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

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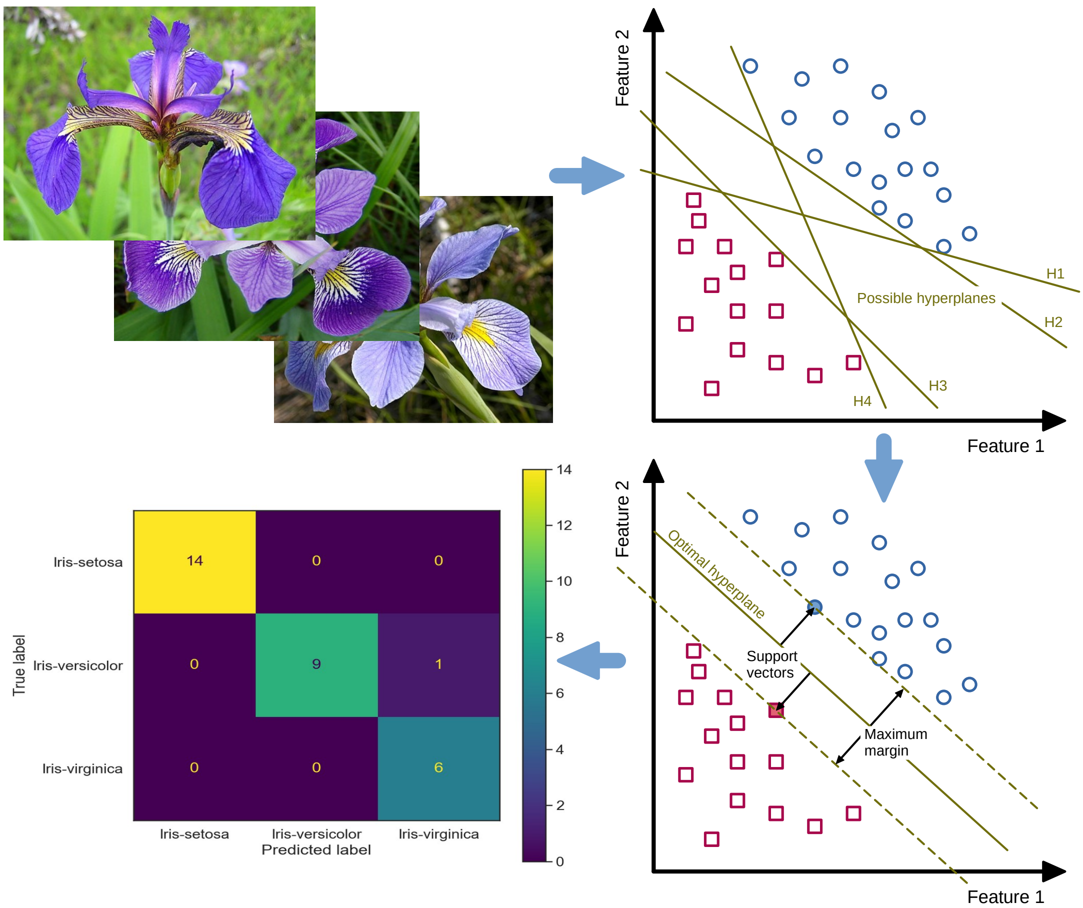


Anyone who wants to seriously deal with the emerging topic of our time "Artificial Intelligence (AI)" cannot avoid dealing with the basic mathematical models and algorithms from the field of "Machine Learning (ML)" as a subset of AI. However, someone who opens the door for the first time to this equally 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 exceptionally beginner-friendly "Iris Dataset". Furthermore, the selection of the "correct" SVC kernel and its parameters are described and their effects on the classification result are shown.

# Contents

# 1 Introduction

## 1.1 English introduction

In the **digitized 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. Depending on the strength of the degree of flexibility, this **situational adaptivity** can often only be realized by applying mathematical models and algorithms from the field of **Machine Learning (ML)** as a subset of **Artificial Intelligence (AI)**.

Examples of such AI applications in work environments can range from comparatively simple **voice assistance systems** (similar, for example, to Siri or Alexa from the private sphere) to partially or **highly automated systems**. The transition from **automation to autonomy** is currently the subject of much controversy among experts and can be viewed in terms of the transition of responsibility from humans to technical systems.

By definition, a system is called **autonomous** only when it can achieve a given goal **independently** and adapted to the situation **without human control** or detailed **programming**.

However, the distinction between the degree of automation and the autonomy of a technical system is relatively vague and difficult to define, depending on the technical context and the degree of abstraction. Crucial for the classification are the degrees of **self-determination**, **independence** as well as the **freedom of decision or action** of a technical system towards **human intervention** or preprogrammed behavior patterns.

In contrast to highly automated systems, autonomous systems are only able to act autonomously, solve problems, and learn to constantly improve in the process through the use of AI algorithms.

For example, **driverless transport systems (AGVs)** can navigate **autonomously** through larger industrial facilities using self-learned self-updated maps shared with other AGVs, and avoid locationchanging obstacles by independently finding and optimizing suitable routes. However, at a higher level of abstraction, new logistics tasks are given to them by human operators, which is why AGVs tend to be **highly automated systems** from a human perspective.

In addition to the many very interesting advantages, e.g. in terms of economic efficiency and workload reduction, such highly automated systems and, depending on the point of view, autonomous subsystems are characterized 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 interlinked imaging and non-imaging safety sensors for monitoring the driving space to avoid collisions).

Very high requirements are placed on such autonomous systems and the AI algorithms used for this purpose with regard to **functional safety**. However, the requirements for safety evaluability in terms of **transparency** and **explainability** of decisions made by AI are currently very difficult or impossible to achieve, especially when using AI algorithms from the field of **deep learning**. Therefore, current research projects are investigating the transparency and explainability of **deep neural networks**.

Furthermore, in terms of their **recognition rates** and thus the **reliability of their decisions**, today's AI algorithms very often do not meet the functional safety requirements to achieve higher safety levels, even under the most favorable conditions. For example, a software-based safety function with a performance level d ($PL_d$) typically required for machines in accordance with ISO 13849-1 may only fail dangerously with a probability of $10^{-7} - 10^{-6}$ per hour during continuous use.

An appropriate assessment or even **testing** with regard to the required functional safety according to uniform and ideally standardized criteria has numerous consequences for the future orientation and organization of technical **occupational safety and health (OSH)** in Germany and in Europe. In addition to the currently still very difficult safety-related assessability, an important point is that the previous clear separation between **placing on the market law** (see e.g. Machinery Directive) and **occupational safety and health law** (see European Framework Directive for Occupational Safety and Health and German Ordinance on Occupational Safety and Health) can no longer be continued in this way. The reason for this is that **safety-related properties** will also change, especially of systems **continuously learning** at runtime, due to new or **adapted behaviors** learned during operation. From today's point of view, systems based on **learned-out** and at runtime **invariable models** are not affected by this.

For these reasons, especially the actors of technical occupational safety and health who will deal with the evaluation of such autonomous systems capable of learning or system components with AI algorithms in the future should familiarize themselves in depth with the software structures used for this purpose as early as possible. This is the only way to ensure that the rapid development of systems capable of learning can be accompanied by OSH and their testing authorities in a constructive, critical and technically appropriate manner. If this is omitted, it must be assumed on the basis of the experiences of recent years that 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 more likely to occur due to inadequately designed AI-based work systems.

However, the safety-related evaluation of such learning-capable systems requires a more in-depth technical entry into the world of **machine learning** as a subfield of **artificial intelligence**. For this purpose, it is necessary to deal with the basic operation of typical 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. In addition to reading general technical literature, it is advisable to consult introductory and systematic tutorials.

This Getting Started tutorial has exactly this goal, demonstrating systematically and step-by-step the typical ML workflow using the very powerful **Support Vector Classifier (SVC)** as an example.

This tutorial will be presented in the context of a workshop at the **Conference "Artificial Intelligence"**, hosted by the German Social Accident Insurance (DGUV), 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.

Besides the **deep neural networks**, which are very present in the media, there is a very rich diversity of other very powerful ML algorithms - suitable for the particular use case. For a more generally comprehensible introduction, the SVC algorithm was deliberately chosen for the target audience of the workshop. Its operating principles are easy to convey to ML novices as well as in the time frame given for the workshop - quite in contrast to the entry into the world of deep neural networks.

The following main sections will demonstrate the typical ML workflow step-by-step. In **step 0**, specific guidance is provided for selecting hardware and software suitable for machine learning. To allow an ML novice to first familiarize themselves with the ML algorithms, tools, libraries, and programming systems, the ready-made and very beginner-friendly **Iris dataset** is involved in **step 1**. Only after a comprehensive acquaintance with the application of ML tools would it make sense to examine one's own environment for ML-suitable applications and to obtain suitable datasets from them. However, this is beyond the scope of this introductory tutorial.

One of the most important steps in the entire ML process is **step 2**, in which the dataset included in step 1 is examined using typical data analysis tools. In addition to exploring the **data structure** and **internal correlations** in the dataset, errors such as gaps, duplications, or obvious misentries must also be found and corrected where possible. This is enormously important so that the classification can later provide plausible results.

After exploring the dataset, in **step 3** one has to decide on a specific ML algorithm based on certain selection criteria. Among other ML algorithms suitable for the Iris dataset (such as the decision-tree-based **random-forests classifier**), the reasoned choice here in the tutorial falls on the **support vector classifier**. A dedicated SVC model is now being implemented.

In **step 4** the dataset is prepared for the actual classification by SVC. Depending on the selected ML algorithm as well as the data structure, it may be necessary to prepare the data before training (e.g., by standardization, normalization, or binarization based on thresholds). After splitting the dataset into a training and test dataset, the SVC model is trained with the training dataset in **step 5**. Subsequently, classification predictions are made with the trained SVC model based on the test data. In **step 6**, the quality of the classification result is evaluated using known **metrics** such as the **confusion matrix**.

Since the classification in step 5 was initially performed with standard parameters (so-called **hyper-parameters**), their meaning is explained in **step 7** and then their effect on the classification result is demonstrated by manually varying the individual hyper-parameters.

In the final **step 8**, two approaches to systematic hyper-parameter search are presented: **Grid Search** and **Randomized Search**. While the former exhaustively considers all parameter combinations for given values, the latter selects a number of candidates from a parameter space with a particular random distribution.

## 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 die Anwendung mathematischer Modelle und Algorithmen aus dem Bereich des **Maschinellen Lernens (ML)** als Teilmenge der **Künstlichen Intelligenz (KI)** realisiert werden.

Beispiele für solche KI-Anwendungen in der Arbeitswelt reichen von vergleichsweise einfachen **Sprachassistenzsystemen** (ähnlich z. B. Siri oder Alexa aus dem privaten Umfeld) bis hin zu teil- oder **hochautomatisierten Systemen**. Der Übergang von **Automatisierung zu Autonomie** wird derzeit in der Fachwelt sehr kontrovers diskutiert und kann unter dem Aspekt des Übergangs der Verantwortung vom Menschen zum technischen System betrachtet werden.

Definitionsgemäß wird ein System erst dann als **autonom** bezeichnet, wenn es **ohne menschliche Steuerung** oder detaillierte **Programmierung** ein vorgegebenes Ziel **selbstständig** und an die Situation angepasst erreichen kann.

Allerdings ist die Unterscheidung des Grades der Automatisierung bis hin zur Autonomie eines technischen Systems relativ fließend und je nach fachlichem Kontext und Abstraktionsgrad nur schwer zu definieren. Maßgeblich für die Einordnung sind die Grade der **Selbstbestimmtheit**, die **Unab-**

**hängigkeit** sowie die **Entscheidungs- bzw. Handlungsfreiheit** eines technischen Systems gegenüber **menschlichem Eingriff** oder vorprogrammierter Verhaltensmuster.

Im Gegensatz zu hochautomatisierten Systemen sind autonome Systeme nur durch Einsatz von KI-Algorithmen in der Lage, eigenständig zu agieren, Probleme zu lösen und dabei zu lernen, sich ständig zu verbessern.

Beispielsweise können **fahrerlose Transportsysteme (FTS)** anhand selbst erlernter, selbstständig aktualisierter und mit anderen FTS geteilter Karten **autonom** durch größere Industrieanlagen navigieren und ortsveränderlichen Hindernissen ausweichen, indem sie selbstständig geeignete Routen finden und optimieren. Jedoch werden ihnen in einer höheren Abstraktionsebene neue Logistikaufträge durch menschliche Bediener vorgegeben, weswegen es sich bei FTS aus menschlicher Perspektive eher um **hochautomatisierte Systeme** handelt.

Neben den vielen sehr interessanten Vorteilen z. B. bzgl. Wirtschaftlichkeit und Arbeitserleichterung kennzeichnet solche hochautomatisierten und je nach Betrachtung autonomen Teilsysteme 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 ihre **Sicherheitsfunktionen** (z. B. Auswertung miteinander verknüpfter bildgebender und nicht-bildgebender Sicherheitssensorik zur Überwachung des Fahrraums zur Kollisionsvermeidung).

An solche autonomen Systeme und die hierfür eingesetzten KI-Algorithmen werden sehr hohe Anforderungen hinsichtlich der **funktionalen Sicherheit** gestellt. Jedoch sind die Anforderungen für eine sicherheitstechnische Bewertbarkeit bezüglich der **Transparenz** und **Erklärbarkeit** der durch KI getroffenen Entscheidungen insbesondere bei Einsatz von KI-Algorithmen aus dem Bereich des **Deep Learnings** derzeit nur sehr schwer oder gar nicht erreichbar. Deshalb werden durch aktuell laufende Forschungsprojekte die Transparenz und Erklärbarkeit von **tiefen neuronalen Netzen** untersucht.

Weiterhin erfüllen heutige KI-Algorithmen hinsichtlich ihrer **Erkennungsraten** und damit der **Zuverlässigkeiten ihrer Entscheidungen** selbst unter günstigsten Bedingungen sehr oft nicht die Anforderungen an die funktionale Sicherheit, um höhere Safety-Level zu erreichen. Beispielsweise darf eine software-gestützte Sicherheitsfunktion mit einem für Maschinen typischerweise geforderten Performance Level d ($PL_d$) nach ISO 13849-1 bei kontinuierlicher Nutzung nur mit einer Wahrscheinlichkeit von $10^{-7} - 10^{-6}$ pro Stunde gefährlich ausfallen.

Eine hinsichtlich der geforderten funktionalen Sicherheit angemessene Bewertung oder gar **Prüfung** nach einheitlichen und idealerweise genormten Maßstäben hat viele Konsequenzen für die zukünftige Ausrichtung und Gestaltung des **technischen Arbeitsschutzes** in Deutschland und in Europa. Neben der derzeit noch sehr schwierigen sicherheitstechnischen Bewertbarkeit von KI-Algorithmen ist ein wichtiger Punkt, dass die bisherige klare Trennung zwischen **Inverkehrbringensrecht** (siehe z. B. Maschinenrichtlinie) und **betrieblichem Arbeitsschutzrecht** (siehe Arbeitsschutz-Rahmenrichtlinie und Betriebssicherheitsverordnung) so nicht mehr aufrechterhalten werden kann. Grund hierfür ist, dass sich auch die **sicherheitsrelevanten Eigenschaften** insbesondere von zur Laufzeit **weiterlernenden Systemen** durch während des Betriebs erlernte, neue oder **angepasste Verhaltensweisen** verändern werden. Systeme auf Basis **ausgelernter** und zur Laufzeit **unveränderlicher Modelle** sind aus heutiger Sicht hiervon nicht betroffen.

