -1 to 1,
# and set 'annotation=True' to display the correlation values on the heatmap
heatmap = sns.heatmap(irisdata_df_enc.corr(), vmin=-1, vmax=1,
                      annot=True, cmap='PRGn_r')

# give a title to the heatmap
# 'pad=12' defines the distance of the title from the top of the heatmap
heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':18}, pad=16)
plt.show()
```

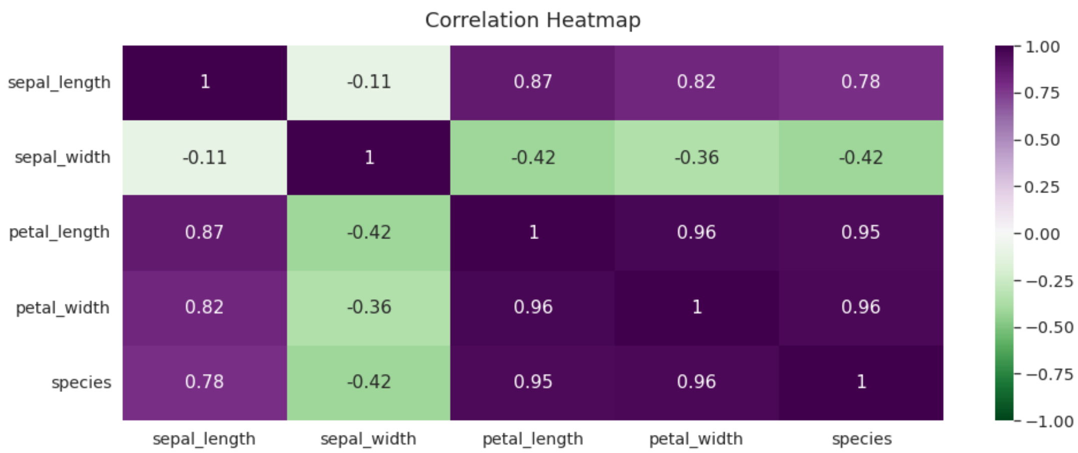

Figure 6: Correlation heatmap to explore coherences between single variables in the iris dataset

Triangle correlation heatmap When looking at the correlation heatmaps above, you would not lose any information by **cutting** away half of it **along the diagonal** line marked by 1-s.

The **numpy** function `np.triu()` can be used to isolate the upper triangle of a matrix while turning all the values in the lower triangle into 0.

[34]:
```
import numpy as np

np.triu(np.ones_like(irisdata_df_enc.corr()))
```

[34]:
```
array([[1., 1., 1., 1., 1.],
       [0., 1., 1., 1., 1.],
       [0., 0., 1., 1., 1.],
       [0., 0., 0., 1., 1.],
       [0., 0., 0., 0., 1.]])
```

Use this mask to cut the heatmap along the diagonal:

[35]:
```
plt.figure(figsize=(16, 6))

# define the mask to set the values in the upper triangle to 'True'
mask = np.triu(np.ones_like(irisdata_df_enc.corr(), dtype=bool))

heatmap = sns.heatmap(irisdata_df_enc.corr(), mask=mask,
                      vmin=-1, vmax=1, annot=True, cmap='PRGn_r')

heatmap.set_title('Triangle Correlation Heatmap', fontdict={'fontsize':18}, pad=16)
plt.show()
```

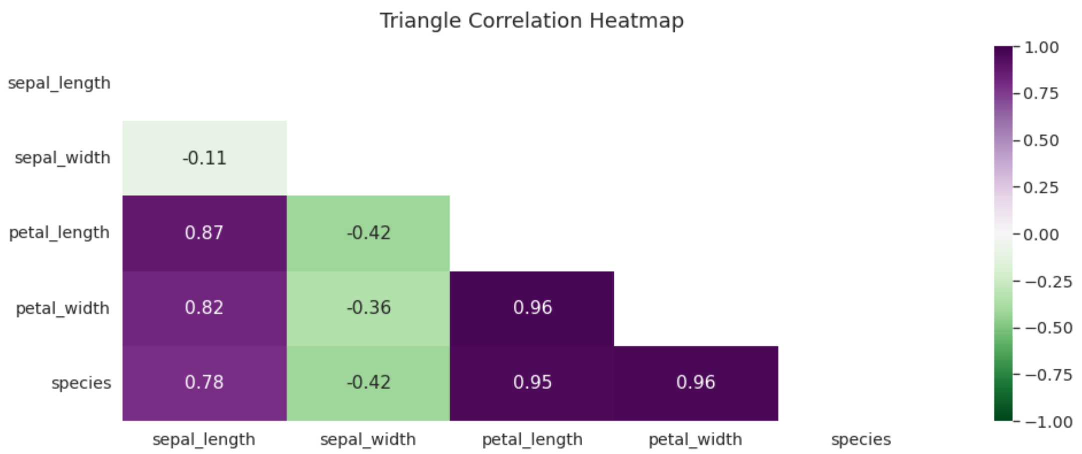

Figure 7: Correlation heatmap, which was cut at its main diagonal without losing any information

As a result from the **heatmaps** we can see, that the shape of the **petals** are the **most correlationed columns** (0.96) with the **type of flowers** (species classes).

Somewhat lower correlates **sepal length** with **petal length** (0.87).

4.6.2 Visualise data with scatter plot

In the following, Seaborn is applied which is a library for making statistical graphics in Python. It is built on top of matplotlib and closely integrated with pandas data structures.

To investigate whether there are dependencies (e.g. correlations) in `irisdata_df` between individual variables in the data set, it is advisable to plot them in a **scatter plot**.

[36]:
```
# There are five preset seaborn themes: darkgrid, whitegrid, dark, white, and ticks.
sns.set_style("whitegrid")
# set scale of fonts
sns.set_context("notebook", font_scale=1.3, rc={"lines.linewidth": 2.5})

# 'sepal_length', 'petal_length' are iris feature data
# 'height' used to define height of graph
# 'hue' stores the class/label of iris dataset
sns.FacetGrid(irisdata_df, hue ="species",
              height = 7).map(plt.scatter,
                              'petal_width',
                              'petal_length').add_legend()


