Universitat Oberta de Catalunya (UOC)

Masters in Data Science

MASTER'S DEGREE FINAL PROJECT

Area: Medicine Area (TFM-Med)

Deep Convolutional Autoencoder for control brain MRI

Development and Applications

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FICHA DEL TRABAJO FINAL

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To Be Done.

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To Be Done. Si se considera oportuno, mencionar a las personas, empresas o instituciones que hayan contribuido en la realización de este proyecto.

Abstract

The analysis of brain MRI is critical for a proper diagnosis and treatment of neurological diseases. Improvements in this field lead to better health quality. Numerous branches can be still enhanced due to the nature of MRI recompilation: disease detection and segmentation, data augmentation, improvement in data collection, or image enhancement are some of them.

For several years, many approaches have been taken to address this. Machine Learning and Deep Learning emerge as very popular approaches to solve problems. Several kinds of data mining problems (supervised, unsupervised, dimension reduction, generative models, etc) and algorithms can be applied to the problem-solving of MRI. Besides, new emerging deep learning architectures for another kind of image task can be helpful. New types of convolution, autoencoders or generative adversarial networks are some of them.

Therefore, the purpose of this work is to apply one of these new techniques to T1 weighted brain MRI. We will develop a Deep Convolutional Autoencoder, which can be used to help some problems with neuroimaging. The input of the Autoencoder will be control T1WMRI and aims to return the same image, with the problematic that, inside its architecture, the image travels through a lower-dimensional space, so the reconstruction of the original image becomes more difficult. Thus, the Autoencoder represents a normative model.

This normative model will define a distribution (or normal range) for the neuroanatomical variability for the illness absence. Once trained with these control images, we will discuss the potential application of the autoencoder like noise reducer or disease detector.

Keywords: Deep Learning, Brain MRI, Deep Convolutional Autoencoder, Image denoising.

Resumen

El análisis de las resonancias magnéticas cerebrales es fundamental para un diagnóstico y tratamiento adecuados de las enfermedades neurológicas. Se pueden mejorar ámbitos del análisis debido a la naturaleza de la recopilación de resonancias: detección y segmentación de enfermedades, aumento de datos, mejora en la extracción o mejora de imágenes.

El aprendizaje automático y el aprendizaje profundo surgen como nuevas alternativas populares para resolver estos problemas. Se pueden aplicar varios enfoques de minería de datos y algoritmos para la resolución de problemas relacionados con la neuroimagen (supervisados, no supervisados, reducción de dimensionalidad, modelos generativos, etc.). Además, las nuevas arquitecturas emergentes de aprendizaje profundo, desarrolados para otro tipo de tareas de imagen, pueden ser útiles. Algunas de ellas son nuevos tipos de convolución, autoencoders o GAN.

Por lo tanto, el propósito de este trabajo es aplicar una de estas nuevas técnicas a resonancias cerebrales tipo T1. Desarrollaremos un Autoencoder convolucional profundo, que puede usarse para ayudar con algunos problemas de neuroimagen. La entrada del Autoencoder será el imágenes de control T1WMRI y tendrá como objetivo devolver la misma imagen, con la problemática de que, dentro de su arquitectura, la imagen viaja por un espacio de menor dimensión, por lo que la reconstrucción de la imagen original se vuelve más difícil. El autoencoder representa un modelo normativo.

Este modelo normativo definirá una distribución (o rango normal) para la variabilidad neuroanatómica para la ausencia de enfermedad. Una vez entrenado con imágenes de control, discutiremos la aplicación potencial del Autoencoder como reductor de ruido o detector de enfermedades.

Keywords: Aprendizaje profundo, Imágenes cerebrales de resonancias magnéticas, Autoencoder convolucional profundo, eliminación de ruido de imágenes.

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Chapter 1

Introduction

Not Final Note: This color ('TBD' tag in latex) are going to be used in non-final versions of the memory to highlight the non-final sentences or things to be changed in the final version.

In this chapter we will introduce the main background, and aims of the project, basing it on its non-solved tasks and relevance.

1.1 Problem overview and relevance

1.1.1 MRI general problems

Neuroimaging in medicine allows studying the morphological features of the human brain. With the objective of improving the detection systems, diagnostic and treatment, correlations between the morphological features and the neurological disorders can be addressed in order to achieve that [4]. If we improve brain magnetic resonance image analysis 1.1, we will improve the detection systems and treatments for neurological diseases, so the social relevance of the field is very important.