Aus diesen Gründen sollten sich insbesondere die Akteure des technischen Arbeitsschutzes, die sich zukünftig mit der Prüfung solcher lernfähigen Systeme oder Systemkomponenten mit KI-Algorithmen befassen werden, möglichst frühzeitig mit den hierfür eingesetzten Software-Strukturen vertieft auseinandersetzen. Nur dadurch lässt sich erreichen, dass die stürmische Entwicklung lernfähiger Systeme durch den Arbeitsschutz und dessen Prüfinstitute konstruktiv, kritisch und fachlich angemessen begleitet werden kann. Wird dies versäumt, muss aufgrund der Erfahrungen der vergangenen Jahre davon ausgegangen werden, dass das Arbeitsschutzsystem durch die wirtschaftlichen Interessen global agierender Softwaregiganten skrupellos umgangen oder ausgehebelt werden wird. Dies hätte die Folge, dass schwere oder tödliche Arbeitsunfälle wegen unzulänglich gestalteter KI-basierter Arbeitssysteme wahrscheinlicher werden.

Allerdings erfordert die sicherheitstechnische Bewertung solcher lernfähigen Systeme einen tiefer gehenden fachlichen Einstieg in die Welt des **maschinellen Lernens** als Teilgebiet der **künstlichen Intelligenz**. Hierzu muss sich mit den grundlegenden Funktionsweisen typischer ML-Algorithmen, entsprechenden Software-Werkzeugen, Bibliotheken und Programmiersystemen auseinander gesetzt werden.

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 neben dem Lesen allgemeiner Fachliteratur, einführende und systematische Anleitungen zu Rate zu ziehen.

Genau dieses Ziel verfolgt das vorliegende Getting-Started-Tutorial, indem systematisch und Schritt-für-Schritt der typische ML-Arbeitsablauf am Beispiel des sehr leistungsfähigen **Support Vector Classifier (SVC)** demonstriert wird.

Dieses Tutorial wird im Rahmen eines Workshops auf der **Fachtagung "Künstliche Intelligenz"**, ausgerichtet durch die Deutsche Gesetzliche Unfallversicherung (DGUV), voraussichtlich im November 2022 in Dresden vorgestellt. Der Workshop richtet sich an interessierte ML-Neulinge im technischen Arbeitsschutz der gesetzlichen Unfallversicherungsträger.

Neben den medial sehr präsenten **tiefen neuronalen Netzen** gibt es eine sehr reichhaltige Auswahl anderer sehr leistungsfähiger ML-Algorithmen - passend für den jeweiligen Anwendungsfall. Für einen allgemein verständlicheren Einstieg wurde für die Zielgruppe des Workshops der SVC-Algorithmus bewusst gewählt. Dessen Arbeitsweise ist sowohl für ML-Neulinge als auch in dem für den Workshop vorgegebenen Zeitrahmen leicht vermittelbar - ganz im Gegensatz zum Einstieg in die Welt der tiefen neuronalen Netze.

Die folgenden Hauptabschnitte demonstrieren den typischen ML-Arbeitsablauf Schritt-für-Schritt. Im **Schritt 0** werden konkrete Hinweise für die Auswahl der für das maschinelle Lernen geeigneten Hardware und Software gegeben. Damit sich ein ML-Neuling zunächst mit den ML-Algorithmen, Werkzeugen, Bibliotheken und Programmiersystemen vertraut machen kann, wird im **Schritt 1** der fertige und sehr einsteigerfreundliche **Iris-Datensatz** hinzugezogen. Erst nach einer umfassenden Einarbeitung in die Anwendung der ML-Werkzeuge wäre es sinnvoll, die eigene Umgebung auf ML-taugliche Anwendungen hin zu untersuchen und daraus geeignete Datensätze zu gewinnen. Dies geht jedoch über den Rahmen dieses einführenden Tutorials hinaus.

Mit der wichtigste Schritt im gesamten ML-Prozess ist **Schritt 2**, in dem der in Schritt 1 einbezogene Datensatz mit Hilfe typischer Datenanalyse-Werkzeuge untersucht wird. Neben der Erkundung der **Datenstruktur** sowie **innerer Zusammenhänge** im Datensatz müssen auch Fehler wie z. B. Lücken, Dopplungen oder offensichtliche Fehleingaben gefunden und nach Möglichkeit behoben werden. Dies ist enorm wichtig, damit die Klassifikation später plausible Ergebnisse liefern kann.

Nach der Erkundung des Datensatzes muss man sich im **Schritt 3** anhand bestimmter Auswahlkriterien für einen konkreten ML-Algorithmus entscheiden. Neben anderen für den Iris-Datensatz passenden ML-Algorithmen (wie z. B. der entscheidungsbaum-basierte **Random-forests-Classifier**) fällt die begründete Auswahl hier im Tutorial auf den **Support-Vector-Classifier**. Ein entsprechendes SVC-Modell wird nun implementiert.

Im **Schritt 4** wird der Datensatz für die eigentliche Klassifikation per SVC vorbereitet. Je nach gewähltem ML-Algorithmus sowie der Datenstruktur kann es erforderlich sein, dass die Daten vor dem Training aufbereitet werden müssen (z. B. durch Standardisierung, Normalisierung oder Binärisierung anhand von Schwellwerten). Nach der Aufteilung des Datensatzes in einen Trainings- und Testdatensatz, wird das SVC-Modell im **Schritt 5** mit dem Trainingsdatensatz trainiert. Anschließend werden mit dem trainierten SVC-Modell anhand der Testdaten Klassifikationsvorhersagen getroffen. Im **Schritt 6** wird die Güte des Klassifikationsergebnisses anhand bekannter **Metriken** wie z. B. der **Konfusionsmatrix** evaluiert.

Da die Klassifikation im Schritt 5 zunächst mit Standard-Parametern (den sogenannte **Hyper-Parametern**) durchgeführt wurde, wird ihre Bedeutung im **Schritt 7** erklärt und danach ihr Einfluss auf das Klassifikationsergebnis durch manuelle Variation der einzelnen Hyper-Parameter demonstriert.

Im abschließenden **Schritt 8** werden zwei Ansätze zur systematischen Hyper-Parameter-Suche vorgestellt: **Grid Search** und **Randomized Search**. Während bei ersterer für gegebene Werte erschöpfend alle Parameterkombinationen betrachtet werden, wird beim zweiten Ansatz eine Anzahl von Kandidaten aus einem Parameterraum mit einer bestimmten zufälligen Verteilung ausgewählt.

## 1.3 Steps of the systematic ML process

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

# 2 STEP 0: Select hardware and software suitable for ML

In this step, specific guidance is provided for selecting hardware and software suitable for machine learning.

## 2.1 Hardware

When considering hardware requirements, two systems and their use cases must be taken into account: the **training system** and the **application system**.

### 2.1.1 Training system

The **training phase** requires a lot of **computational power** and **memory (RAM)**, depending on the **amount of data** to be processed and the **ML algorithm (so-called estimator)** chosen.

Depending on the estimator model, highly parallel processing on a **Graphics Processing Unit (GPU)** can provide significant **speed advantages** over processing on a **Central Processing Unit (CPU)** (e.g., when training deep neural networks in the area of **deep learning**). To take advantage of this speed benefit, the AI application must be suitable in terms of **parallelizability** of the estimator model used as well as **GPU support** through special driver layers, the so-called Operating System Abstraction Layer (OSAL) (Wikipedia: OSAL 2022).

Such GPUs are installed on powerful **3D graphics cards**. However, these must be explicitly qualified for the application for AI - not every game-suitable 3D graphics card from any manufacturer can be used. The manufacturer **Nvidia** offers GPUs suitable for AI in its high-performance graphics cards with **CUDA architecture**. CUDA stands for "Compute Unified Device Architecture" and is a **programming interface** (API) developed by Nvidia, with which program parts can be processed by the graphics processor (Wikipedia: CUDA 2022). The GPU works significantly faster than the CPU, especially with highly parallelizable program sequences (high data parallelism). This speed advantage can be considerable despite currently available CPU technologies like **Multicore** and **Hyper-Threading** with Intel CPUs!

Nvidia graphics cards with CUDA-supporting GPUs are ranked based on their **compute capability** (NVIDIA.Developer 2022).

However, it should be mentioned that currently only the manufacturer Nvidia offers 3D graphics cards with CUDA implementation, since CUDA is a **proprietary** framework. In addition, there is also the much less well-known **open source** alternative **OpenCL**, which has now been implemented by a large number of graphics card manufacturers (Wikipedia: OpenCL 2022). Since OpenCL is an **open industry standard**, Intel and AMD chips and their GPUs, ATI Radeon cards of the 5, 6, 7 and R9 series as well as various Nvidia GeForce cards are supported, for example.

Regarding the **code execution performance** of both alternatives in direct comparison, there are different statements in the technical literature. The 2011 paper A Performance Comparison of CUDA and OpenCL sees the CUDA implementation as the clear favorite (Karimi, Dickson, and Hamze 2011). More recent publications point out the strong dependence of performance on **code quality**, **algorithm type** and the **GPU hardware** used, among other things - see e.g. here: CUDA vs OpenCL: Which to Use for GPU Programming (Exterman 2021).

It is therefore recommended that the decision for **CUDA or OpenCL** should depend on the extent to which most of the applications employed and the GPU hardware used are better supported by one of the two approaches in each case.

The **state of the art** should be also taken into account when selecting the rest of the training system's hardware. Otherwise, seemingly (price-wise) inexpensive components could very quickly nullify the speed advantage of the GPU. In addition to a mainboard suitable for one (or more) high-performance 3D graphics cards with a correspondingly powerful BUS system (e.g. PCI Express), the RAM should be as large as possible (min. 64 GB) and fast. A large RAM allows, for example, the **virtualization** of several parallel systems in the form of **virtual machines** and thus a significantly better utilization of the available computing capacity (Wikipedia: VM 2022). The permanent memory should also be as large and fast as possible - high-performance **solid-state drives (SSDs)** should be clearly preferred over classic hard disks (HDDs).

### 2.1.2 Application system

In the **application phase** of the trained estimator model, considerably less computing power and RAM are usually required. If the concrete application does not require **continuous learning during operation**, significantly less expensive systems (in terms of acquisition costs, power consumption, etc.) can also be used. Such application-specific **embedded systems** have only one CPU (usually in **ARM architecture**), comparatively limited RAM (e.g. 1 - 8 GB) and usually no GPU. A popular **embedded computer** that is very well supported in terms of ML software is the **Raspberry Pi** (Wikipedia: Raspi 2022). In addition to its ARM CPU, the Raspberry Pi also has a GPU installed on the same processor in the so-called **System on a Chip design (SoC)**. However, the SoC manufacturer **Broadcom** does not support the CUDA API.

There are references in the technical literature that the open source alternative **OpenCL** can be installed on the Raspberry Pi and that the AI framework **TensorFLow** (see section "Software") can be compiled with **SYCL** support, where SYCL stands for "Single Source OpenCL" (Wikipedia: SYCL 2022). However, a first rough review gives the impression that support for this approach is still very experimental at the moment. Therefore, parallelizing the AI application on the GPU of the Raspberry Pi does not seem to be an option (yet). Here are some links for further reading:

- Deep learning with Raspberry Pi and alternatives in 2022 (Politiek 2022a)
- Benchmarking Machine Learning on the New Raspberry Pi 4, Model B (Allan 2019)
- Portable Computer Vision: TensorFlow 2.0 on a Raspberry Pi (Johnson 2019)
- Install OpenCL on Raspberry Pi 3 B+ (Politiek 2022b)
- Does TensorFlow Support OpenCL? (IndianTechWarrior 2022)
- TensorFlow for OpenCL using SYCL (Iwanski 2016)

## 2.2 Software

### 2.2.1 Operating system

**@TODO:** Rephrase and translate!!

These are general requirements to the operating system:

- Offenheit (Verfügbarkeit sehr guter Schnittstellen-Dokumentation und idealerweise quelloffener Software)
- Verfügbarkeit (Installations- und Konfigurationsrechte)
- Kommunikation (ungefilterte und bidirektionale Kommunikation im lokalen Netzwerk sowie ins Internet auf allen notwendigen Protokollen)
- leichte Erweiterbarkeit
  - SW-Installation + Updates über zentrale Paketmanagementsysteme wie z. B. `apt`, `pip` oder `conda`
  - Einbindung zusätzlicher SW-Bibliotheken oder externer HW-Sensoren

### 2.2.2 Programming IDEs

#### RStudio (based on R language)

#### JupyterLab (Python language used)

### 2.2.3 Packages for data analytics and libraries for ML (Python only)

#### Data analytics

`NumPy`

`Pandas`

#### Data visualization

`matplotlib`

`seaborn`

#### Machine learning

`Scikit-Learn`

**`TensorFlow`, `Keras`, `CUDA Toolkit`** The package `TensorFlow` offers, among other things, the possibility to create and train **artificial neural networks (ANN)** based on Google AI. However, the installation and application is very much beyond the scope of this beginner tutorial. Further information can be found here: `https://www.tensorflow.org`.

## 2.3 Community Support

When selecting and deciding for or against the use of certain hardware and software components, in addition to purely technical or financial characteristics, significant attention should be paid to broad **support from a well-networked community**. This community should consist of a balanced share of **manufacturers** of hardware components (e.g. GPU suppliers, manufacturers of embedded systems or sensors), **software developers** ideally from the **open source** ecosystem, and an active **user community** (e.g. for reporting hardware and software bugs or providing help in forums).

The author's many years of development experience show that the technically best hardware or software component is worthless if you are (apparently) the only user. This impression arises either because the component is actually very exotic and has only a few users or because the development takes place "behind closed doors", i.e. in the company's internal **closed source** domain.

Without the support of an active community, you are (almost) on your own when it comes to questions or problems. Progress in the development and maintenance of an AI application is therefore very difficult! The clear recommendation is therefore: Go for the (technically, price-wise) **second-best alternative** with an even bigger **community**.

## 2.4 Import Python packages

The aim of this section is to import globally used Python packages for data analysis and ML, such as `Pandas`, `NumPY`, `matplotlib` and `Scikit-Learn`.