plt.title('Scatterplot of petal length and width')
plt.show()
```

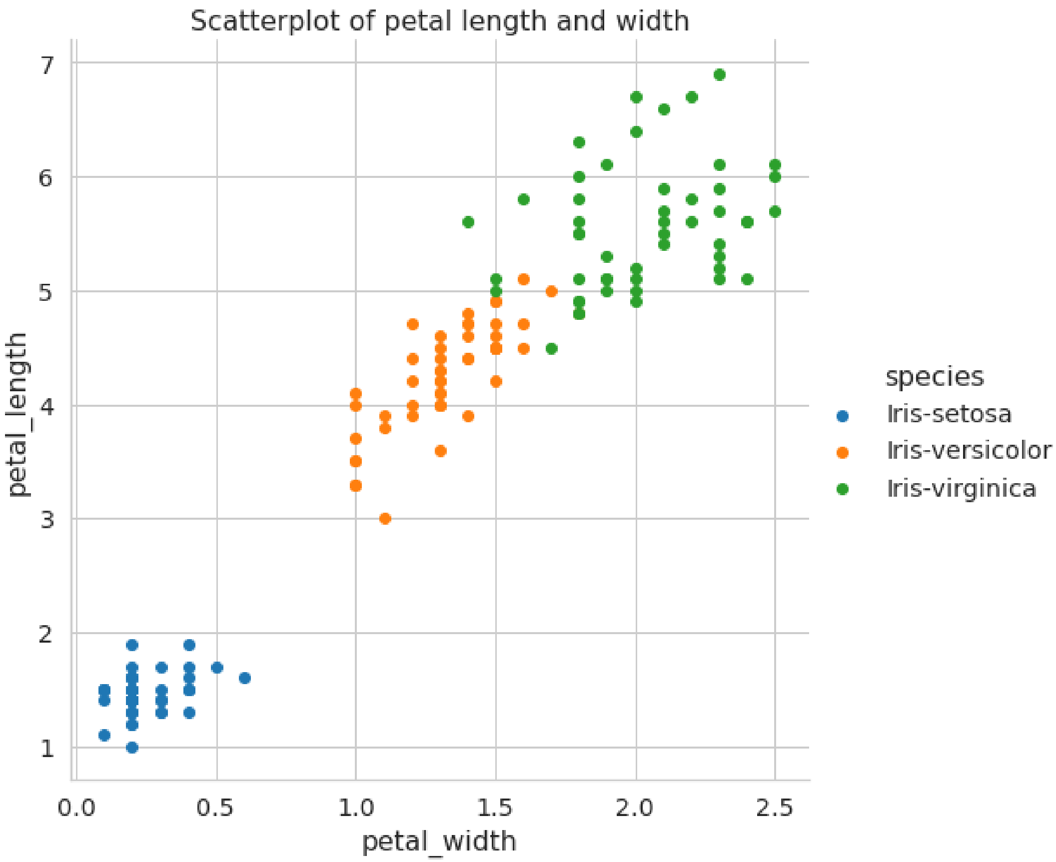

Figure 8: Plotting two individual variables of the iris dataset in the scatterplot to explore the relationships between these two

4.6.3 Visualise data with pairs plot

For systematic investigation of dependencies, all variables (each against each) are plotted in separate scatter plots.

With this so called **pairs plot** it is possible to see both **relationships** between two variables and **distribution** of single variables.

This function will create a grid of Axes such that **each numeric variable** in `irisdata_df` will by shared in the y-axis across a single row and in the x-axis across a single column.

[195]:
```
sns.set(font_scale=1.0)
sns.set_style("white")

g = sns.pairplot(irisdata_df, diag_kind="kde", hue='species',
                 palette='Dark2', height=2.5)

g.map_lower(sns.kdeplot, levels=4, color=".2")
# y .. padding between title and plot
g.fig.suptitle('Pairs plot of the Iris dataset', y=1.05)
plt.show()
```

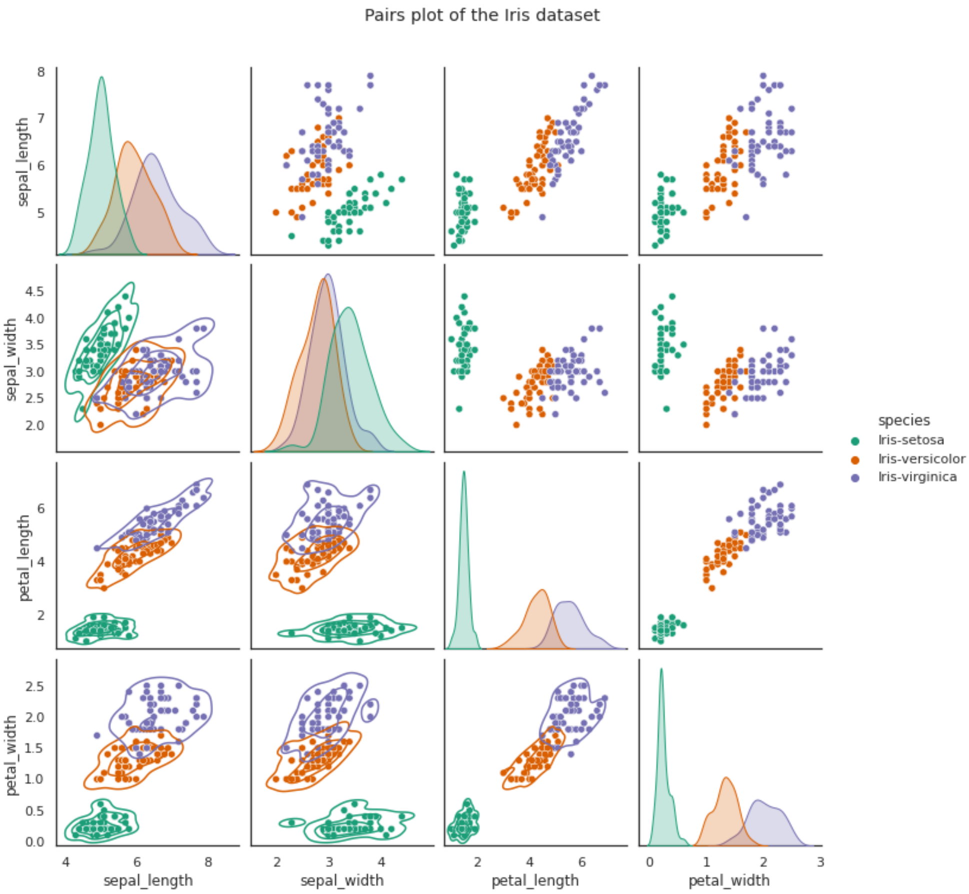

Figure 9: Plot all individual variables of the Iris dataset in pairs plot to see both the relationships between two variables and the distribution of the individual variables

5 STEP 2: Prepare the dataset

Through the intensive exploration of the data in Step 1 (STEP 1: Exploring the dataset), we know that special **preparation** of the data is **not necessary**. The values are **complete** and **without gaps** and there are **no duplicates**. The values are in similar ranges, which **does not require normalization** of the data.

Furthermore, we know that the **classes** are very **evenly distributed** and thus bias tendencies should be avoided.

6 STEP 3: Classify by support vector classifier - SVC

6.1 Operating principal

> Support Vectors Classifier tries to **find the best hyperplane to separate** the different classes by maximizing the distance between sample points and the hyperplane (source: In Depth: Parameter tuning for SVC).

The figure **??** shows the operating principal of the SVC algorithm: the hyperplanes *H1* till *H4* (left graphic) do separate the classes. A good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin, the lower the generalization error of the classifier (source: Support-vector machine).

The right graphic shows the optimal hyperplane characterized by maximising the margin between the classes. The perpendicular distance of the closest data points to the hyperplane determines their position and orientation. These perpendicular distances are the **support vectors** of the hyperplane - this is how the algorithm got its name.

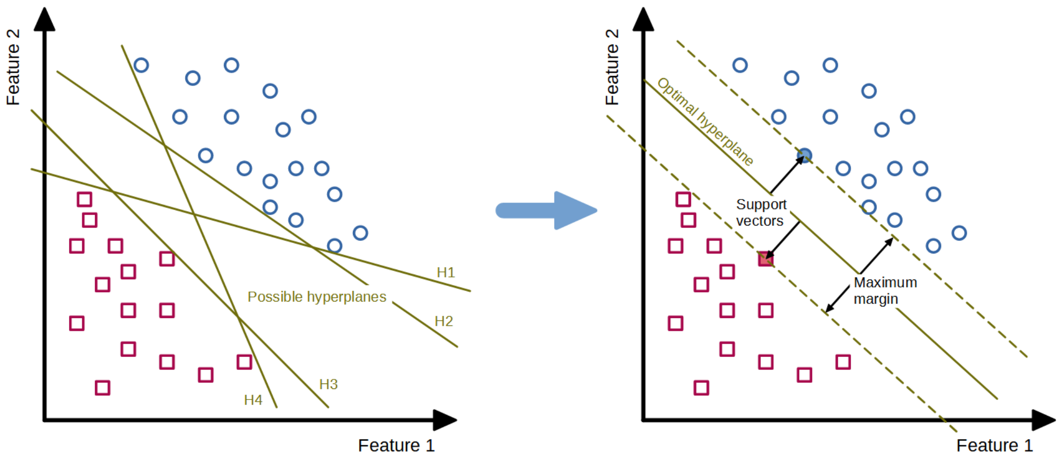

Figure 10: Support Vectors Classifiers (SVC) separate the data points in classes by finding the best hyperplane by maximizing the margin to its support vectors

6.2 Split the dataset

In the next very important step, the dataset is split into **2 subsets**: a **training dataset** and a **test dataset**. As the names suggest, the training dataset is used to train the ML algorithm. The test data set is then used to check the quality of the trained ML algorithm (here the **recognition rate**). For this purpose, the **class labels** are **removed** from the training data set - after all, these are to be predicted.

Typically, the **test dataset** should contain about **20%** of the entire dataset.

[63]:
```
from sklearn.model_selection import train_test_split