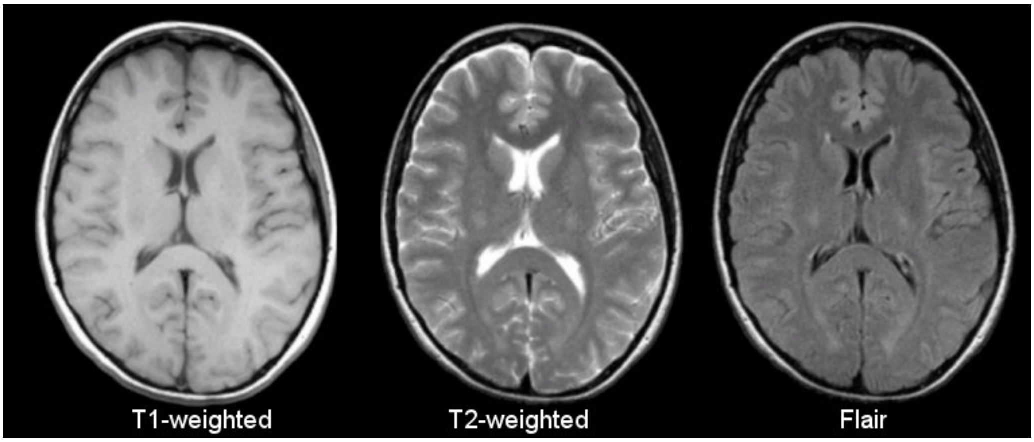


Figure 1.1: Brain MRI examples [1]

The relevance of the project is also shown that there are a lot of branches in which neuroimaging analysis can improve. Machine learning, and more recently Deep Learning and Computer Vision, has irrupted in this field for helping in some tasks:

- **Disease detection: segmentation and classification**. There are still several problems to solve in classification and segmentation problems. Brain MRIs are high dimensional, so we have to recruit big amount of images to properly develop a Machine Learning model that be able to achieve high accuracy. It is very difficult to recruit a large number of images, especially disease images. Even if it performs well, machine learning algorithms have been criticized due to the difficult of extract a clear knowledge of them (black-boxes). [5]. So a experimental approach is disease detection based on outliers from a normative model Patients with pathologies will be outliers in the distribution build by the normative model (they will be out of normal range defined by the normative model) [6] [7].

- **Data Augmentation**. Lack of data problem can be addressed by Data Augmentation techniques, which look for improve our Machine Learning models [8].

- **Improvement of data collection**. Recently high-impact FastMRI[1] release from Facebook for improving the speed in MRI scans [9].

- **Image enhancement**. Clinical evaluation is critical for good disease treatment. Experts and algorithms need good quality images to carry out their tasks. This is a problem we want to address, so we will explain it deeper in the document [3] [5].

[1] https://fastmri.org/

1.1.2 MRI Image enhancement

We are going to focus on the problem of image enhancement, specifically the problem of noise removal, see 1.2. If we achieved good performance in this task, we would research about how to apply this solution to disease detection or data augmentation.