[16]:
```
import time

from IPython.display import HTML

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

# 3 STEP 1: Acquire the ML dataset

To allow an ML novice to first familiarize themselves with the ML algorithms, tools, libraries, and programming systems, the ready-made and very beginner-friendly **Iris dataset** is involved in this step. Only after a comprehensive acquaintance with the application of ML tools would it make sense to examine one's own environment for ML-suitable applications and to obtain suitable datasets from them. However, this is beyond the scope of this introductory tutorial.

Several details, for example, on the history of the creation of the Iris flower dataset can be found e.g. on Wikipedia (see Wikipedia: Iris dataset 2022).

It can be downloaded on Kaggle: Iris Flower Dataset (Srinagar 2018). Furthermore, the dataset is available via Python in the machine learning package Scikit-learn, so that users can access it without having to find a special source for it.

[2]:
```
# import Iris dataset for exploration
irisdata_df = pd.read_csv('./datasets/IRIS_flower_dataset_kaggle.csv')
```

# 4 STEP 2: Explore the ML dataset

One of the most important steps in the entire ML process is this step, in which the dataset included in Step 1 is examined using typical data analysis tools. In addition to exploring the **data structure** and **internal correlations** in the dataset, errors such as **gaps**, **duplications**, or obvious **misentries** must also be found and corrected where possible. This is enormously important so that the classification can later provide plausible results.

## 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 datasets:
   - Do the data have **gaps** or **duplicates**? → Does the dataset 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 dataset need to be enriched with additional data for balance?
5. Find a first rough **idea of which correlations** could be in the dataset

## 4.2 Clarify the origins history

> The **Iris flower datasets** is a multivariate dataset introduced by the British statistician and biologist *Ronald Fisher* in his paper "The use of multiple measurements in taxonomic problems" (Fisher 1936). It is sometimes called *Anderson's Iris dataset* because Edgar Anderson collected the data to quantify the morphologic variation of Iris flowers of three related species (Wikipedia: Iris dataset 2022).

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 (Fisher 1936)

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

## 4.3 Overview of the internal structure and organization of the data

The dataset consists of 50 samples from each of three species of Iris: *Iris setosa*, *Iris virginica* and *Iris versicolor*, so there are 150 samples in total (Wikipedia: Iris setosa 2022, Wikipedia: Iris virginica 2022 and Wikipedia: Iris versicolor 2022).

Four features were measured from each sample: the length and the width of the **sepals** and **petals**, in centimetres (Wikipedia: Sepal 2022 and Wikipedia: Petal 2022). Here you can see a principle illustration of a flower in which, among other things, the sepals and petals are shown:

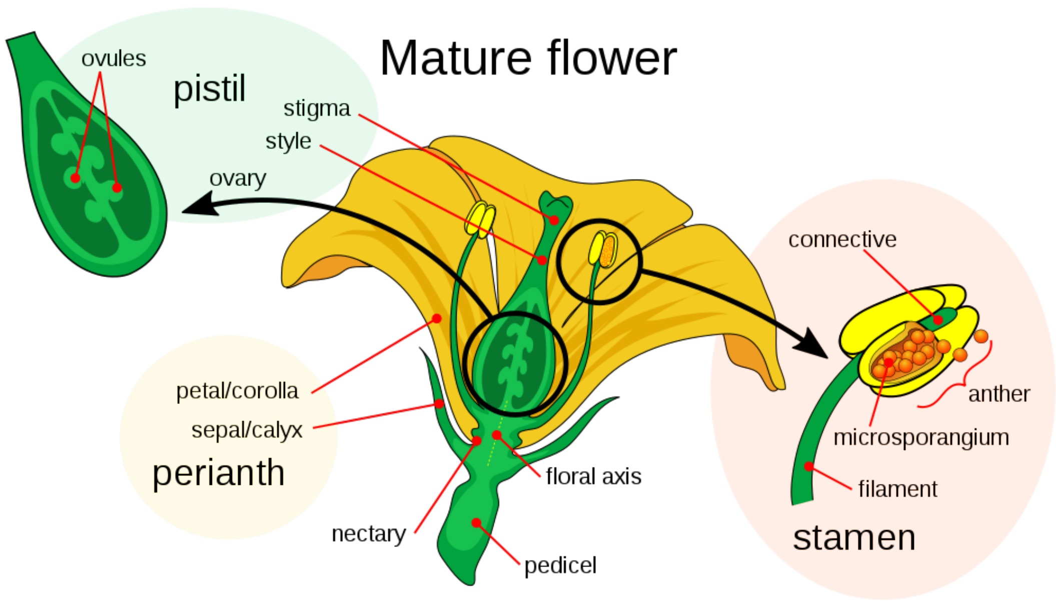


Figure 1: Principle illustration of a flower with sepal and petal (source: Mature_flower_diagram.svg, license: public domain)

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.

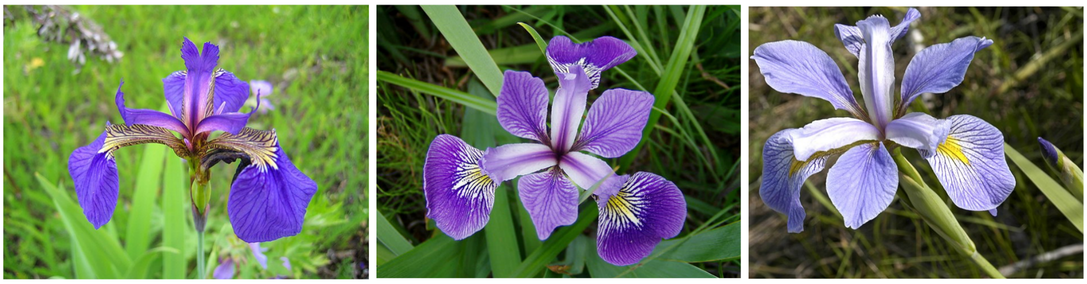

Figure 2: Left: *Iris setosa* (source: Irissetosa1.jpg, license: public domain); middle: *Iris versicolor* (source: Iris_versicolor_3.jpg, license: CC-SA 3.0); right: *Iris virginica* (source: Iris_virginica.jpg, license: CC-SA 2.0)

#### 4.3.1 Inspect structure of dataframe

Print first or last 5 rows of dataframe:

[3]:
```
irisdata_df.head(10)
```

[3]:

| | 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 |

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

[4]:

| | 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.

[5]:
```
irisdata_df
```

[5]:

| | 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:

[6]:
```
pd.set_option('display.max_rows', None)
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 |
| 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

[7]:
```
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
```

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

[8]:

| | 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**.

[9]:
```
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()
```

### 4.4 Identify anomalies in the datasets

#### 4.4.1 Find and repair gaps in dataset

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

**Check 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**.

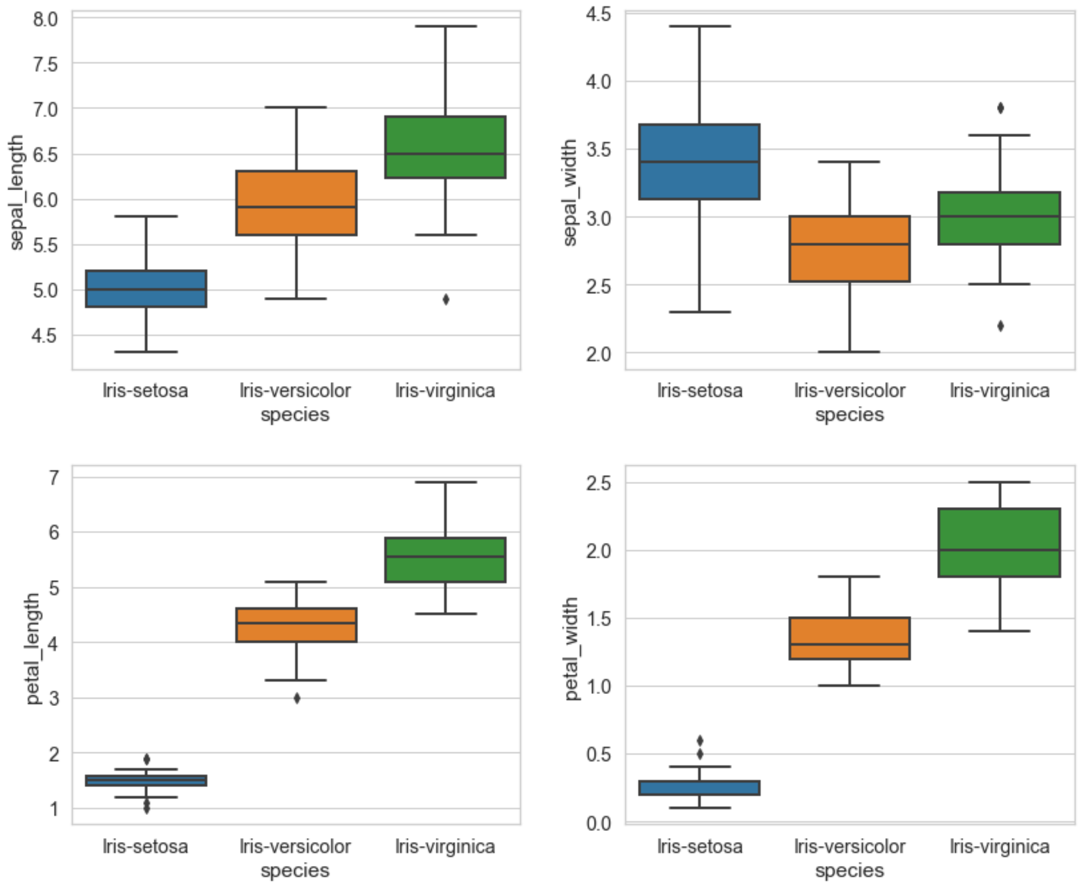


Figure 3: Boxplots used to explore the data ranges in the Iris dataset

[10]:
```
pd.set_option('display.max_rows', 40)
pd.set_option('display.min_rows', 30)
```

[11]:
```
irisdata_df.isnull()
```

[11]:
```
     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:

[12]:
```
irisdata_df_gaps = irisdata_df[irisdata_df.isnull().any(axis=1)]
irisdata_df_gaps
```

[12]:
```
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

[13]:
```
# import data to dataframe from csv file
employees_df = pd.read_csv("./datasets/employees_edit.csv")

# highlight cells with nan values
#employees_df_hl = employees_df.style.highlight_null('yellow')
#employees_df_hl

employees_df
```

[13]:
```
    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:

[14]:
```
employees_df_gaps = employees_df[employees_df.isnull().any(axis=1)]

# highlight cells with nan values
#employees_df_gaps = employees_df_gaps.style.highlight_null('yellow')

employees_df_gaps
```

[14]:
```
    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 in missing *string* values with `fillna()`** Now all null values (NaN) in the column "Gender" of the data type String are filled with *"No gender"*.

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

[15]:
```
# filling a null values using fillna()
employees_df["Gender"].fillna("No Gender", inplace = True)

# highlight cells by condition
#employees_df_hl = employees_df.style.apply(lambda x: ["background: yellow" if v ==
    'No Gender' else "" for v in x], axis = 1)
#employees_df_hl

employees_df
```

[15]:
```
      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]
```

**Fill in missing *numerical* values with mean values** Missing integer or float values can be filled with the mean values of the corresponding column.

**@TODO:**
Incorporate section "4.1.3 Fehlende Werte ergänzen" of the book `mitp_Praxishandbuch_Machine_Learning_Python_Scikit-learn_TensorFlow_2018_Anm_bk.pdf` (see Raschka and Mirjalili 2018).

**Drop 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).

[11]:
```python
# making a new dataframe with dropped NaN values
employees_df_dropped = employees_df.dropna(axis = 0, how ='any')
employees_df_dropped
```

[11]:
```
     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
…           …         …         …           …       …       …
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
…                    …                     …
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.

[17]:
```python
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

**Check 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**:

[12]:
```python
# import (again) data to dataframe from csv file
employees_df = pd.read_csv("./datasets/employees_edit.csv")
```

[13]:
```python
# find duplicate rows across all columns
duplicateRows = employees_df[employees_df.duplicated()]
duplicateRows
```

[13]:
```
    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
```

[14]:
```
# argument keep='last' displays the first duplicate rows instead of the last
duplicateRows = employees_df[employees_df.duplicated(keep='last')]
duplicateRows
```

[14]:
```
    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**:

[15]:
```
# identify duplicate rows across 'First Name' and 'Last Login Time' columns
duplicateRows = employees_df[employees_df.duplicated(
                    subset=['First Name', 'Last Login Time'])]
duplicateRows
```

[15]:
```
    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
```

[16]:
```
# 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
```

[16]:
```
    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
```

**Drop 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'])`

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

Remove duplicate rows across **all columns**:

[17]:
```
# remove duplicate rows across all columns
employees_df.drop_duplicates(inplace=True)
employees_df
```

[17]:
```
     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
…          …      …          …               …       …        …
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
…                    …                   …
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**:

[18]:
```
# 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
```

[18]:
```
     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
…           …      …          …               …       …         …
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
…                    …                   …
999              False        Distribution
1000             False             Finance
1001             False             Product
1002             False  Business Development
1003              True               Sales

[994 rows x 8 columns]
```

#### 4.4.3 Compare the edited dataset with the original dataset side-by-side

**@TODO:**

Incorporate following sources: - Compare two DataFrames and output their differences side-by-side - pandas compare two data frames and highlight the differences - How to Compare Two Pandas DataFrames and Get Differences

#### 4.4.4 Save edited dataset to new CSV file

**@TODO:**
Add explanation and python code here.

### 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

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

[20]:
```
# count unique values without missing values in a column,
# ordered descending and normalized
irisdata_df['species'].value_counts(ascending=False, dropna=False, normalize=True)
```

[20]:
```
Iris-setosa        0.333333
Iris-versicolor    0.333333
Iris-virginica     0.333333
Name: species, dtype: float64
```

[21]:
```
# 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)
```

[21]:
```
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**.

[22]:
```
employees_df.hist(column=['Salary'])
plt.show()
```


Figure 4: Histogram for frequency distribution of the salary

[23]:
```
employees_df.hist(column='Salary', by='Gender')
plt.show()
```

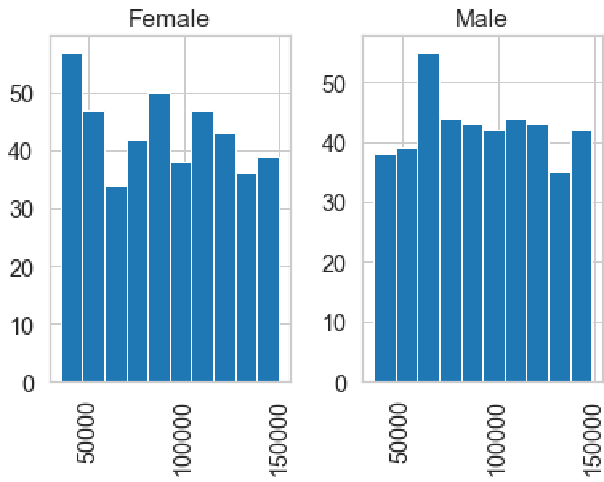


Figure 5: Histogram for the frequency distribution of the salary in comparison between men and women

## 4.6 First idea of correlations in dataset

To get a rough idea of the **dependencies** and **correlations** in the dataset, 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 dataset 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:

[24]:
```
# encoding the class column
irisdata_df_enc = irisdata_df.replace({"species":  {"Iris-setosa":0,
                                                     "Iris-versicolor":1,
                                                     "Iris-virginica":2}})