X = irisdata_df.drop('species', axis=1)
y = irisdata_df['species']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20)
```

For training, do not use only the variables that correlate best with each other, but all of them.

Otherwise, the result of the prediction would be significantly worse. Maybe this is already an indication of **overfitting** of the ML model.

[39]:
```
# DO NOT USE THIS!!
X_train, X_test, y_train, y_test = train_test_split(X[['sepal_length',
                                                        'sepal_width']],
```

```
                                                    y, test_size = 0.20)
```

6.3 Create the SVM model

In this step we create the SVC model and fit it to our training data.

[54]:
```
from sklearn.svm import SVC
classifier = SVC(kernel = 'linear', random_state = 0)

# fit the model for the data
classifier.fit(X_train, y_train)
```

[54]:
```
SVC(kernel='linear', random_state=0)
```

6.4 Make predictions

[55]:
```
y_pred = classifier.predict(X_test)
#X_test
```

7 STEP 4: Evaluate the classification results - metrics

And finally for checking the accuracy of the model, the **confusion matrix** is used for the **cross validation**.

By using the function `sklearn.metrics.confusion_matrix()` a confusion matrix of the true digit values versus the predicted digit values is plotted.

7.1 Textual confusion matrix

[56]:
```
cm = metrics.confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[ 9  0  0]
 [ 0 10  0]
 [ 0  0 11]]
```

7.2 Colored confusion matrix

The function `sklearn.metrics.ConfusionMatrixDisplay()` plots a colored confusion matrix.

[57]:
```
sns.set_style("white")

# print colored confusion matrix
cm_colored = metrics.ConfusionMatrixDisplay.from_predictions(y_test, y_pred)

cm_colored.figure_.suptitle("Colored Confusion Matrix")
cm_colored.figure_.set_figwidth(8)
cm_colored.figure_.set_figheight(7)

cm_colored.confusion_matrix

# save figure as PNG
plt.tight_layout()
plt.savefig('images/confusion_matrix.png', dpi=150, pad_inches=5)
```

```
plt.show()
```

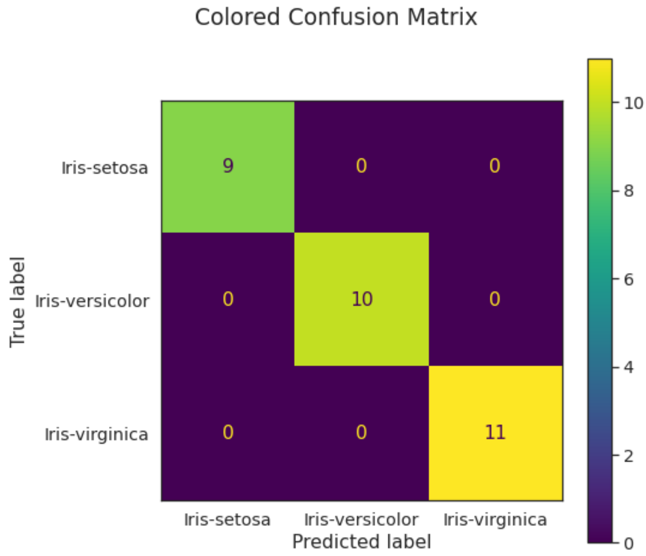

Figure 11: Checking the accuracy of the model by using the confusion matrix for cross-validation

7.3 Classification accuracy

[58]:
```
from sklearn.model_selection import cross_val_score

accuracies = cross_val_score(estimator = classifier, X = X_train,
                             y = y_train, cv = 10)

print("Accuracy: {:.2f} %".format(accuracies.mean()*100))
print("Standard Deviation: {:.2f} %".format(accuracies.std()*100))
```

```
Accuracy: 97.50 %
Standard Deviation: 7.50 %
```

8 STEP 5: Select SVC kernel and vary parameters

This section was inspired by In Depth: Parameter tuning for SVC

In this section, the 4 SVC parameters `kernel`, `gamma`, `C` and `degree` will be introduced one by one. Furthermore, their influence on the classification result by varying these single parameters will be shown.

Disclaimer: In order to show the effects of varying the individual parameters in 2D graphs, only the best correlating variables `petal_length` and `petal_width` are used to train the SVC.

8.1 Prepare dataset

[142]:
```
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
import numpy as np

# import iris dataset again
irisdata_df = pd.read_csv('./datasets/IRIS_flower_dataset_kaggle.csv')
```

```
# encode the class column from class strings to integer equivalents
irisdata_df_enc = irisdata_df.replace({"species":  {"Iris-setosa":0,
                                                     "Iris-versicolor":1,
                                                     "Iris-virginica":2}})
#irisdata_df_enc
```

8.1.1 Prepare datasets for parameter variation and plotting

These datasets will be used for parameter variation and plotting only. In particular, for later **2D plotting** of the effects of parameter variation, only **2 variables** of the iris dataset can be used.

However, as seen in the previous section, this selection is very much at the expense of detection accuracy. Therefore, it is not useful to make predictions with this subset of data - it is not necessary to divide it into a training and a test data set.

[143]:
```
# copy only 2 feature columns
# and convert pandas dataframe to numpy array
X_plot = irisdata_df_enc[['petal_length', 'petal_width']].to_numpy(copy=True)
#X_plot = irisdata_df_enc[['sepal_length', 'sepal_width']].to_numpy(copy=True)
#X_plot
```

[144]:
```
# convert pandas dataframe to numpy array
# and get a flat 1D copy of 2D numpy array
y_plot = irisdata_df_enc[['species']].to_numpy(copy=True).flatten()
#y_plot
```

8.1.2 Prepare dataset for prediction and evaluation

To **evaluate the recognition accuracy** by parameter variation, the complete iris data set with all variables must be used. To make predictions with test data, the data set is again divided into a training and a test data set.

[145]:
```
X = irisdata_df.drop('species', axis=1)
y = irisdata_df['species']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20)
```

8.2 Plotting functions

This function helps to visualize the modifications by varying the individual SVC parameters:

[146]:
```
def plotSVC(title, svc, X, y, xlabel, ylabel):
    # create a mesh to plot in
    x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1

    # prevent division by zero
    if x_min == 0.0:
        x_min = 0.1

    h = (x_max / x_min)/1000
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))

    plt.subplot(1, 1, 1)
    Z = svc.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
```