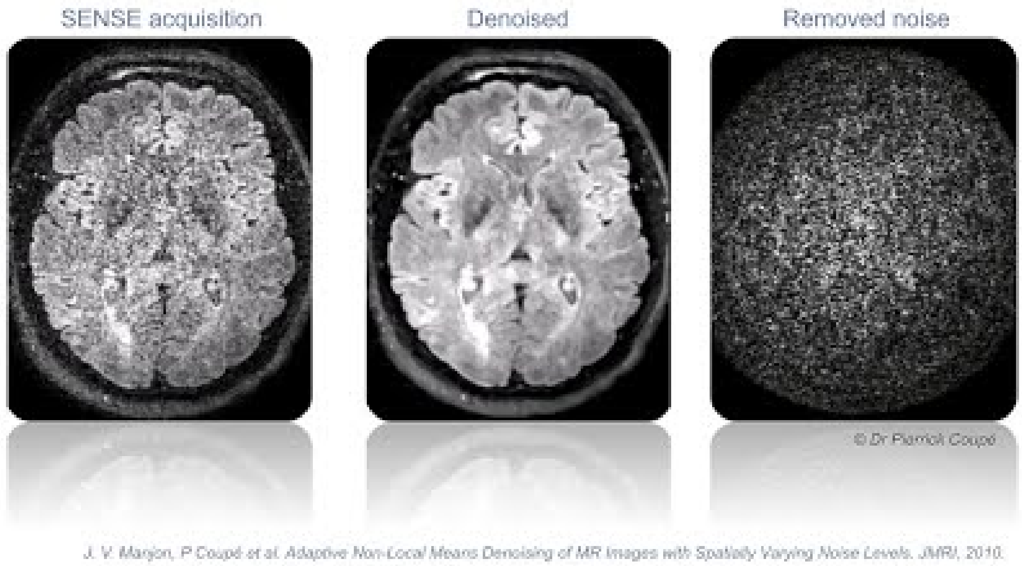


Figure 1.2: Noised and Denoised MRI [2]

Magnetic resonance images are collected with MR scans and the scan process, even though it is improved continually, adds some failures to the MR image. MR images have some random **noise** and **artifacts** due to this fact [10]. This noise and artifacts are present in the image due to different reasons: hardware-reasons (magnetic fields, etc.), body motion during scanning, thermal noise, weak signal intensity (which causes low signal-to-noise ratio), etc. The difference between noise and artifact is that noise can hide the characteristics of an image, whereas artifacts appear to be characteristic but are not. If the 'problem' is structured, it is probably an artifact, while if it is random, it is probably noise.

1.1.3 Noise and artifact reduction with Deep Learning

To address this problem many approaches have been done, all of them with some disadvantages. Advanced filtering methods [11] or retrospective correction approaches have been proposed, but, with the rise of **Deep Learning**, other methods have been proposed that take advantage of this approach. Deep Learning is very powerful in high-dimensional spaces and non-linear problems, so it can make a better job in feature extraction or information compression. Therefore, it will have good performance with images, where the **underlying structure of the images will be captured and foreign elements such as noise or artifacts can be eliminated**.

There are some approaches to reduce the noise and artifacts in MRI images. An recent and outstanding review is made by D.Tamada [3]. In this paper D.Tamada summarize Deep Learning Architectures and applications to MRI. We notice the big relevance of denoiser MRI Deep Learning methods in this review. Although there are many methods, we will focus in brain MRI denoisers.

There are some Deep Learning Architectures to address in the problem of denoise an brain MRI: Single-scale CNN, Denoising CNN, Autoencoders, and GAN-based architectures. **We will choose the Autoencoder Architecture for this project**.

Autoencoders [12] encode the input into a lower-dimensional space. It extracts important information from the higher-dimensional space, encodes it, and then decodes it to reconstruct the higher-dimensional spacer from the lower one. This architecture will be deeply explained in 4 in further stages of the project.

1.1.4 Our approach

In this project, we will design a **Deep Learning autoencoder for reconstructing brain magnetic resonance images removing noise. In other words, we will train a autoencoder with disease-free neuroimaging data and, with this trained autoencoder, we could define a distribution (or normal range) for the neuroanatomical variability for the illness absence with the main purpose of removing noise. Once trained, the autoencoder should be able to encode a input image and decode it removing noise.**

If the main objective of the project is completed, we could research the application of this model in data augmentation and disease detection fields. In the case of **data augmentation**, we will then attempt to reconstruct magnetic resonance images from patients with brain pathologies, with a further view to using the autoencoder to generate 'pathology-free' versions of the said images. In the case of **disease detection**, we could take an approach like the one in [13] (creating a measure for the difference between input and output image and classify it as healthy or control based on this measure). Patients with pathologies will be outliers in the distribution build by the autoencoder (they will be out of normal range defined by the autoencoder) [6] [7]. This assumption of patients as outliers (based in [7]) is used in [13] for abnormal brain structure detection.

Of course, we will need **data**. For this project, we will use **T1-weighted MRI images of control subjects** (no disease). As the project is of fairly limited length, we won't need to detect disease as a principal objective, but only learn to reconstruct normal MRI images, so we won't need pathology images for this project. In addition, we will investigate whether our method of reconstruction can filter out noise and/or artefacts. So, in essence, we will have n 3D MRI volumes (n can be any number greater than 100) from healthy subjects, we will preprocess it (data augmentation based on adding noise, remove parts...), and train our model to reconstruct the source MRI volumes. We will have access magnetic brain resonance images from control subjects for training the autoencoder. This data is arranged from different sources. Concrete sources of data images used in the project will be discussed in further stages but we have some clear options in this moment:

- The IXI dataset[2] (Most likely to be chosen).
- Other data sources such as Open Neuro[3].