#irisdata_df_enc
```

[25]:
```
irisdata_df_enc.corr()
```

[25]:

| | 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.

[26]:
```
# 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()
```

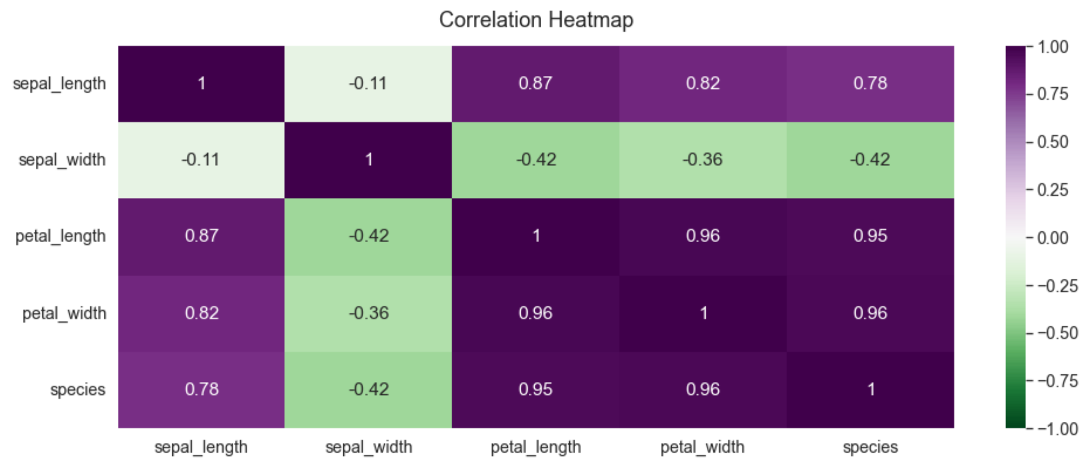


Figure 6: Correlation heatmap to explore coherences between single variables in the iris dataset

**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.

[27]:
```
np.triu(np.ones_like(irisdata_df_enc.corr()))
```

[27]:
```
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:

[28]:
```
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()
```

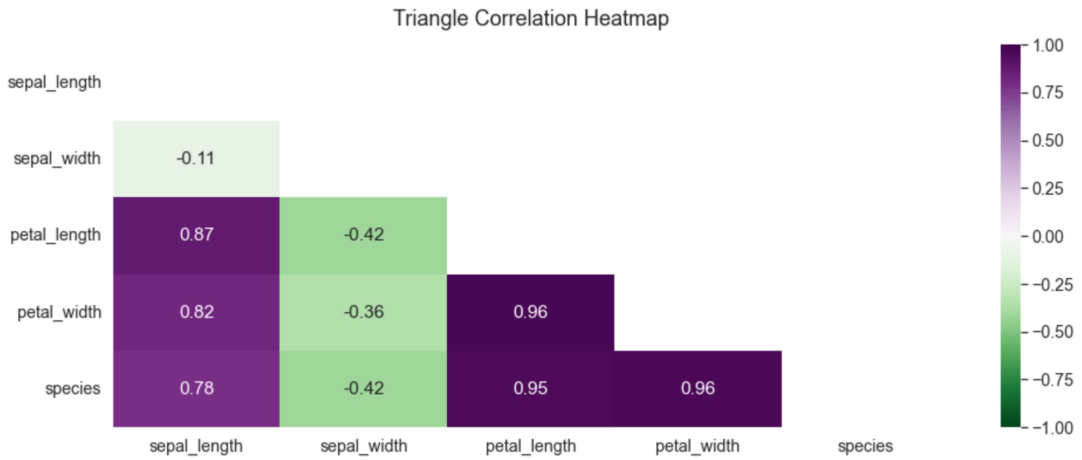


Figure 7: Correlation heatmap, which was cut at its main diagonal without losing any information

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 dataset, it is advisable to plot them in a **scatter plot**.

[29]:
```
# 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()
```

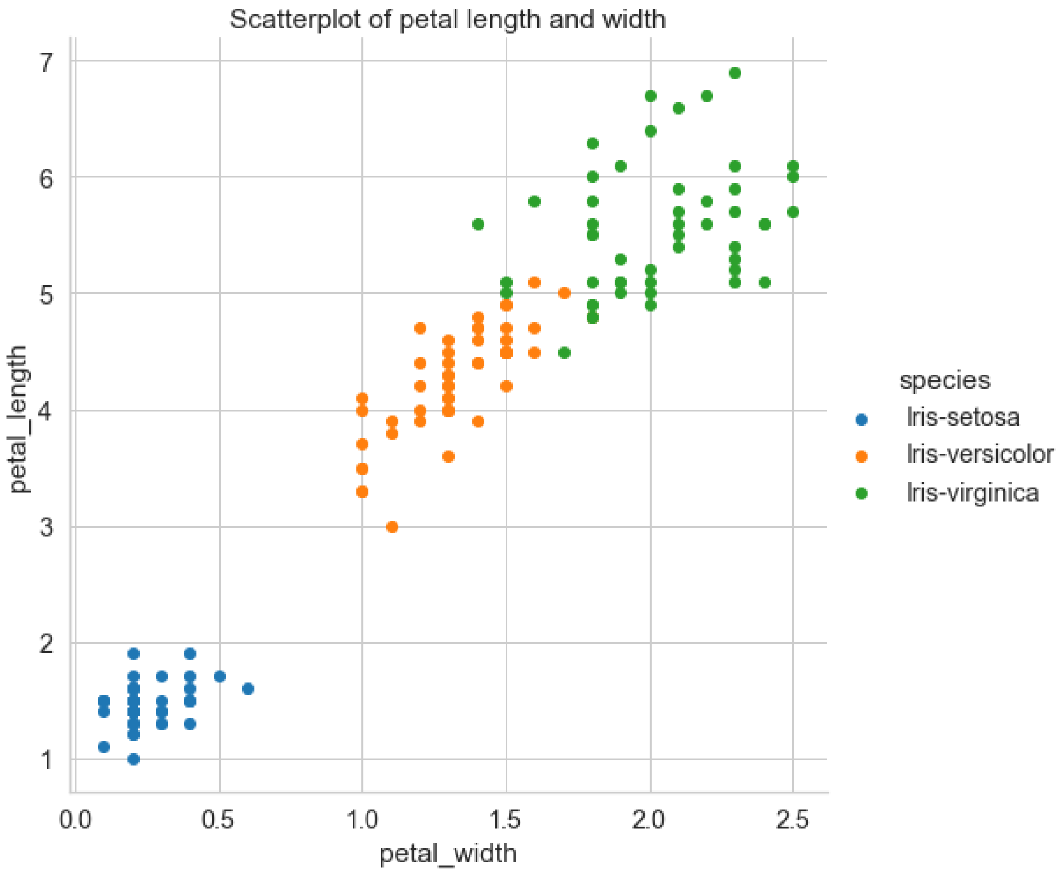


Figure 8: Plotting two individual variables of the iris dataset in the scatterplot to explore the relationships between these two

### 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.

[30]:
```
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()
```

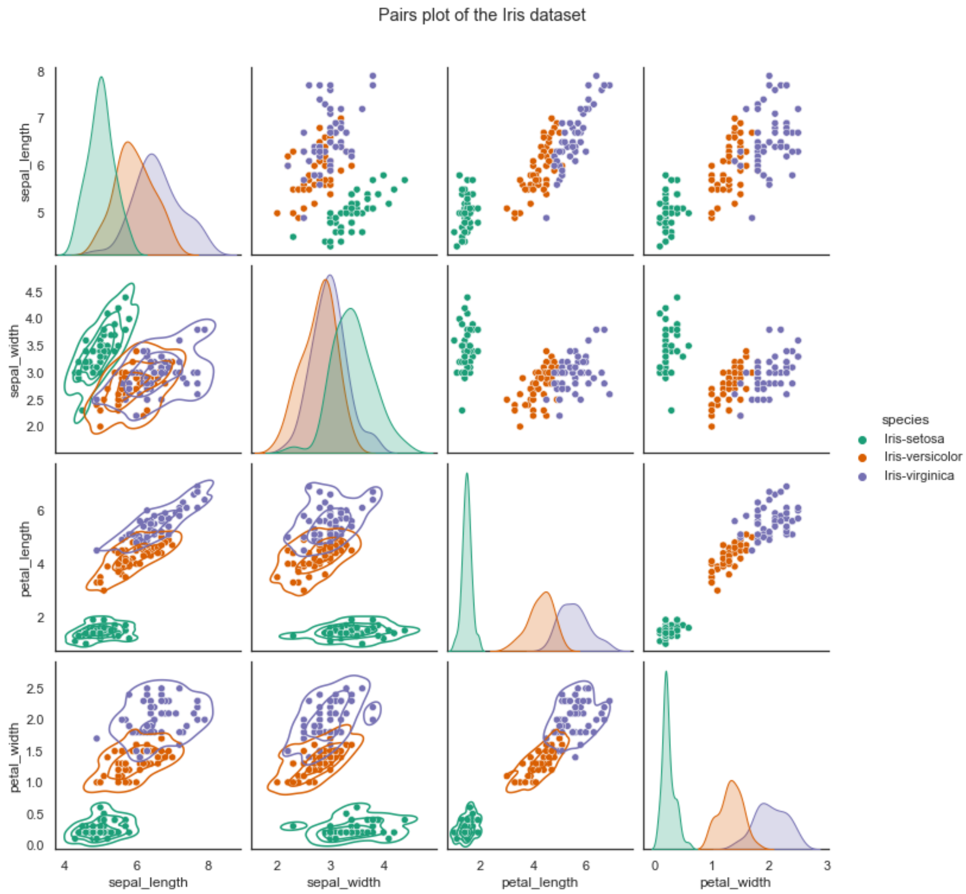


Figure 9: Plot all individual variables of the Iris dataset in pairs plot to see both the relationships between two variables and the distribution of the individual variables

# 5 STEP 3: Choose and create the ML model

After exploring the dataset, in this step one has to decide on a specific ML algorithm based on certain selection criteria.

However, since the AI or ML world is so huge and impossible for a ML novice to overlook, a brief description of the **relationship between AI and ML** is given in the following sections. Furthermore, a **taxonomy** of the different **learning types** is presented by also providing some example algorithms.

## 5.1 Short overview of the AI world and its ML algorithms

### 5.1.1 Relationship between AI, ML and others

**@TODO:** Include in this section the presentation `IFA_Steimers_KI_Grundlagen_Neuronaler_Netze_2021-03-22.pdf` by Prof. Steimers (IFA): - slides 6-7 "Definition of KI" - slides 10-12 "ML: Categories based on the data, task and algorithms"

In the **science world**, the term **artificial intelligence (AI)** refers to machines and systems that are capable of performing tasks that are characteristic of human intelligence.

In the **business world**, on the other hand, AI typically refers to mechanisms that perceive environmental factors and take autonomous actions. This is seen as an opportunity to achieve **predefined goals** with maximum success - without human intervention. Ultimately, this view is a mapping of **input information** to controlled **output actions** of a system. This expectation of AI-driven systems is thus hardly higher than what can be expected from today's modern automation systems.

**Machine Learning (ML)**, on the other hand, addresses the mathematical models and algorithms that enable a computer system to recognize (new) correlations in huge amounts of sample data from various sources by inferring them independently. For scientists, machine learning is a subset of AI.

The umbrella term AI covers a very large research area. It includes a number of techniques that enable computers to learn independently and solve complex problems:

- Computer-Vision (CV)
- Supervised and Unsupervised Learning
- Reinforcement Learning and Genetic Algorithms
- Computational Linguistics
- Robotics
- etc.

The following Venn diagram shows the relationship between Artificial Intelligence (AI), Machine Learning (ML) and other integrated technologies. The quantities that do not belong to the main category represent techniques that can function as stand-alone techniques and do not necessarily fall into the artificial intelligence group in all cases (for further details see Emerging technologies based on artificial intelligence to assess quality and consumer preference of beverages).

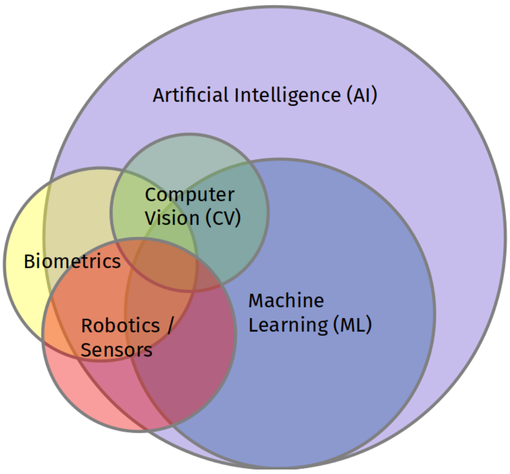


Figure 10: Venn diagram showing the relationship between Artificial Intelligence (AI), Machine Learning (ML) and other integrated technologies (source: Kasper, adapted from Emerging technologies based on artificial intelligence to assess quality and consumer preference of beverages, license: CC-BY-SA 4.0)

### 5.1.2 Taxonomy of machine learning

The field of machine learning can be divided into the following **types of learning**:

- Supervised learning

- Unsupervised learning
- Semi-supervised learning
- Reinforcement learning

Here are some further sources:

- Taxonomy of machine learning algorithms
- Comprehensive Survey of Machine Learning Approaches in Cognitive Radio-Based Vehicular Ad Hoc Networks
- A Taxonomy of Machine Learning Techniques
- ML Algorithms: One SD
- Machine Learning Map

**Supervised learning** The goal of **supervised learning (SL)** is to learn a **function** that maps a **input to an output**, based on example input-output pairs. This involves inferring a relationship describable by a mathematical function from **labeled training data** consisting of a set of training examples (see Supervised Learning).

A few well-known algorithms from the field of **supervised learning** are mentioned here:

- Naive Bayes
- Linear Regression
- Logistic Regression
- Artificial Neural Networks (ANN)
- Support Vector Classifier (SVC)
- Decision Trees
- Random Forests

**Unsupervised learning** The algorithms of this category look for internal structures in the data of a dataset, such as **grouping** or **clustering of data points**. These algorithms can thus learn relationships from test data that have not been labeled, classified, or categorized. Rather than responding to feedback (as in supervised learning), unsupervised learning algorithms detect **commonalities in the data** and respond based on the presence or absence of such commonalities in each new dataset (see Unsupervised learning).

Here are some algorithms from the field of **unsupervised learning**:

- K-means Clustering
- Spectral Clustering
- Hierarchical Clustering
- Principal Component Analysis (PCA)

**Semi-supervised learning** This type of learning falls between **unsupervised** learning (without any labeled training data) and **supervised** learning (with completely labeled training data). Some of the training examples are missing training labels, yet many machine-learning researchers have found that unlabeled data, when used in conjunction with a small amount of labeled data, can produce a considerable improvement in learning accuracy (source: Semi-supervised learning).