```
    plt.contourf(xx, yy, Z, cmap=plt.cm.Paired, alpha=0.6)
    plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Paired)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.xlim(xx.min(), xx.max())
    plt.title(title)
    plt.show()
```

This function cares for cross validation:

[168]:
```
def crossValSVC(X_train, y_train, kernel='rbf', gamma='scale', C=1.0, degree=3):
    # train the SVC
    svc = svm.SVC(kernel=kernel,
                  gamma=gamma,
                  C=C,
                  degree=degree).fit(X_train, y_train)
    # calculate accuracies
    accuracies = cross_val_score(estimator = svc, X = X_train,
                                 y = y_train, cv = 10)

    accuracy = accuracies.mean()*100
    return accuracy
```

This function plots the variation of the SVC parameters against the prediction accuracy to show the effect of variation and its limits regarding the phenomenon **overfitting**:

[182]:
```
def plotParamsAcc(param_list, acc_list, param_name, log_scale=False):
    fig, ax = plt.subplots(figsize=(10,6))
    title_str = 'Variation of {} parameter '.format(param_name) \
                +'and its effect to prediction accuracy'
    plt.title(title_str)
    ax.plot(param_list, accuracy_list)
    if log_scale:
        # set the X axis scale to logarithmic
        ax.set_xscale('log')
    plt.xlabel(param_name)
    plt.ylabel('accuracy [%]')
    plt.grid()
    plt.show()
```

8.3 Vary `kernel` of SVC

The `kernel` parameter selects the type of hyperplane that is used to separate the data. Using `linear` (linear classifier) kernel will use a linear hyperplane (a line in the case of 2D data). The `rbf` (radial basis function kernel) and `poly` (polynomial kernel) kernel use non linear hyperplanes. The **default** is `kernel=rbf`.

[149]:
```
kernels = ['linear', 'rbf', 'poly', 'sigmoid']

xlabel = 'Petal length'
ylabel = 'Petal width'

for kernel in kernels:
    svc_plot = svm.SVC(kernel=kernel).fit(X_plot, y_plot)
    accuracy = crossValSVC(X_train, y_train, kernel=kernel)
    title_str = 'kernel: \''+str(kernel)+'\', '+'Acc. prediction: {:.2f}%'.
 ↪format(accuracy)
```

```
plotSVC(title_str, svc_plot, X_plot, y_plot, xlabel, ylabel)
```

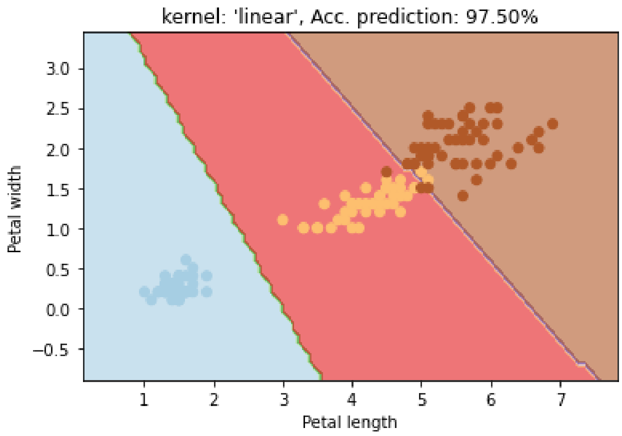

Figure 12: This group of images shows the effect on the classification by the choice of the different SVC kernels ('linear', 'rbf', 'poly' and 'sigmoid')

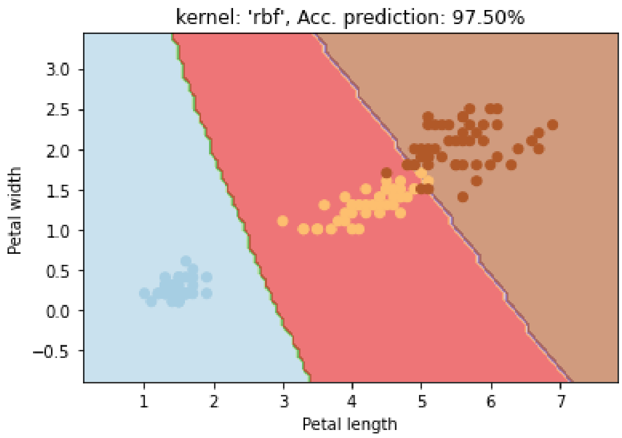

Figure 13: This group of images shows the effect on the classification by the choice of the different SVC kernels ('linear', 'rbf', 'poly' and 'sigmoid')

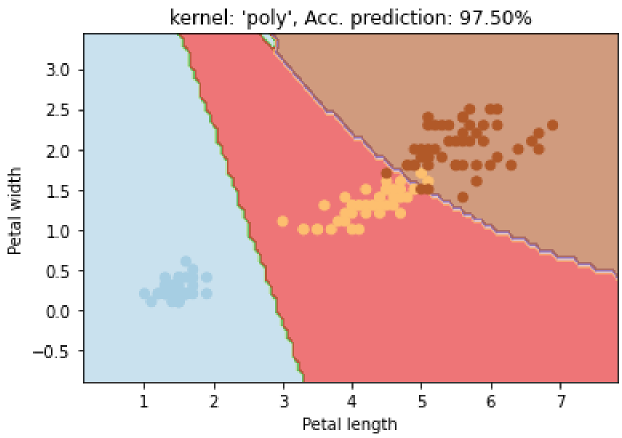

Figure 14: This group of images shows the effect on the classification by the choice of the different SVC kernels ('linear', 'rbf', 'poly' and 'sigmoid')

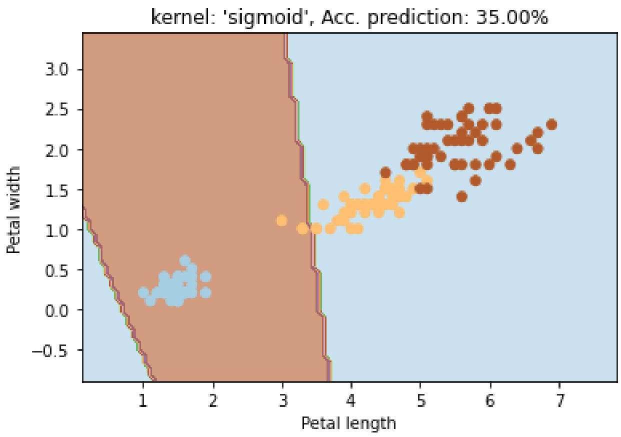

Figure 15: This group of images shows the effect on the classification by the choice of the different SVC kernels ('linear', 'rbf', 'poly' and 'sigmoid')

8.4 Vary `gamma` parameter

The `gamma` parameter is used for **non linear hyperplanes**. The higher the `gamma` float value it tries to exactly fit the training data set. The **default** is `gamma='scale'`.

[175]:
```
gammas = [0.1, 1, 10, 100, 200]

xlabel = 'Petal length'
ylabel = 'Petal width'