1.2 Personal motivation

My personal motivation to carry out the project arises from several factors. My first steps in the world of Machine Learning were in the last year of my career at the University of Burgos. I was lucky enough to collaborate last year with the ADMIRABLE[4] research department. The project that I did (in which we continue working) was on the use of biomarkers extracted from the voice for the construction of classifiers that detect Parkinson's disease[5]. The project include topics like **signal processing**, **supervised learning**, **unsupervised learning** and **transfer learning**. The project was very successful and we had a lot of impact at that time. We are currently in the process of meeting with the Burgos hospital to continue developing the model and the application (project and impact recompilation in Github[6]).

[2] https://brain-development.org/ixi-dataset/
[3] https://openneuro.org
[4] http://admirable-ubu.es/
[5] https://adrianarnaiz.github.io/TFG-Neurodegenerative-Disease-Detection/
[6] https://github.com/AdrianArnaiz/TFG-Neurodegenerative-Disease-Detection

This project has fully opened me the doors the world of artificial intelligence and machine learning, which is a field of knowledge that I love. I have always liked math, problem-solving and since I started my career I love programming. Therefore, I find this field the ideal that aligns with my tastes and interests. As I said before, I have done lot of jobs with supervised learning or data analysis, but only with tabular data sets or text-datasets, so I wanted to break in the world of image processing and Deep Learning.

Then I worked half year in Ernst and Young, developing Machine Learning systems for RPA tasks (classify emails at Telefónica, Chatbot for Maxium or Fuzzy Name Matching for Xunta de Galicia).

In addition, I believe that the application of AI to medicine is one of the fields that may be of greater general interest to society. By advancing in the speed and quality of medical diagnoses and treatments, it will be possible to achieve health of higher quality, speed and accessibility for all. Also, computer vision and deep learning have helped to achieve big advances in this field nowadays.

1.3 State of art: related works

In later stages of the project, the resume of related works and state of art will be replaced in other place of the document.

The world relevance and impact of this problem is also shown in the related articles of this subject. The state of art of Deep Learning Autoencoders applied to brain MRI shows the relevance of this field. In this stage of the project (September 25, 2020), we have deeply read 3 papers for building the first bricks and identify the goals and methodology of the project.

- Walter Pinaya, 2018 [13]:

  Classic methods and approaches based on sMRI (structural magnetic resonance imaging) can't get a good performance in abnormal brain structural detection because neuroanatomical alterations in neurological disorders can be subtle and spatially distributed. Another approach based on Machine Learning methods could improve performance. ML algorithms are sensitive to these subtle characteristics. The downside of this road is the need for a large amount of image data (control and disease) and that the models are black-boxes with no information on the critical characteristics used for the decision. With this Deep Autoencoder, they put this matter up for discussion.

In this project, they address the problem of creating a normative model using a deep autoencoder trained with control subjects. With this autoencoder defining a distribution for control patients, they define a deviation metric to measure the neuroanatomical deviation in patients. Patients with some disorder should be outliers in this distribution.

Architecture and technique used in the experiment:

- Semi-supervised autoencoder: reconstruction of the image and prediction of age and sex.
- 3 hidden layers with SELUs activation function.
- Output layer with Linear activation function.
- Loss function: MSE from reconstructed and original image + cross-entropy for age + cross-entropy for years + Unsupervised cross-covariance.
- 2000 epochs.
- ADAM optimizer (adaptive moment estimation) with adaptative learning rate.
- 64 samples mini-batches.
- Transformation of input image:
  * Add Gaussian noise (0, 0.1).
  * Feature scaling (normalization).
- One-hot encoding for `sex` and `age` labels.

- We made a recompilation of papers reviewed in Table 1 of D. Tamada, 2020 [3] and by our own, with some removals and additions based in our goal of the project (see 1.1). In further stages we will explain deeply some papers from the table 1.1. From the table of D. Tamada we only obtain 1 autoencoder study [14], 3 sCNN and DnCNN approaches [15] [16] [17] and 1 GAN study. The other 5 papers have been compiled by our own (Autoencoder based: [13] [18] [19] [20], GAN-Autoencoder-based: [21]).