**Reinforcement learning** This is an area of machine learning concerned with how **intelligent agents** ought to **take actions in an environment** in order to maximize the notion of cumulative **reward**. Due to its generality, the field is studied in many other disciplines, such as **game theory** and **control theory**.

Reinforcement learning differs from supervised learning in **not needing labeled input/output pairs** be presented, and in not needing sub-optimal actions to be explicitly corrected. Instead the focus is on **finding a balance** between **exploration** (of uncharted territory) and **exploitation** (of current knowledge) (source: Reinforcement learning).

Here are some algorithms from the field of **reinforcement learning**:

- Iterative Policy
- Q-Learning
- SARSA
- Learning Classifiers
- Stochastic Gradient
- Genetic Algorithm

## 5.2 Decision graph for selecting an suitable algorithm

Now that the iris dataset has been analyzed in terms of its data structure and internal correlations, the most difficult task on the way to solving a problem using machine learning arises: finding the "right" ML algorithm (also called **estimator**).

The diverse estimators available are more or less well qualified for the respective problems with their partly very different data types. The good news is that the ML software package **Scikit-Learn** provides the following **flowchart** as a rough **guide** in choosing the right estimator for the particular task (see: Choosing the right estimator).

However, it must also be emphasized that a considerable **level of experience** through systematic trial and error is crucial to be successful in finding an "optimal" estimator.

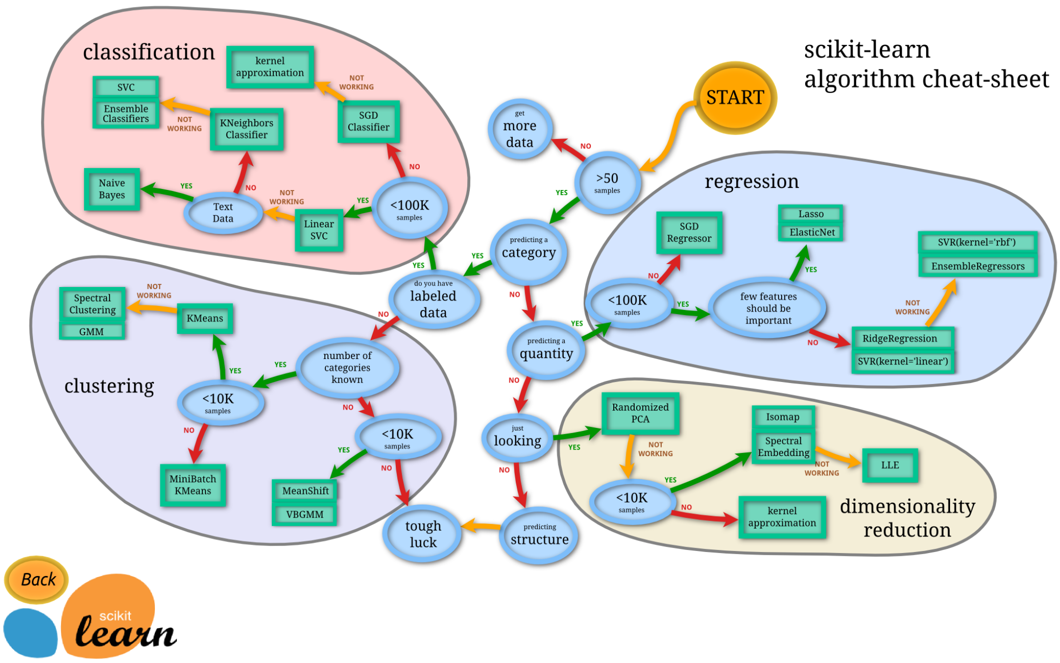


Figure 11: Decision graph for choosing an appropriate ML algorithm (source: Choosing the right estimator, license: unknown)

## 5.3 Reasons for choosing Support Vector Classifier (SVC)

Among other ML algorithms suitable for the Iris dataset (such as the decision-tree-based **random-forests classifier**), the reasoned choice here in this tutorial falls on the **support vector classifier (SVC)**.

The following **reasons** led to the decision for the **Support Vector Classifier (SVC)**:

- the aim is to predict the species using unlabeled test data, so the task is to **classify**
- the iris dataset is **fully labeled** (by designating the iris species)
- the dataset contains significantly **less than 100k samples**

But the most important reason is that it is **easy to understand** how it works - so it is exactly suitable for a beginner tutorial ;)

## 5.4 Operating principal of SVC

> Support Vector Classifiers (SVC) try 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 maximizing 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.

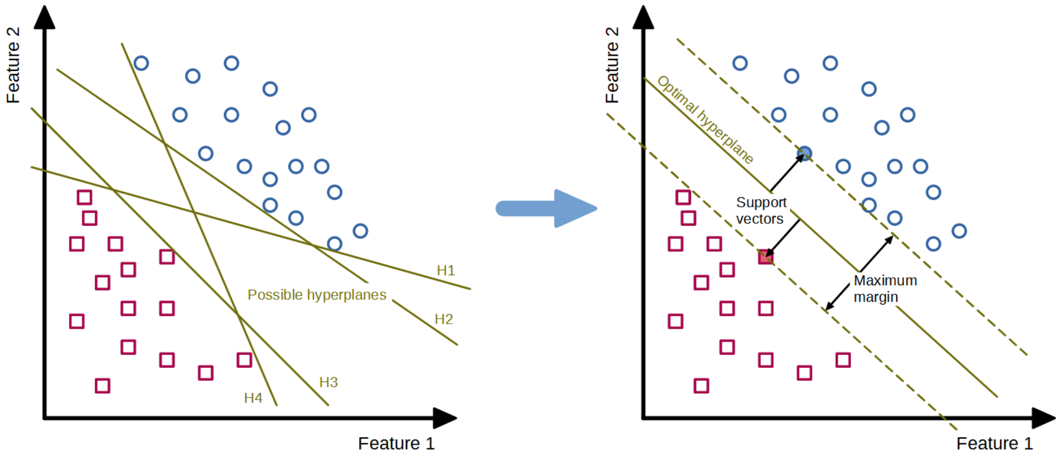


Figure 12: Support Vector Classifiers (SVC) separate the data points in classes by finding the best hyperplane by maximizing the margin to its support vectors (source: Kasper, license: CC-BY-SA 4.0)

## 5.5 Create the SVC model

In this step we create the SVC model choosing a **linear kernel** with default parameters.

[31]:
```
from sklearn.svm import SVC
classifier = SVC(kernel = 'linear', random_state = 0)
```

# 6 STEP 4: Prepare the dataset for training

In this step the dataset is prepared for the actual classification by SVC. Depending on the selected ML algorithm as well as the data structure, it may be necessary to prepare the data before training (e.g., by **standardization**, **normalization**, or **binarization** based on thresholds). Furthermore, errors in the dataset (e.g. **data gaps**, **duplicates** or obvious **misentries**) should be corrected now at the latest.

Through the intensive exploration of the data in (STEP 2: Explore the ML 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.

For further details about **Standarization** and **Normalization** read here: What are standarization and normalization? Test with iris data set in Scikit-learn.

[32]:
```
# import Iris dataset for exploration (again)
irisdata_df = pd.read_csv('./datasets/IRIS_flower_dataset_kaggle.csv')
```

### 6.1 Standarization

Standardize the feature values by computing the **mean**, subtracting the mean from the data points, and then dividing by the **standard deviation**.

**@TODO:**
Incorporate section "Skalieren von Merkmalen" of the book `OReilly_Praxiseinstieg_Machine_Learning_Scikit-Learn` (see Géron 2018).

[39]:
```
from sklearn.preprocessing import StandardScaler

#scaler = StandardScaler()
#X_train = scaler.fit_transform(X_train)
#X_test = scaler.transform(X_test)
irisdata_df

#X_train
```

[39]:
```
     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]
```

### 6.2 Normalization

## 7 STEP 5: Carry out training, prediction and testing

### 7.1 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 dataset 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 dataset - after all, these are to be predicted.

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

In particular, to **avoid bias** in the sorted iris dataset due to splitting, the **order** of the data rows must be **randomized**. This is done with the parameter `shuffle=True`.

[35]:
```
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,␣
↪shuffle=True)
```

Check that the split datasets are still balanced and that no **bias** has been created by the splitting.

For this test, the previously separated labels `y_train` must be added back to the training dataset `X_train`.

[37]:
```
# make a deep copy of 'X_train'
X_train_bias_test_df = X_train.copy(deep=True)

# add list of labels to test dataframe
X_train_bias_test_df['species'] = y_train

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

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Input In [37], in <cell line: 2>()
      1 # make a deep copy of 'X_train'
----> 2 X_train_bias_test_df = X_train.copy(deep=True)
      4 # add list of labels to test dataframe
      5 X_train_bias_test_df['species'] = y_train

TypeError: copy() got an unexpected keyword argument 'deep'
```

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.

[38]:
```
# 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)
```

## 7.2 Train the SVC

In this step the SVC is trained with the training data. Training means to **fit** the SVC to the **training data**.

[39]:
```
# fit the model for the data
classifier.fit(X_train, y_train)
```

[39]:
```
SVC(kernel='linear', random_state=0)
```

## 7.3 Make predictions

In this step the aim is to **predict the species** using unlabeled test data.

[40]:
```
y_pred = classifier.predict(X_test)
#X_test
#y_pred
```

# 8 STEP 6: Evaluate model's performance

Subsequently to the training of the SVC model and the classification predictions made based on the test data, this step evaluates the **quality of the classification result** using known **metrics** such as the **accuracy score** as well as the **confusion matrix**.

## 8.1 Accuracy Score

In a multilabel classification (such as the Iris dataset), this **Accuracy classification score** computes the subset accuracy. For further details see sklearn.metrics.accuracy_score.

[41]:
```
from sklearn.metrics import accuracy_score

acc_score = accuracy_score(y_test, y_pred)

print("Accuracy score: {:.2f} %".format(acc_score.mean()*100))
```

```
Accuracy score: 80.00 %
```

## 8.2 Classification Report

The classification report shows a representation of the main **classification metrics on a per-class basis**. This gives a deeper intuition of the classifier behavior over global accuracy which can mask functional weaknesses in one class of a multiclass problem (see Classification Report).

[42]:
```
from sklearn.metrics import classification_report

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

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         5
Iris-versicolor       0.86      0.75      0.80        16
 Iris-virginica       0.64      0.78      0.70         9

       accuracy                           0.80        30
      macro avg       0.83      0.84      0.83        30
   weighted avg       0.81      0.80      0.80        30
```

## 8.3 Cross-validation score

The function `cross_val_score()` from the Scikit-learn package **trains and tests a model over multiple folds** of your dataset. This cross validation method gives a better **understanding of model performance** over the whole dataset instead of just a single train/test split (see Using cross_val_score in sklearn, simply explained).

**@TODO:**
Incorporate section "Bessere Auswertung mittels Kreuzvalidierung" of the book `OReilly_Praxiseinstieg_Machine_Learning_Scikit-Learn_TensorFlow_2018_Anm_bk.pdf`.

[43]:
```
from sklearn.model_selection import cross_val_score

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

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

```
Cross-validation score: 82.50 %
Standard Deviation: 14.65 %
```

## 8.4 Confusion matrix

The **confusion matrix** measures the quality of predictions from a classification model by looking at how many **predictions** are **True** and how many are **False** (see What the Confusion Matrix Measures?.

### 8.4.1 Textual confusion matrix

For checking the accuracy of the model, the **confusion matrix** can be used for the **cross validation**.

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

[25]:
```
cm = metrics.confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[ 6  0  0]
 [ 0  9  1]
 [ 0  0 14]]
```

### 8.4.2 Colored confusion matrix

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

[44]:
```
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()
```

# 9 STEP 7: Vary parameters of the ML model manually

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.

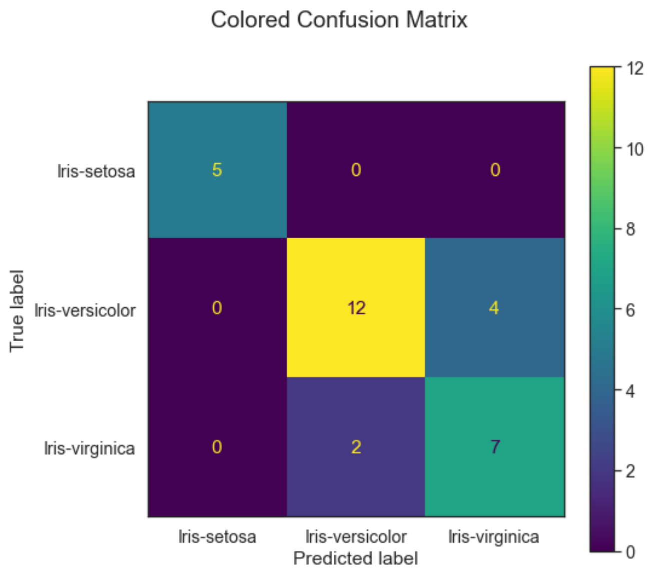


Figure 13: Checking the accuracy of the model by using the confusion matrix for cross-validation

## 9.1 Prepare dataset

[ ]:
```
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
```

### 9.1.1 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 dataset.

[ ]:
```
# 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
```

[ ]:
```
# 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
```

### 9.1.2 Prepare dataset for prediction and evaluation

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

[ ]:
```
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,␣
↪shuffle=True)
```

## 9.2 Plotting functions

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

[ ]:
```
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:

[ ]:
```
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**:

```
[ ]: 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()
```

## 9.3 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`.