for gamma in gammas:
    svc_plot = svm.SVC(kernel='rbf', gamma=gamma).fit(X_plot, y_plot)
    accuracy = crossValSVC(X_train, y_train, kernel='rbf', gamma=gamma)
    title_str = 'gamma: \''+str(gamma)+'\', ' \
                +'Acc. prediction: {:.2f}%'.format(accuracy)
    plotSVC(title_str, svc_plot, X_plot, y_plot, xlabel, ylabel)
```

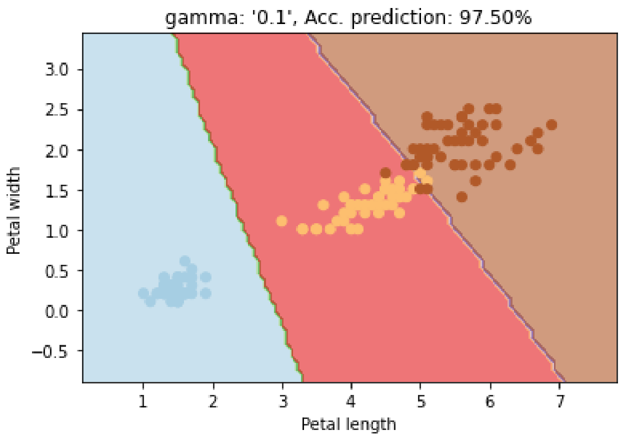

Figure 16: This group of images shows the effect on the classification by the variation of the parameter 'gamma' of the 'rbf' kernel

Show the variation of the SVC parameter `gamma` against the **prediction accuracy**.

As we can see, increasing `gamma` leads to **overfitting** as the classifier tries to perfectly fit the training data.

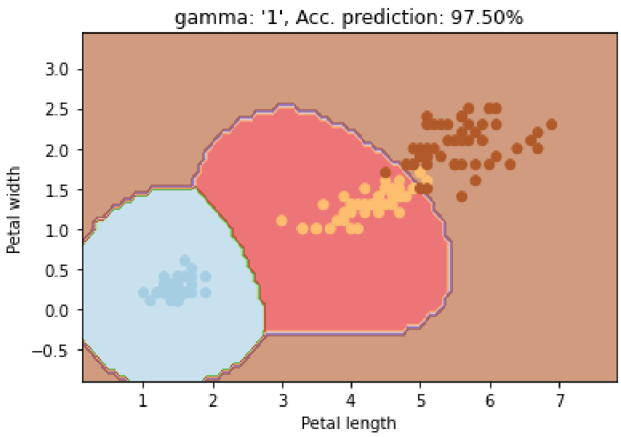

Figure 17: This group of images shows the effect on the classification by the variation of the parameter 'gamma' of the 'rbf' kernel

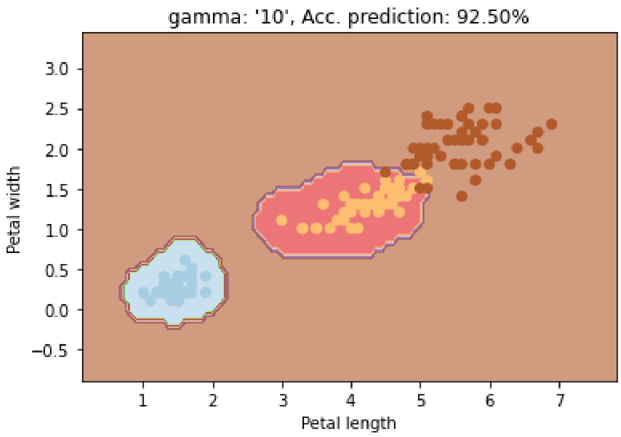

Figure 18: This group of images shows the effect on the classification by the variation of the parameter 'gamma' of the 'rbf' kernel

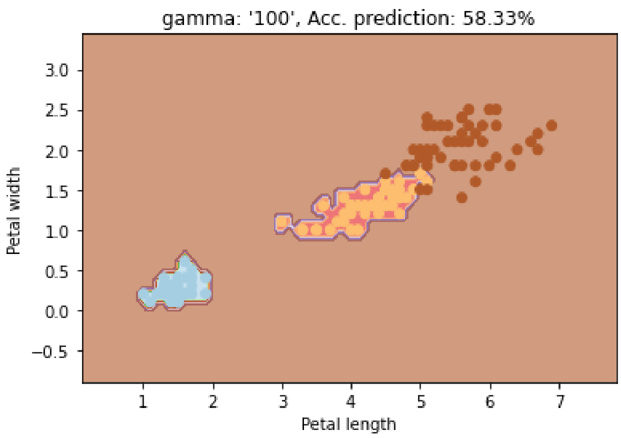

Figure 19: This group of images shows the effect on the classification by the variation of the parameter 'gamma' of the 'rbf' kernel

[184]:
```
gammas = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1, 10, 100, 200]

accuracy_list = list()
```

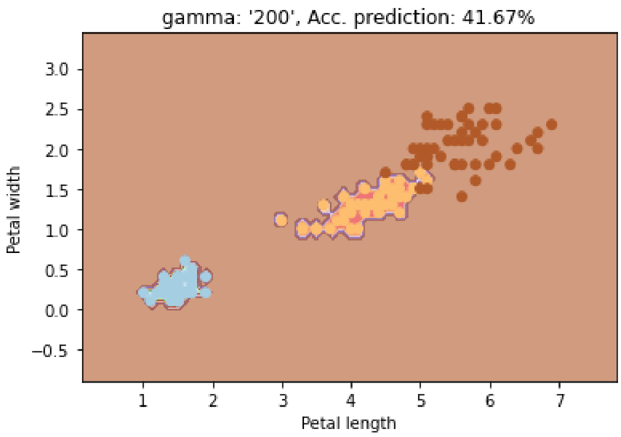

Figure 20: This group of images shows the effect on the classification by the variation of the parameter 'gamma' of the 'rbf' kernel

```
for gamma in gammas:
    accuracy = crossValSVC(X_train, y_train, kernel='rbf', gamma=gamma)
    accuracy_list.append(accuracy)

plotParamsAcc(gammas, accuracy_list, 'gamma', log_scale=True)
```

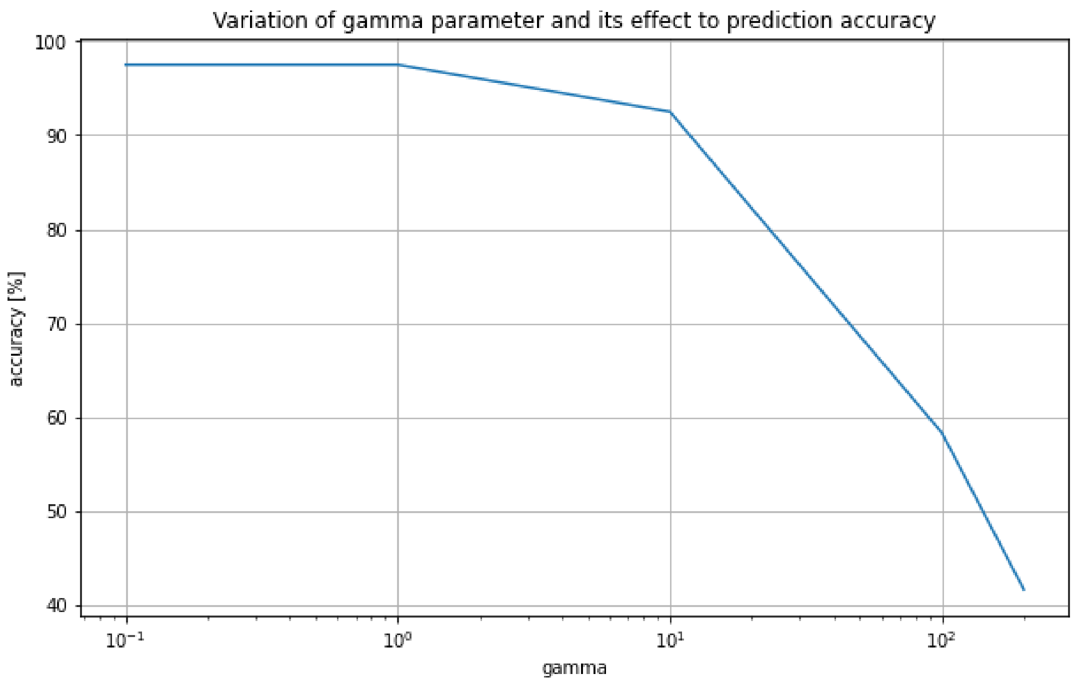

Figure 21: The plot shows the variation of the SVC parameter 'gamma' against the prediction accuracy

8.5 Vary `C` parameter

The `C` parameter is the **penalty** of the error term. It controls the trade off between smooth decision boundary and classifying the training points correctly. The **default** is `C=1.0`.

[172]:
```
cs = [0.1, 1, 5, 10, 100, 1000, 10000]
```