- In next stage (state of art research), we will research the state of art with new techniques and frameworks. Connected Papers[7] is a network science framework to improve the search of papers. There are also other platforms like Papers With Code[8] and Distill[9] that improve the experience of article discovering and article visualization-interaction.

[7] https://www.connectedpapers.com/
[8] https://paperswithcode.com/
[9] https://distill.pub/

Purpose	Year, Authors	Network
	Autoencoders	
Identify brain abnormal structural patterns	2018, W. Pinaya, et al [13]	**Semi-supervised autoencoder for HCP Dataset**
Denoising for T1 weighted brain MRI	2018, C. Bermudez, et al [14]	**Autoencoder with skip connections**
Medical image denoise	2016, L. Gondara, et al [18]	**Convolutional denoising autoencoder**
General image denoising and super resolution	2016, XJ. Mao et all [19] [Code available]	**Convolutional auto-encoders with symmetric skip connections**
Brain MRI denoise	2019, N. Chauhan et al [20]	**Convolutional denoising autoencoder with Fuzzy Logic filters**
	sCNN and DnCNN	
Denoising for T1, T2 and FLAIR brain images	2018, M. Kidoh, et al [15]	Single-scale CNN with DCT
Motion artifact reduction for brain MRI	2018, P. Johnson, et al [22]	Single-scale CNN
Denoising for multishot DWI	2020, M Kawamura et al [17]	DnCNN with Noise2Noise
	GAN	
Motion artifact reduction for brain MRI	2018 BA. Duffy, et al [16]	GAN with HighRes3dnet as generator
Denoise 3D MRI	2019, M. Ran et al [21]	**Wasserstein GAN with Convolutional Autoencoder generator**

Table 1.1: Overview of studies for noise reduction based in Table 1 from D. Tamada [3] (In bold the autoencoder related architecture)

Chapter 2

Scope

In this chapter, we will establish the aims of the project. We have just spoken about the problem to be solved. So now we have to enumerate the concrete objectives of the project.

The objectives will be temporal and will be redefined in further stages.

2.1 Hypothesis

We will build an auto encoder for reconstructing and denoise T1-weighted brain MRI. It will remove noise and will learn the underlying structure of the images in a lower dimensional space, and will reconstruct the image based on this low dimensional representation.

2.2 Primary aims

- To build a **noise-reducing autoencoder** that gets good results with control **T1-weighted brain MRI**: given a T1-WMRI, the autoencoder will return the same image as equal as we can to the original, but removing the noise.
- Research a good autoencoder architecture and parameters (loss function, batch-norm or not batch-norm, regularization, etc).
- Establish a good brain MRI pre-processing.

2.3 Secondary aims

- Develop the Deep Learning code using one of the most relevant framework, Python, and one of the best-known libraries: Tensorflow, Keras, or Pytorch (To Be chosen in further stages) .
- Use an agile methodology: SCRUM. This methodology should be used in the project. We will use the Zenhub tool of Github as a helper in the project management.

These next objectives will be addressed if the primary ones are reached. We could see these aims like a extra for the project. If we achieved good performance in this task, we would research about how to apply this solution to disease detection or data augmentation.

- Build a semi-supervised autoencoder.
- Build a tumor detection system (based on supervised learning or based in the output of the autoencoder [13]).
- Research GAN architectures for noise and artifact reduction.

Chapter 3

Planning and Methodology

In this chapter, we are going to discuss the scheduling for the project and the methodology used in this one.