```
[ ]: 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)
```

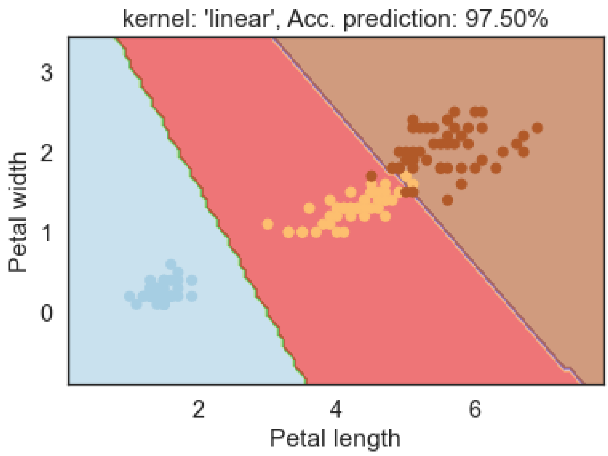


Figure 14: This group of images shows the effect on the classification by the choice of the different SVC kernels ('linear', 'rbf', 'poly' and 'sigmoid')

## 9.4 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 dataset. The **default** is `gamma='scale'`.

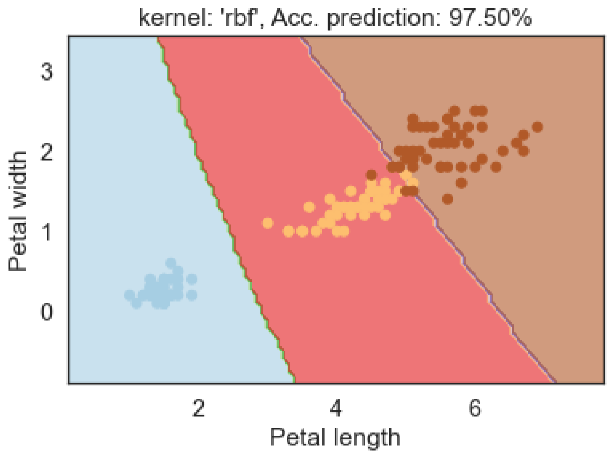


Figure 15: This group of images shows the effect on the classification by the choice of the different SVC kernels ('linear', 'rbf', 'poly' and 'sigmoid')

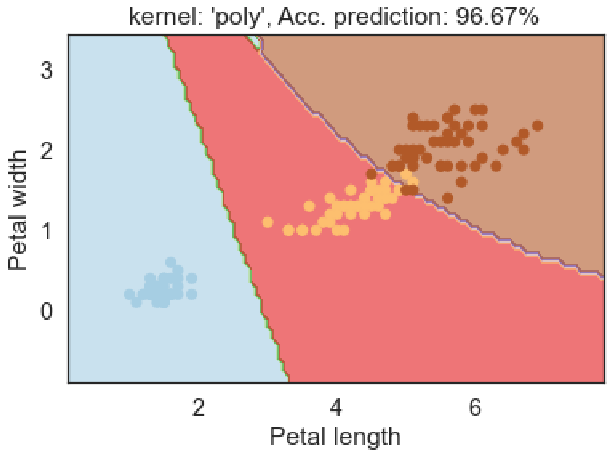


Figure 16: This group of images shows the effect on the classification by the choice of the different SVC kernels ('linear', 'rbf', 'poly' and 'sigmoid')

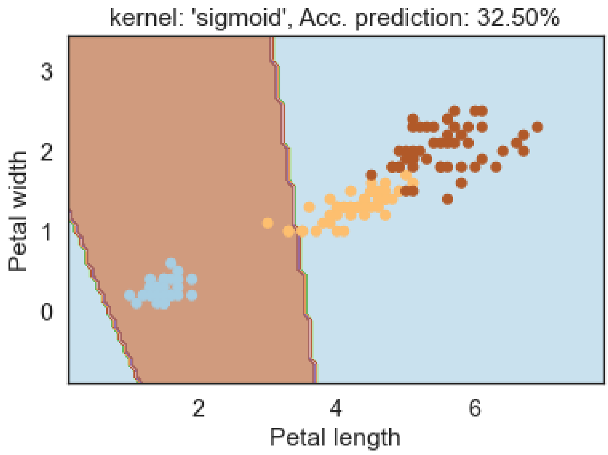


Figure 17: This group of images shows the effect on the classification by the choice of the different SVC kernels ('linear', 'rbf', 'poly' and 'sigmoid')

```
[ ]:
```

```
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)
```

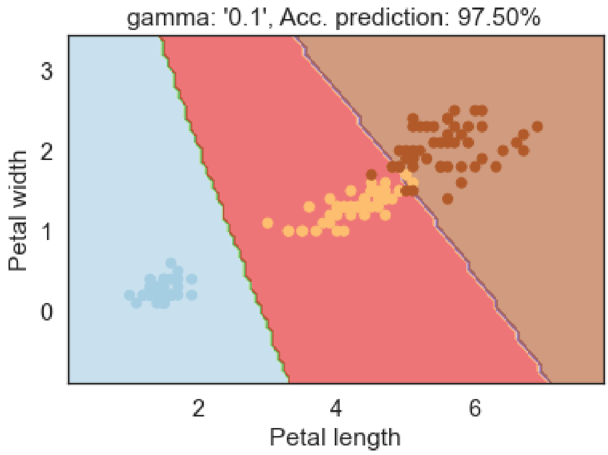


Figure 18: This group of images shows the effect on the classification by the variation of the parameter 'gamma' of the 'rbf' kernel

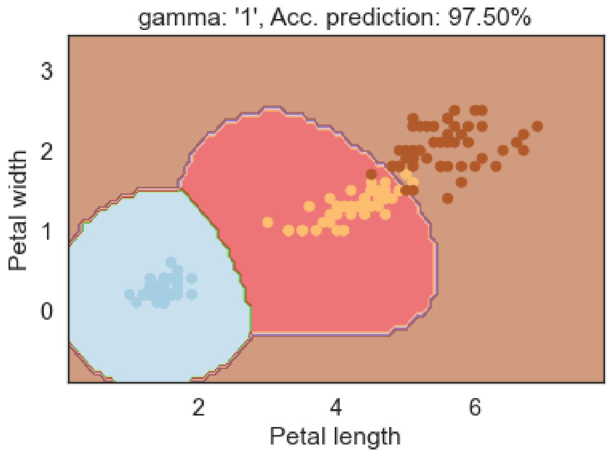


Figure 19: This group of images shows the effect on the classification by the variation of the parameter 'gamma' of the 'rbf' kernel

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.

[ ]:
```
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()
for gamma in gammas:
```

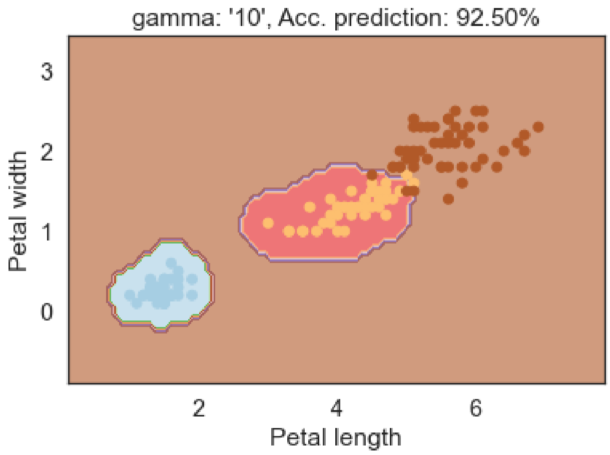


Figure 20: This group of images shows the effect on the classification by the variation of the parameter 'gamma' of the 'rbf' kernel

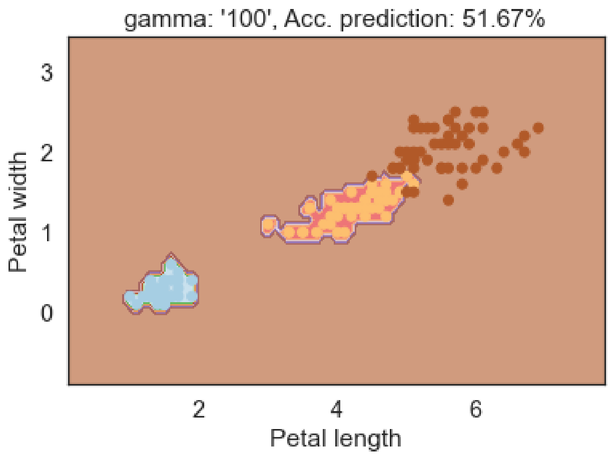


Figure 21: This group of images shows the effect on the classification by the variation of the parameter 'gamma' of the 'rbf' kernel

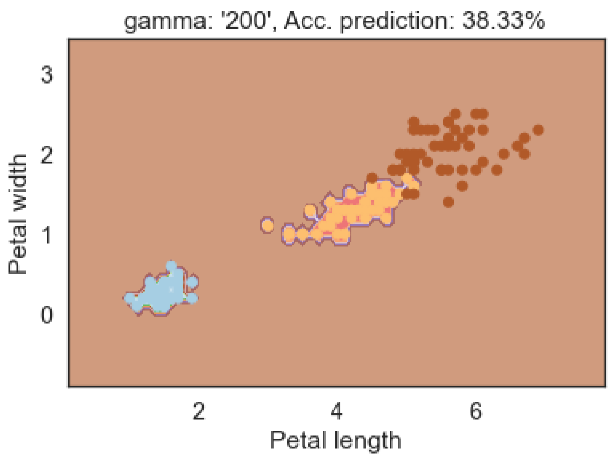


Figure 22: This group of images shows the effect on the classification by the variation of the parameter 'gamma' of the 'rbf' kernel

```
    accuracy = crossValSVC(X_train, y_train, kernel='rbf', gamma=gamma)
```

```
    accuracy_list.append(accuracy)

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

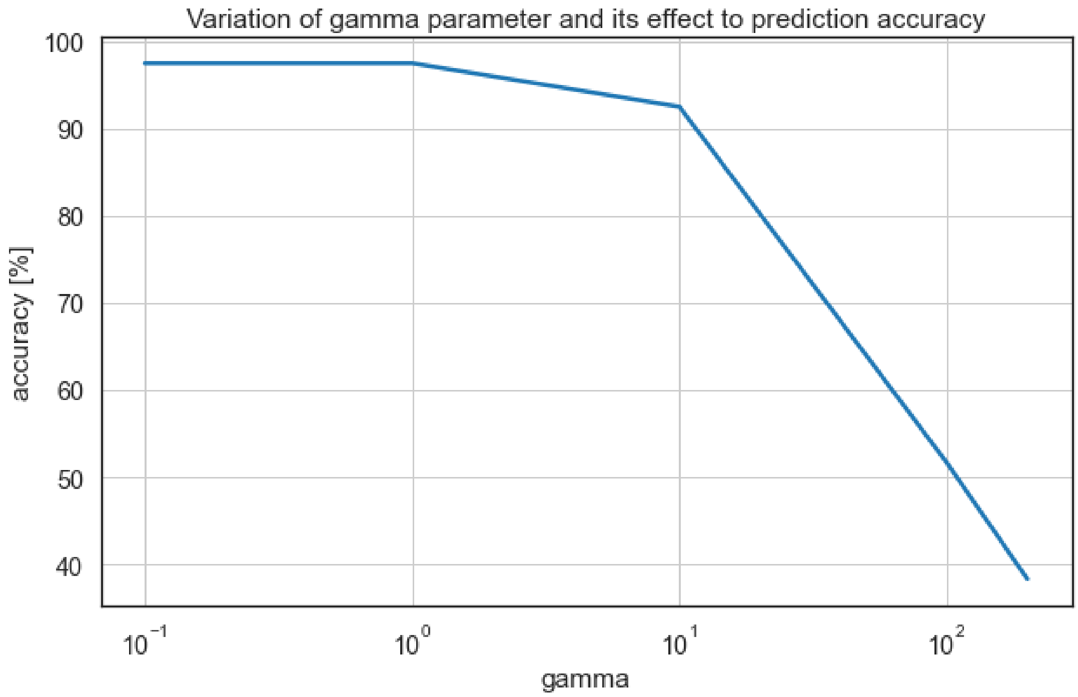


Figure 23: The plot shows the variation of the SVC parameter 'gamma' against the prediction accuracy

## 9.5 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`.

[ ]:
```
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)
```

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.