```
xlabel = 'Petal length'
ylabel = 'Petal width'

for c in cs:
    svc_plot = svm.SVC(kernel='rbf', C=c).fit(X_plot, y_plot)
    accuracy = crossValSVC(X_train, y_train, kernel='rbf', C=c)
    title_str = 'C: \''+str(c)+'\', ' \
                +'Acc. prediction: {:.2f}%'.format(accuracy)
    plotSVC(title_str, svc_plot, X_plot, y_plot, xlabel, ylabel)
```

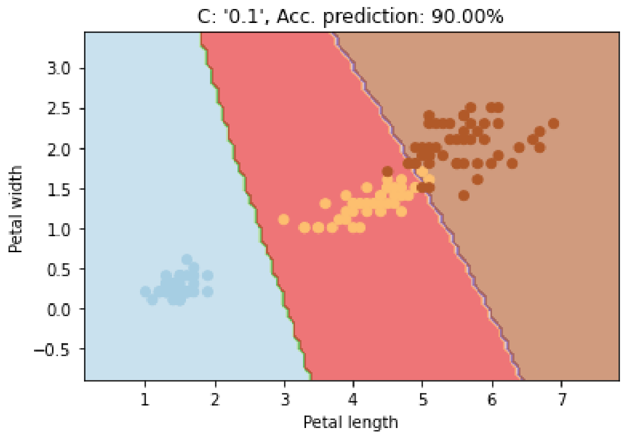

Figure 22: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

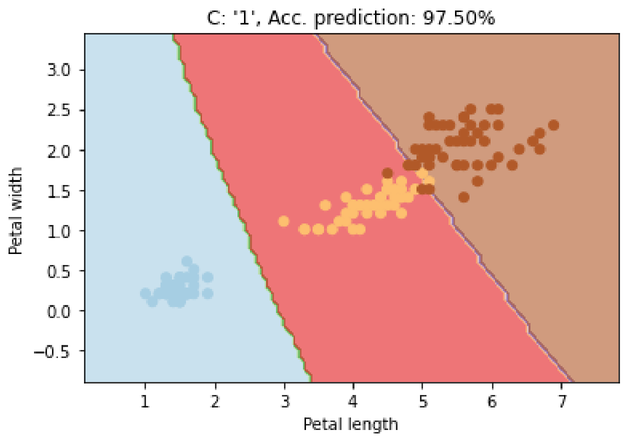

Figure 23: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

Show the variation of the SVC parameter `C` against the **prediction accuracy**.

But be careful: to high `C` values may lead to **overfitting** the training data.

[185]:
```
cs = [0.1, 1, 5, 6, 7, 8, 10, 100, 1000, 10000]

accuracy_list = list()
for c in cs:
    accuracy = crossValSVC(X_train, y_train, kernel='rbf', C=c)
    accuracy_list.append(accuracy)

plotParamsAcc(cs, accuracy_list, 'C', log_scale=True)
```

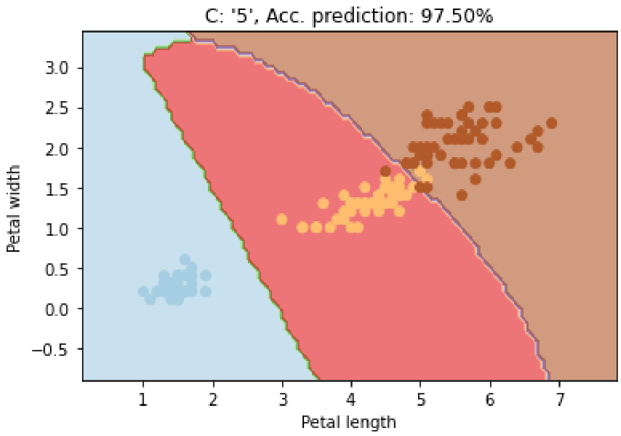

Figure 24: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

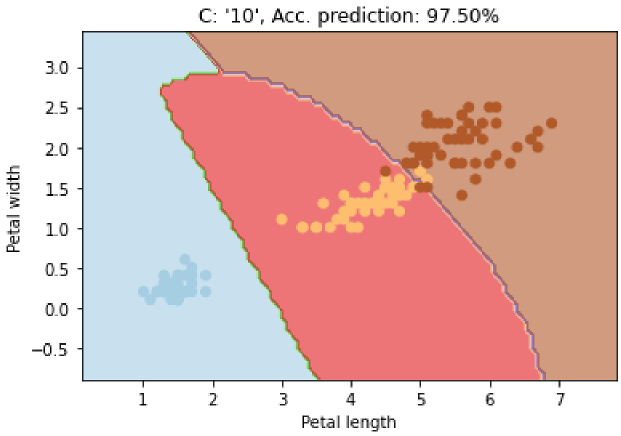

Figure 25: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

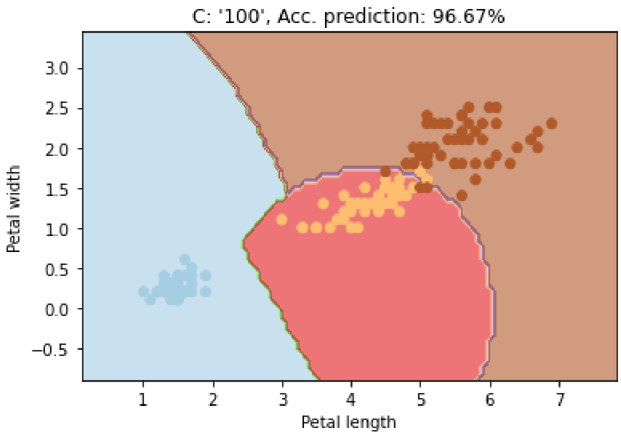

Figure 26: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

8.6 Vary `degree` parameter

The `degree` parameter is used when the `kernel` is set to `poly` and is ignored by all other kernels. It's basically the **degree of the polynomial** used to find the hyperplane to split the data. The **default** is

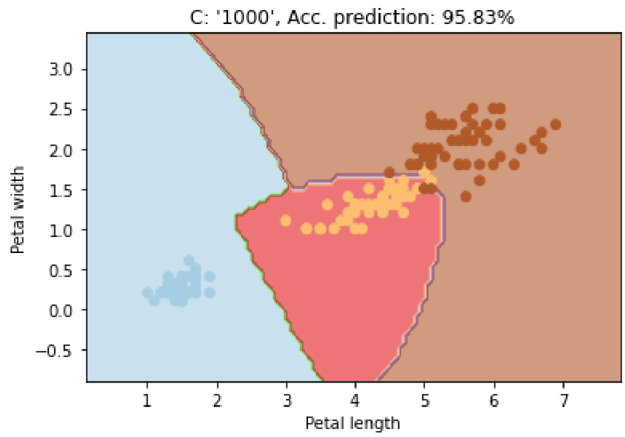

Figure 27: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

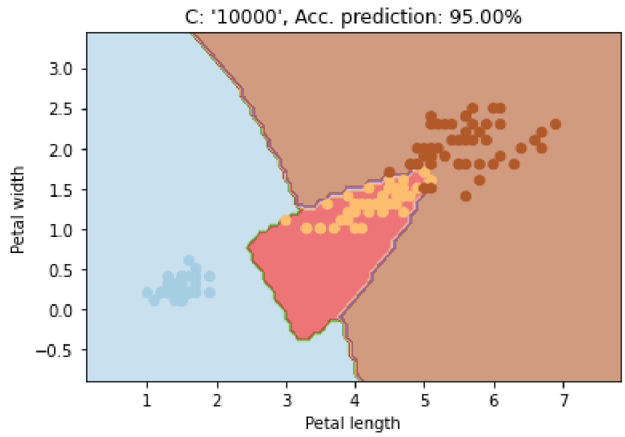

Figure 28: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

`degree=3`.

Using `degree = 1` is the same as using a `linear` kernel. Also, increasing this parameters leads to **higher training times**.

[173]:
```
degrees = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