3.1 Research plan

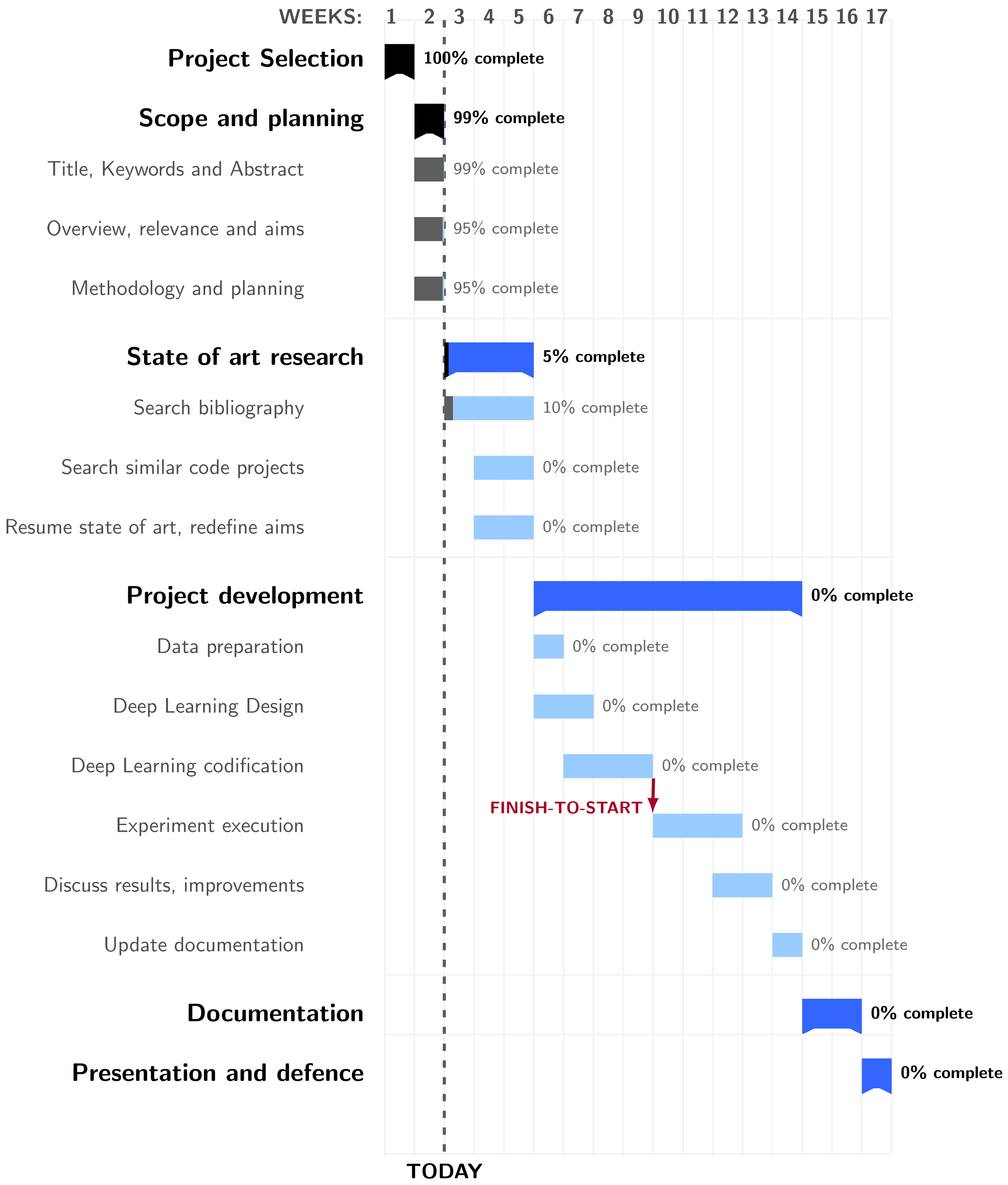
In this section, we are making a time planning for our project. Planning a project is a very important feature, because we can manage the time properly and we can keep a realistic task-calendar. For this purpose, we are going to elaborate a **Gantt Diagram**. This diagram is a very common resource used in project management [23].

Our diagram is a weekly Gannt Diagram. It has 17 weeks ([mm/dd/yyyy]):

- Week 1: from 09/14/2020 to 09/20/2020
- Week 17: from 01/01/2020 to 01/10/2021

It is built by all the main tasks that a master's degree final project must have and some personalized ones for this project. So we will have 6 big phases derived from project submits.

This diagram is up to the date of September 27, 2020. We show it in the next page.



WEEKS: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
Project Selection
100% complete
Scope and planning
99% complete
Title, Keywords and Abstract
99% complete
Overview, relevance and aims
95% complete
Methodology and planning
95% complete
State of art research
5% complete
Search bibliography
10% complete
Search similar code projects
0% complete
Resume state of art, redefine aims
0% complete
Project development
0% complete
Data preparation
0% complete
Deep Learning Design
0% complete
Deep Learning codification
0% complete
FINISH-TO-START
Experiment execution
0% complete
Discuss results, improvements
0% complete
Update documentation
0% complete
Documentation
0% complete
Presentation and defence
0% complete
TODAY

3.2 Methodology

In this section we must choose a common academic Data Mining development methodology, in which there are described the phases, tasks and its relationships.