[ ]:
```
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)
```

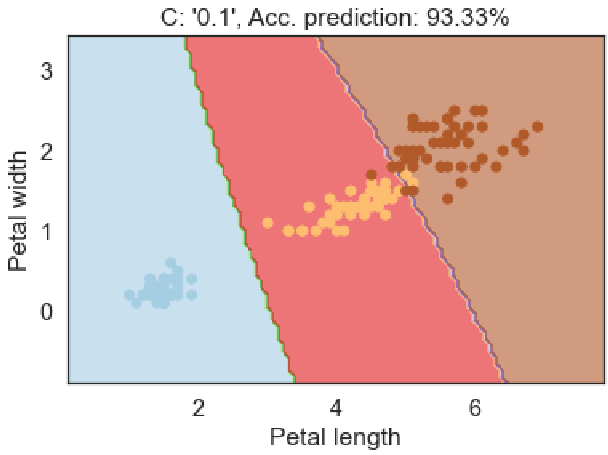


Figure 24: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

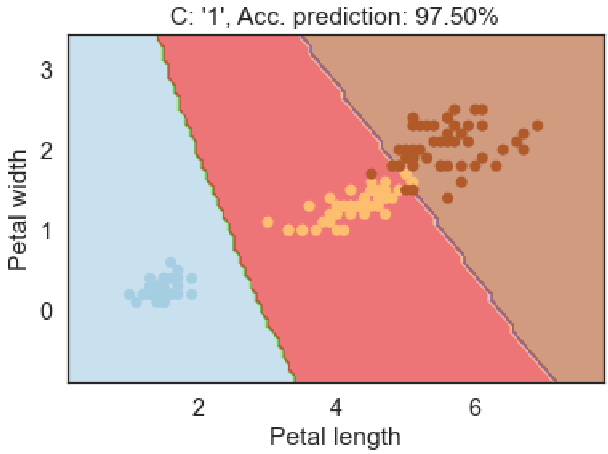


Figure 25: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

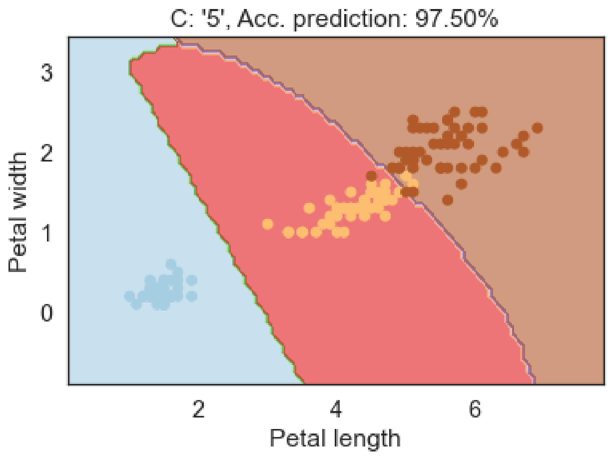


Figure 26: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

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

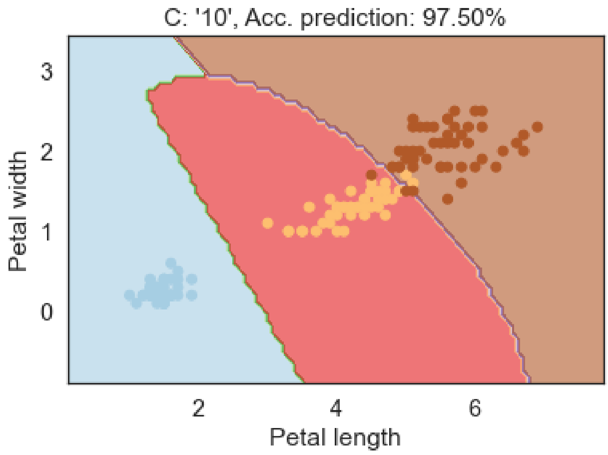


Figure 27: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

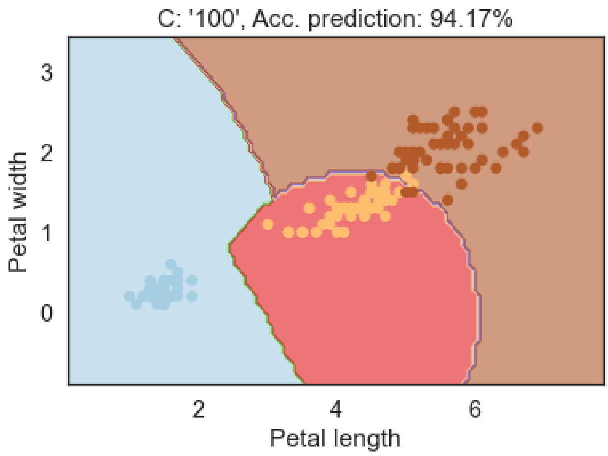


Figure 28: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

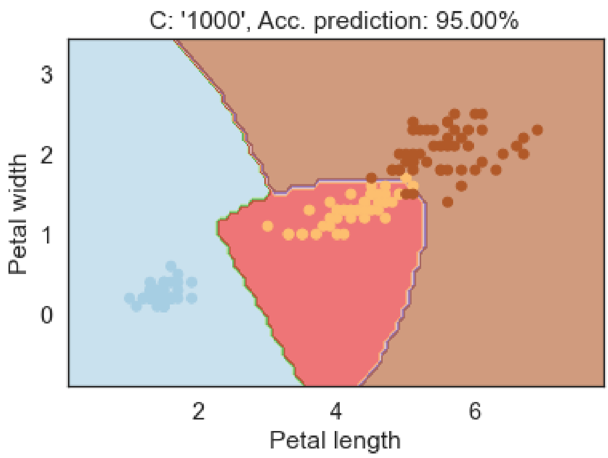


Figure 29: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

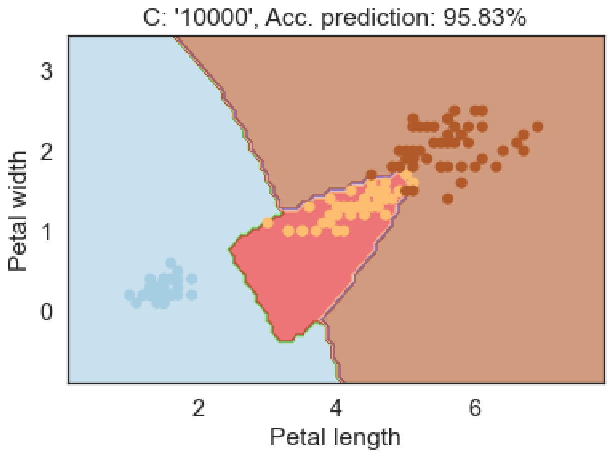


Figure 30: This group of images shows the effect on the classification by the variation of the parameter 'C' of the 'rbf' kernel

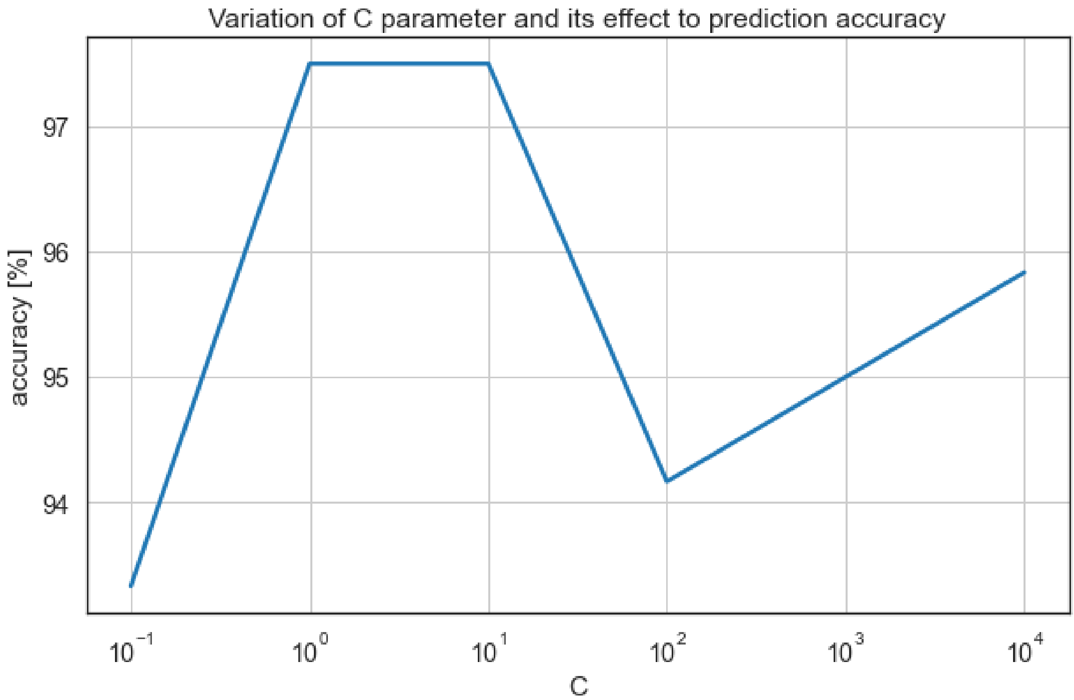


Figure 31: The plot shows the variation of the SVC parameter 'C' against the prediction accuracy

## 9.6 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 `degree=3`.

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

[ ]:
```
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)
```

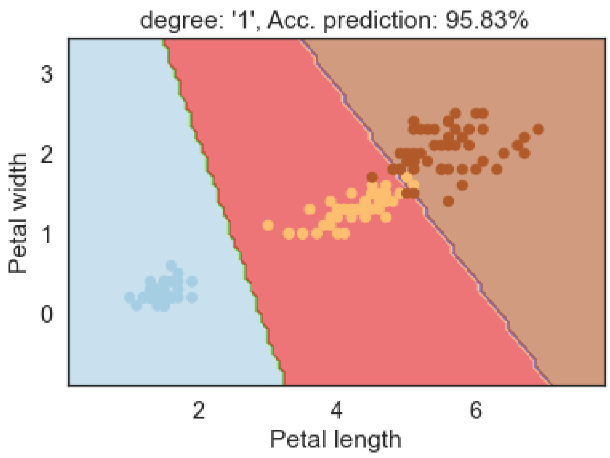


Figure 32: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

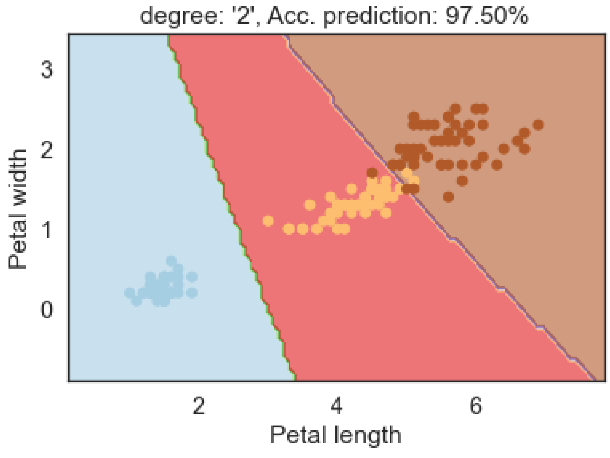


Figure 33: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

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.

[ ]:
```
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)
```

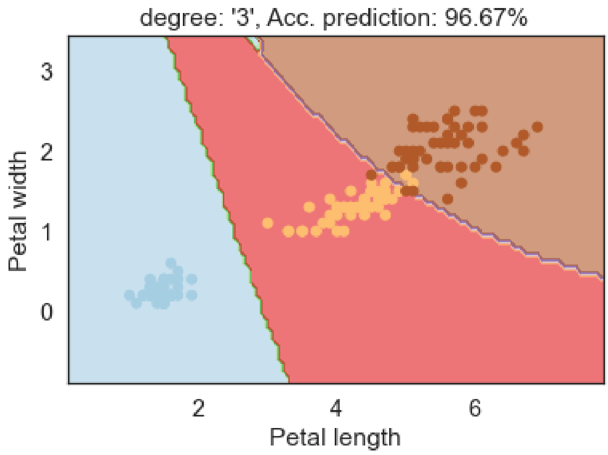


Figure 34: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

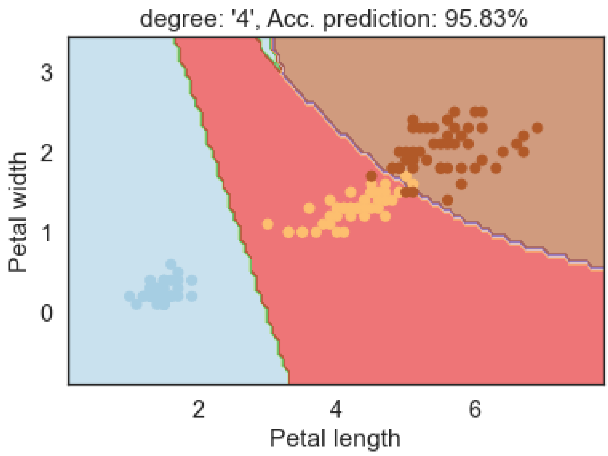


Figure 35: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

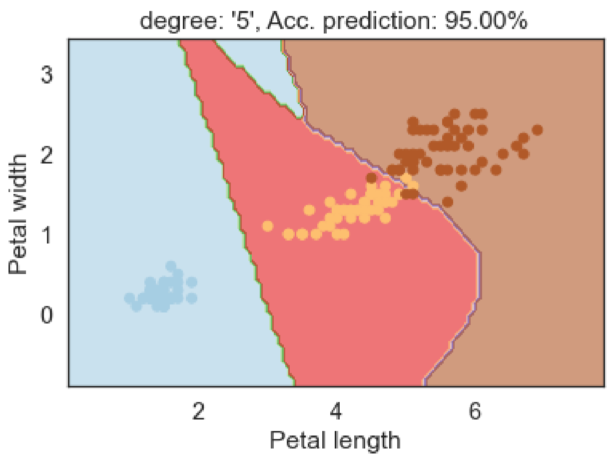


Figure 36: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

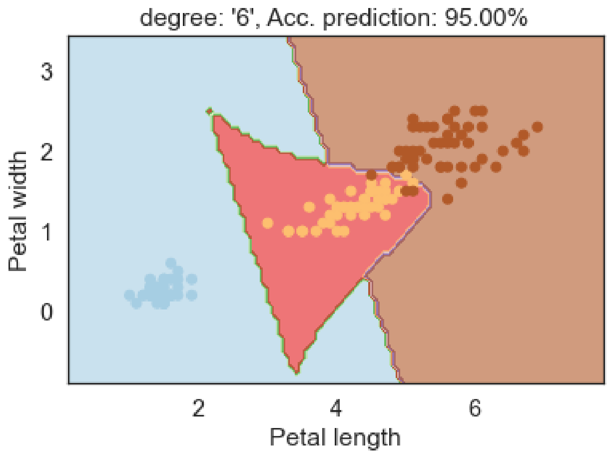


Figure 37: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

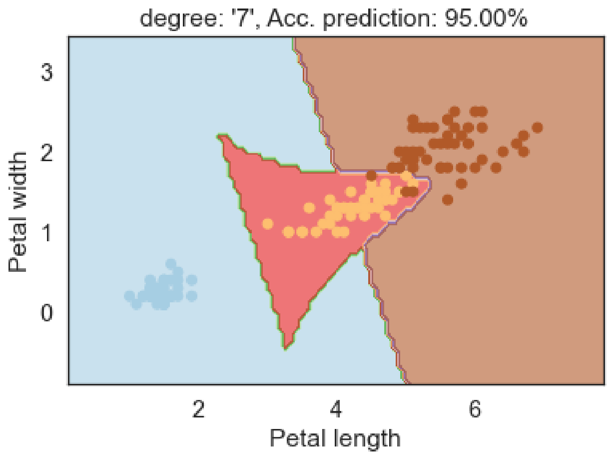


Figure 38: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

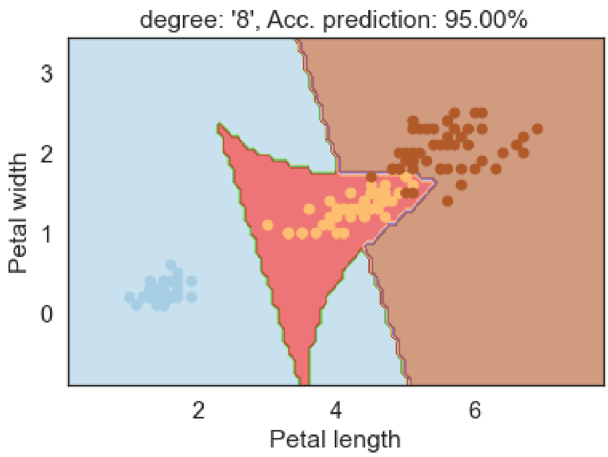


Figure 39: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

# 10 STEP 8: Tune the ML model systematically

In the final step, two approaches to systematic hyper-parameter search are presented: **Grid Search** and **Randomized Search**. While the former exhaustively considers all parameter combinations for

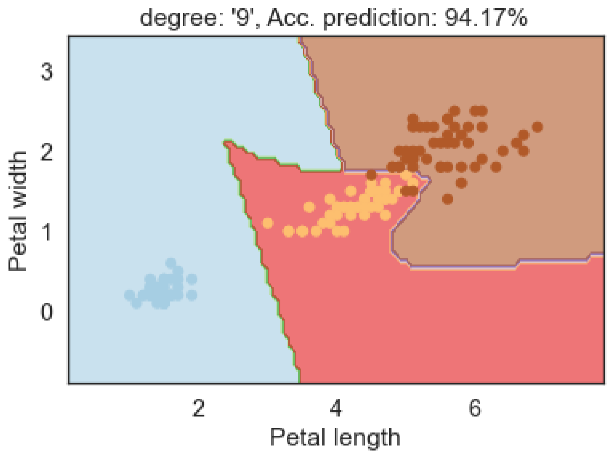


Figure 40: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

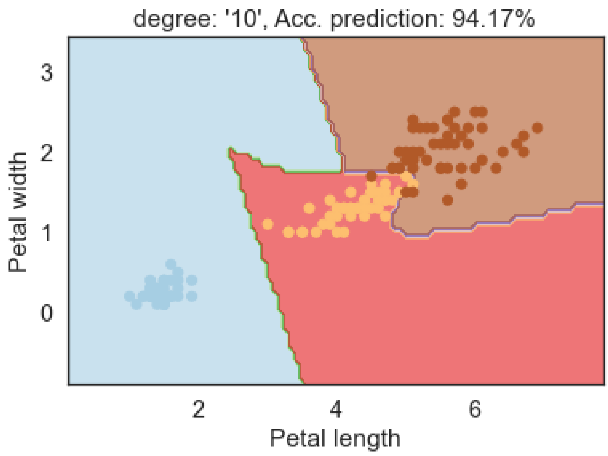


Figure 41: This group of images shows the effect on the classification by the variation of the parameter 'degree' of the 'poly' kernel

given values, the latter selects a number of candidates from a parameter space with a particular random distribution.