xlabel = 'Petal length'
ylabel = 'Petal width'

for degree in degrees:
    svc_plot = svm.SVC(kernel='poly', degree=degree).fit(X_plot, y_plot)
    accuracy = crossValSVC(X_train, y_train, kernel='poly', degree=degree)
    title_str = 'degree: \''+str(degree)+'\', ' \
                +'Acc. prediction: {:.2f}%'.format(accuracy)
    plotSVC(title_str, svc_plot, X_plot, y_plot, xlabel, ylabel)
```

Show the variation of the SVC parameter `degree` against the **prediction accuracy**.

As we can see, increasing the `degree` of the polynomial hyperplane leads to **overfitting** the training data.

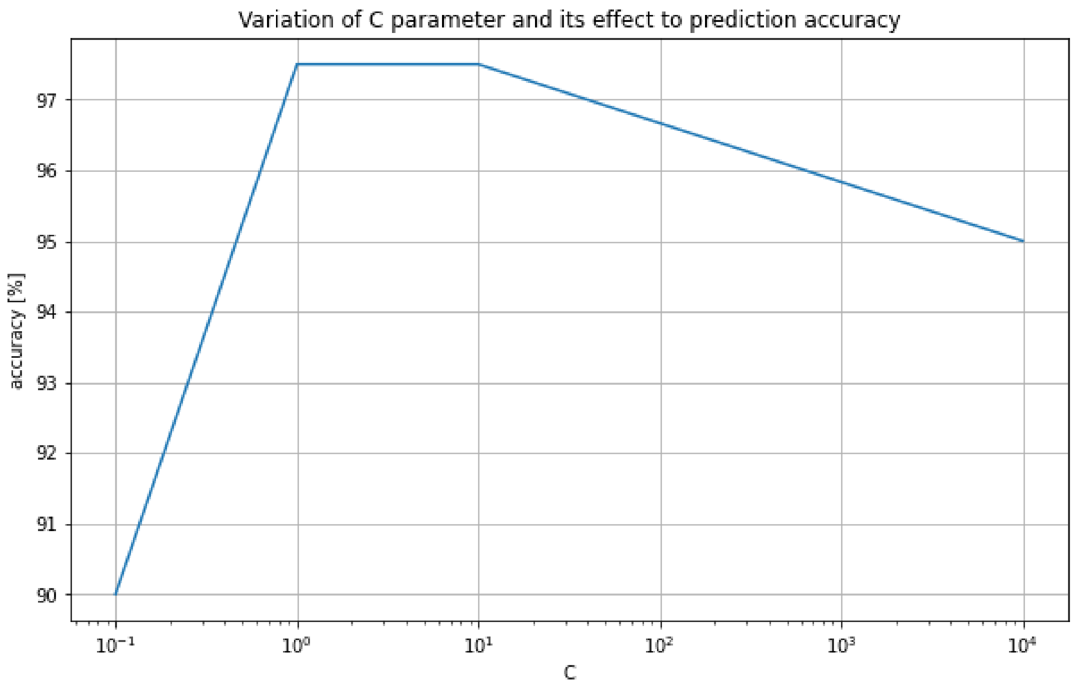

Figure 29: The plot shows the variation of the SVC parameter 'C' against the prediction accuracy

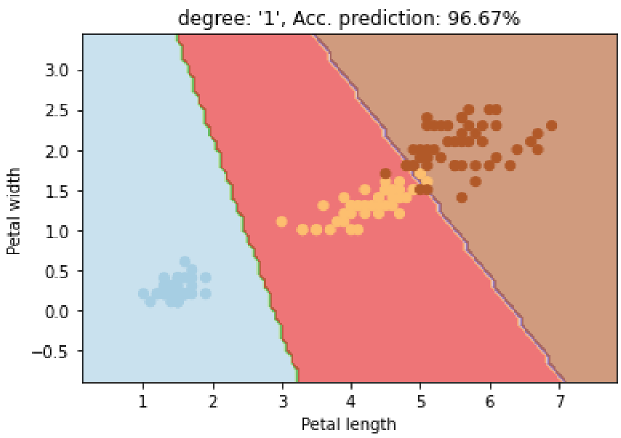

Figure 30: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

[186]:
```
degrees = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

accuracy_list = list()
for degree in degrees:
    accuracy = crossValSVC(X_train, y_train, kernel='poly', degree=degree)
    accuracy_list.append(accuracy)