Sources:

- 3.2. Tuning the hyper-parameters of an estimator
  - sklearn.model_selection.GridSearchCV
  - sklearn.model_selection.RandomizedSearchCV
- Introduction to hyperparameter tuning with scikit-learn and Python
  - Abalone Dataset
- Hyperparameter tuning using Grid Search and Random Search: A Conceptual Guide

Import the necessary packages:

[47]:
```
# general packages
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
#from sklearn.svm import SVC
from sklearn import svm, metrics
```

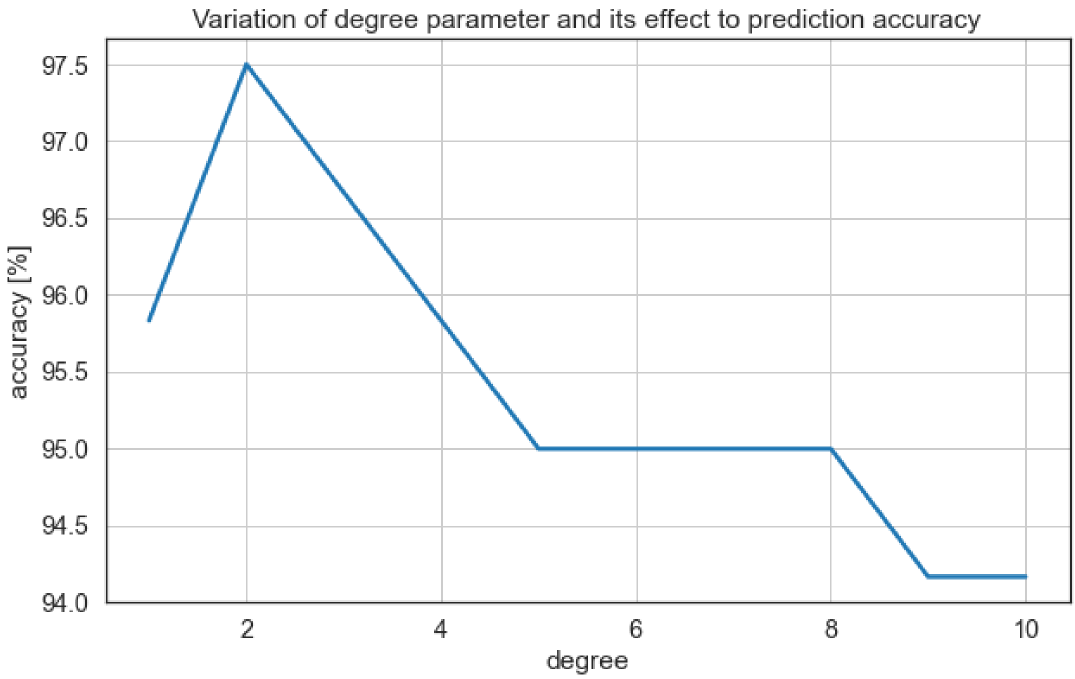


Figure 42: The plot shows the variation of the SVC parameter 'degree' against the prediction accuracy

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# additional packages for grid search
from sklearn.model_selection import RepeatedKFold
from sklearn.model_selection import GridSearchCV

# additional packages for randomized search
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import RepeatedKFold

# import class MeasExecTimeOfProgram from python file MeasExecTimeOfProgramclass.py
from MeasExecTimeOfProgram_class import MeasExecTimeOfProgram
```

Set path and columns of the Iris dataset for import:

[2]:
```
# specify the path of the dataset
CSV_PATH = "./datasets/IRIS_flower_dataset_kaggle.csv"
```

Load dataset and split it into subsets for training and testing in the ratio 80% to 20%:

[23]:
```
# load the dataset, separate the features and labels, and perform a
# training and testing split using 80% of the data for training and
# 20% for evaluation
irisdata_df = pd.read_csv(CSV_PATH)

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,␣
↪shuffle=True)
```

Check that the split datasets are still balanced and that no **bias** has been created by the splitting.

For this test, the previously separated labels `y_train` must be added back to the training dataset `X_train`.

[24]:
```
# make a deep copy of 'X_train'
X_train_bias_test_df = X_train.copy(deep=True)

# add list of labels to test dataframe
X_train_bias_test_df['species'] = y_train

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

[24]:
```
Iris-versicolor    0.358333
Iris-virginica     0.333333
Iris-setosa        0.308333
Name: species, dtype: float64
```

Standardize the feature values by computing the **mean**, subtracting the mean from the data points, and then dividing by the **standard deviation**:

[ ]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

#X_train
```

## 10.1 Finding a baseline

The aim of this sub-step is to establish a baseline on the Iris dataset by training a **Support Vector Classifier (SVC)** with no hyperparameter tuning.

Train the model with **no tuning of hyperparameters** to find the baseline for later improvements:

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

# initiate measuring execution time
execTime = MeasExecTimeOfProgram()
execTime.start()

classifier.fit(X_train, y_train)

# print time delta
print('Execution time: {:.4f} ms'.format(execTime.stop()))
```

```
Execution time: 1.6954 ms
```

Evaluate our model using accuracy score:

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

[56]:
```
# calculate cross validation score
# HINT: do NOT use the accuracy score - it's to inaccurate!
accuracies = cross_val_score(estimator = classifier, X = X_train,
                             y = y_train, cv = 10)

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

```
Cross-validation score: 97.50 %
Standard Deviation: 3.82 %
```

[57]:
```
# print classification report
print(classification_report(y_test, y_pred))
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        13
Iris-versicolor       1.00      0.86      0.92         7
 Iris-virginica       0.91      1.00      0.95        10

       accuracy                           0.97        30
      macro avg       0.97      0.95      0.96        30
   weighted avg       0.97      0.97      0.97        30
```

[58]:
```
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

plt.tight_layout()
plt.show()
```

[42]:
```
classifier.get_params()
```

[42]:
```
{'C': 1.0,
 'break_ties': False,
 'cache_size': 200,
 'class_weight': None,
 'coef0': 0.0,
 'decision_function_shape': 'ovr',
 'degree': 3,
 'gamma': 'scale',
 'kernel': 'linear',
 'max_iter': -1,
 'probability': False,
 'random_state': 0,
 'shrinking': True,
 'tol': 0.001,
 'verbose': False}
```

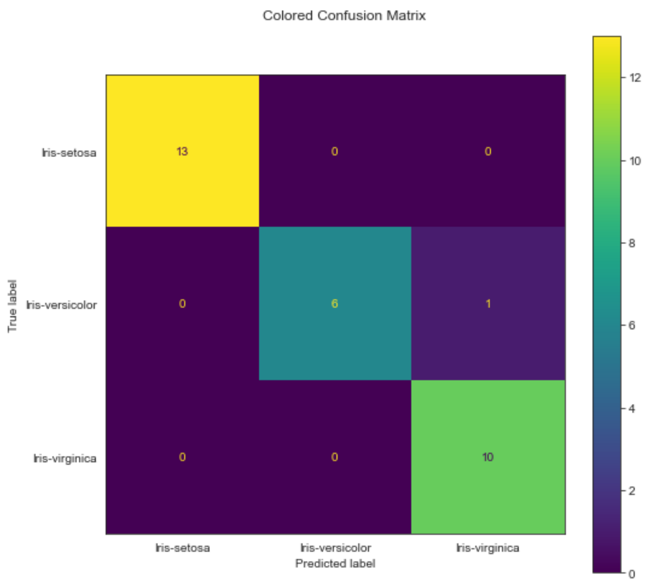


Figure 43:

## 10.2 Grid Search

Initialize the SVC model and define the **space of the hyperparameters** to perform the **grid-search** over:

[45]:
```
classifier = svm.SVC()

kernels = ["linear", "rbf", "sigmoid", "poly"]
gammas = [0.1, 1, 10, 100, 200]
cs = [0.1, 1, 5, 10, 100, 1000, 10000]

# reduce the possible polynomial degrees to reasonable values,
# since with higher degrees the calculation time increases exponentially
degrees = [1, 2, 3, 4, 5]

grid = dict(kernel=kernels, gamma=gammas, C=cs, degree=degrees)
```

Initialize a **cross-validation fold** and **perform a grid-search** to tune the hyperparameters:

[59]:
```
cvFold = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)

gridSearch = GridSearchCV(estimator=classifier, param_grid=grid, n_jobs=-1,
                          cv=cvFold, scoring="accuracy")

# initiate measuring execution time
execTime = MeasExecTimeOfProgram()
execTime.start()

searchResults = gridSearch.fit(X_train, y_train)

# print time delta
print('Execution time: {:.2f} s'.format(execTime.stop()/1000))
```

```
Execution time: 39.64 s
```

Extract the best model and evaluate it:

[61]:
```
# predict labels by best model
bestModel = searchResults.best_estimator_

y_pred = bestModel.predict(X_test)
```

[62]:
```
# calculate cross validation score from the best model
# HINT: do NOT use the accuracy score - it's to inaccurate!
accuracies = cross_val_score(estimator = bestModel, X = X_train,
                             y = y_train, cv = 10)

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

```
Cross-validation score: 98.33 %
Standard Deviation: 3.33 %
```

[63]:
```
from sklearn.metrics import classification_report

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

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        13
Iris-versicolor       1.00      0.86      0.92         7
 Iris-virginica       0.91      1.00      0.95        10

       accuracy                           0.97        30
      macro avg       0.97      0.95      0.96        30
   weighted avg       0.97      0.97      0.97        30
```

[64]:
```
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

plt.tight_layout()
plt.show()
```

[ ]:
```
bestModel.get_params()
```

[ ]:
```
{'C': 5,
 'break_ties': False,
 'cache_size': 200,
 'class_weight': None,
 'coef0': 0.0,
 'decision_function_shape': 'ovr',
 'degree': 1,
 'gamma': 0.1,
 'kernel': 'poly',
 'max_iter': -1,
```

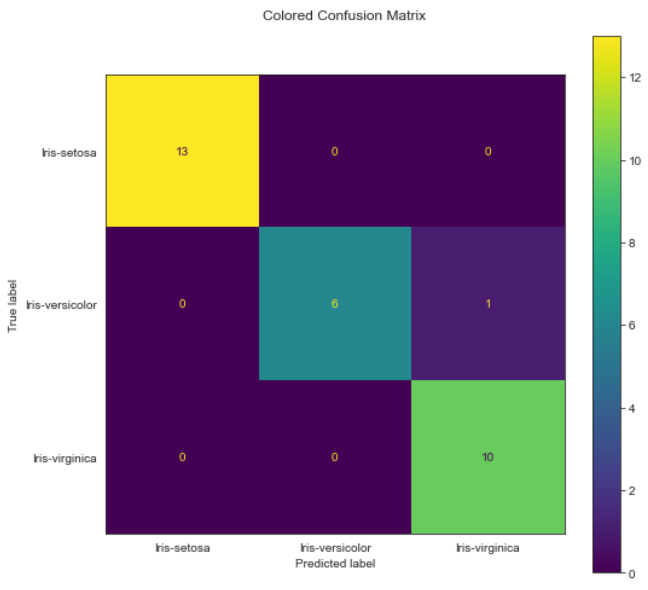


Figure 44:

```
'probability': False,
'random_state': None,
'shrinking': True,
'tol': 0.001,
'verbose': False}
```

## 10.3 Randomized Search

Initialize the SVC model and define the **space of the hyperparameters** to perform the **randomized-search** over:

[72]:
```
classifier = svm.SVC()

kernels = ["linear", "rbf", "sigmoid", "poly"]
gammas = [0.1, 1, 10, 100, 200]
cs = [0.1, 1, 5, 10, 100, 1000, 10000]

# reduce the possible polynomial degrees to reasonable values,
# since with higher degrees the calculation time increases exponentially
degrees = [1, 2, 3, 4, 5]

grid = dict(kernel=kernels, gamma=gammas, C=cs, degree=degrees)
```

Initialize a **cross-validation fold** and **perform a randomized-search** to tune the hyperparameters:

[73]:
```
cvFold = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)

randomSearch = RandomizedSearchCV(estimator=classifier, n_jobs=-1,
                                  cv=cvFold, param_distributions=grid,
                                  scoring="accuracy")

# initiate measuring execution time
execTime = MeasExecTimeOfProgram()
execTime.start()
```

```
searchResults = randomSearch.fit(X_train, y_train)

# print time delta
print('Execution time: {:.3f} s'.format(execTime.stop()/1000))
```

```
Execution time: 0.720 s
```

Extract the best model and evaluate it:

[74]:
```
# predict labels by best model
bestModel = searchResults.best_estimator_

y_pred = bestModel.predict(X_test)
```

[75]:
```
# calculate cross validation score from the best model
# HINT: do NOT use the accuracy score - it's to inaccurate!
accuracies = cross_val_score(estimator = bestModel, X = X_train,
                             y = y_train, cv = 10)

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

```
Cross-validation score: 97.50 %
Standard Deviation: 3.82 %
```

[76]:
```
from sklearn.metrics import classification_report

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

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        13
Iris-versicolor       1.00      0.86      0.92         7
 Iris-virginica       0.91      1.00      0.95        10

       accuracy                           0.97        30
      macro avg       0.97      0.95      0.96        30
   weighted avg       0.97      0.97      0.97        30
```

[77]:
```
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

plt.tight_layout()
plt.show()
```

[78]:
```
bestModel.get_params()
```

[78]:
```
{'C': 10,
 'break_ties': False,
```

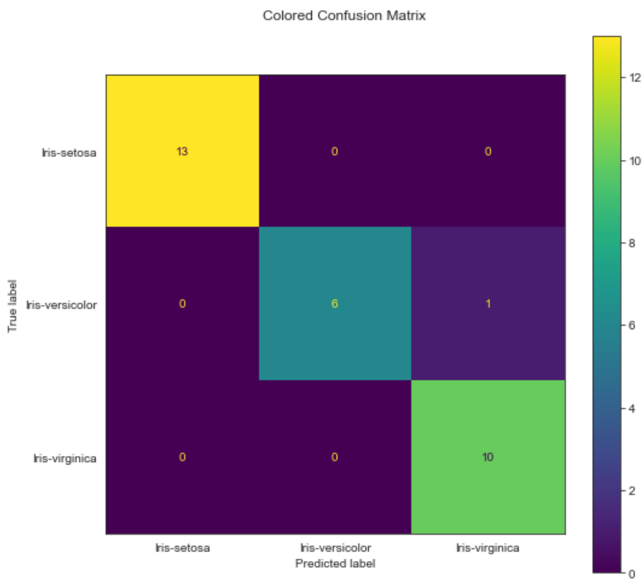


Figure 45:

```
'cache_size': 200,
'class_weight': None,
'coef0': 0.0,
'decision_function_shape': 'ovr',
'degree': 1,
'gamma': 0.1,
'kernel': 'rbf',
'max_iter': -1,
'probability': False,
'random_state': None,
'shrinking': True,
'tol': 0.001,
'verbose': False}
```

# 11 Summary and outlook

## 11.1 English summary

## 11.2 German summary

# 12 Acknowledgments

```
[ ]:
```

# 13 References

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