plotParamsAcc(degrees, accuracy_list, 'degree', log_scale=False)
```

[ ]:
```

```

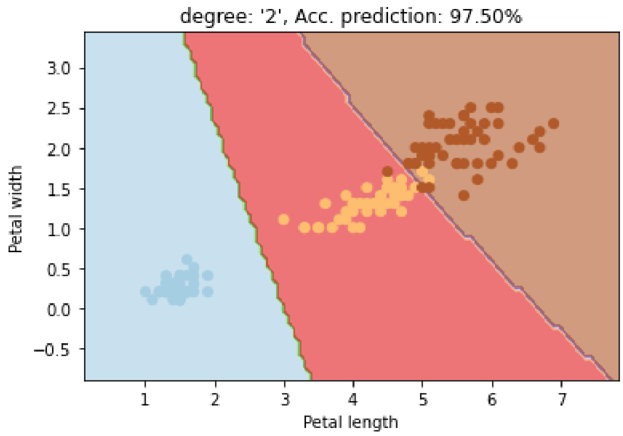

Figure 31: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

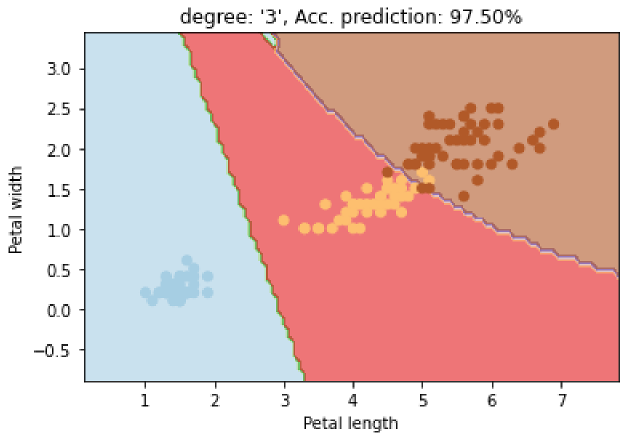

Figure 32: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

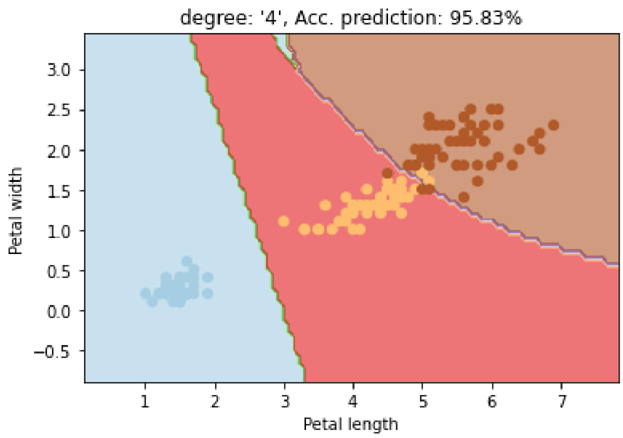

Figure 33: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

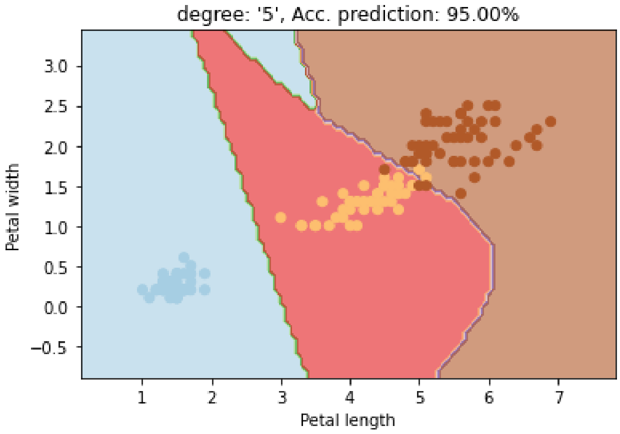

Figure 34: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

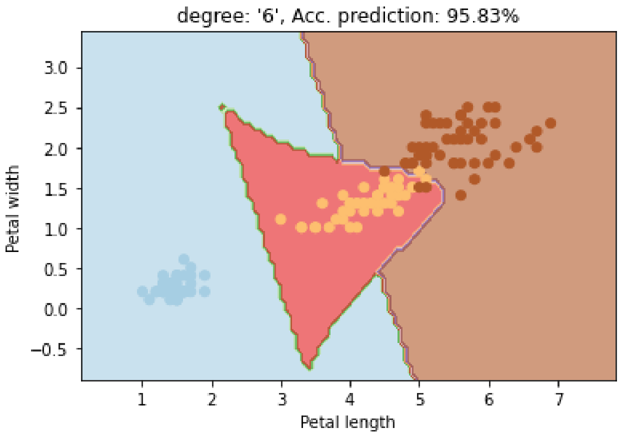

Figure 35: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

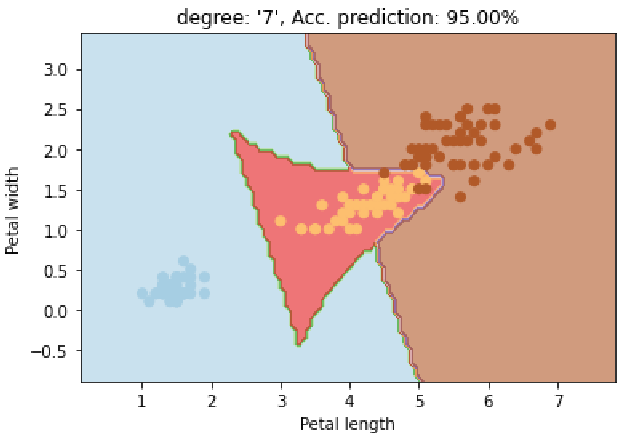

Figure 36: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

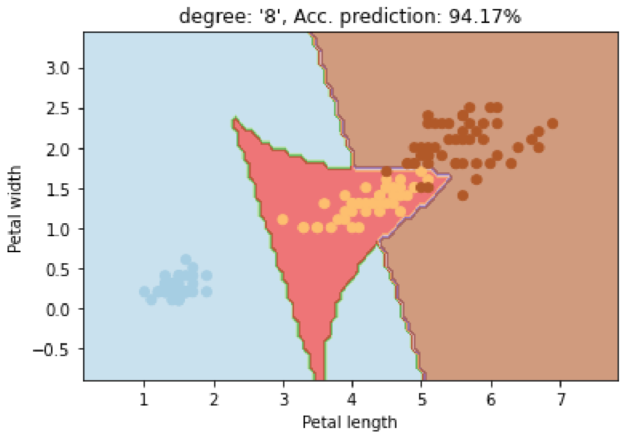

Figure 37: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

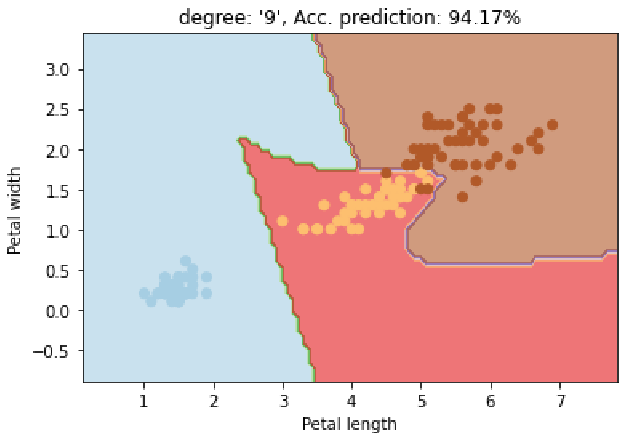

Figure 38: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

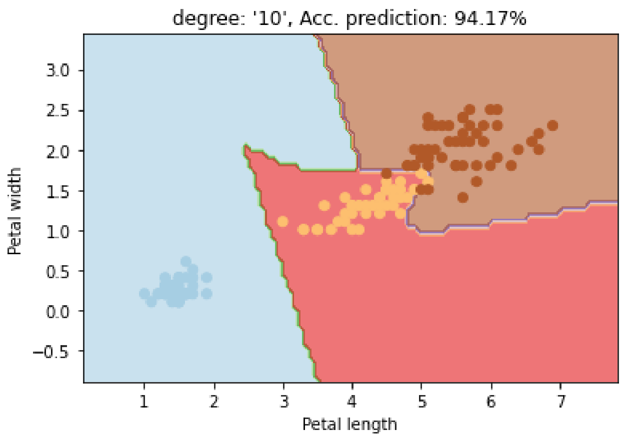

Figure 39: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

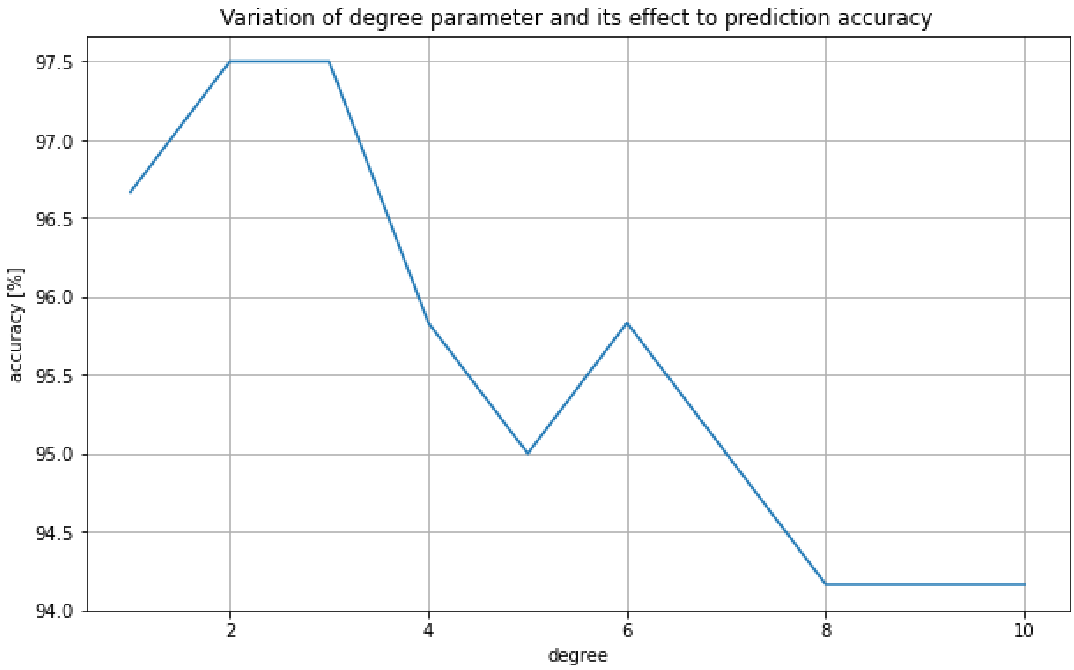

Figure 40: The plot shows the variation of the SVC parameter 'degree' against the prediction accuracy