The description and nature of the project are very helpful at this point because the methodology used in the project will depend on the nature of it. The main characteristic of this project is its research-oriented purpose, so we can label the project as an **academic research project**. Nevertheless, the main objective of this research is to develop a software component (a Deep Convolutional Autoencoder). We can also describe the project as a **software project**. In addition, the project is located in the Machine Learning and Deep Learning areas. These areas are very related to Maths, Statistics, and Computer Science. In all of these fields, the aim is to analyze data in a quantitative way. We analyze how the variables are related, how the autoencoder performance with a concrete measure, how it trains getting concrete metrics (how it learns, time, overfitting...), etc. So our methodology should be **quantitative**. We will take a representative sample of brain MRI, we will train the autoencoder and inference the results to all the population. All this sample and inference techniques are addressed by the validation methods of Machine Learning (Train/test, Cross-validation to reduce bias, etc).

So, due to the nature of the project, we have to apply a methodology for an **quantitative academic research project for data mining software development**.

In a very summarized way, we will start researching the state of art, defining the problem, and proposing a model to solve the target problem. We will choose and prepare our data. Then we will develop the data mining software solution for this problem, evaluating each step. Finally, we will evaluate our model an get a conclusion for our hypothesis. Thus, **CRISP-DM methodology** embed all of these steps and it will be chosen as the project methodology.

The methodology that best suits our project is **CRISP-DM** [24]. The ***CR****oss-***I***ndustry* ***S****tandard* ***P****rocess for* ***D****ata* ***M****ining* is a framework used for creating and deploying machine learning solutions. Moreover, research and quantitative tasks can be embedded in the CRISP-DM phases (i.e. state of art research phase can fit into business understanding CRISP-DM phase and quantitative evaluation can fit into model evaluation).

As we know, agile methodologies are often used in software development. CRIPS-DM is neither an agile methodology nor a waterfall one. This methodology has clear stages, but the order of them is not strict and we could move forward and back whenever we need, in order to improve our data mining final model. In fact, this movement between phases is widely used. Also it has a iterative cycle, in which data, data preparation, modelling and evaluation are improved wit the previous iteration feedback.

Figure 3.1 shows the phase dependencies and order. As we can see, the straight lines define the dependencies between phases as in a classical methodology. Nevertheless, We can see the circle and the two-arrowed straight lines that show the flexibility and the agile similarity of CRISP-DM.

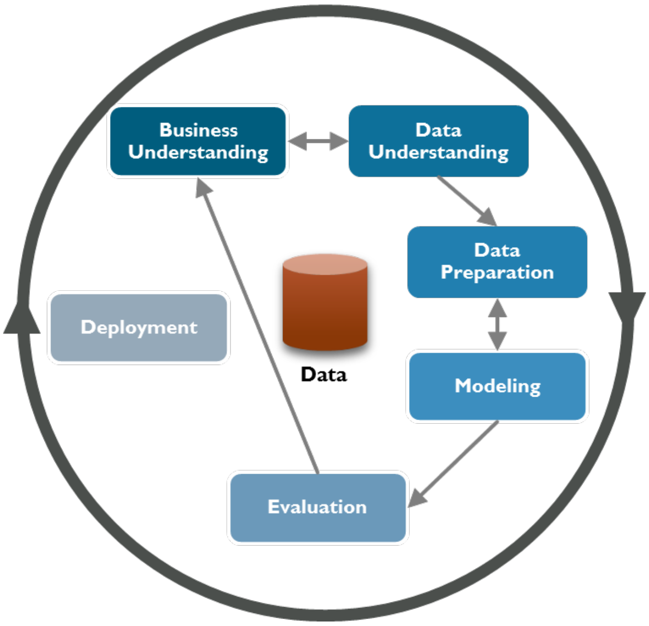


Figure 3.1: CRISP-DM Cycle

The phases of CRISP-DM [24] are the following (In later stages, references will be made to the specific sections of the document where the phases are carried out):

Business Understanding : deep analysis of the business needs. In this phase we can establish an objective. In our case, we can research the state of art for Deep Convolutional Autoencoder for brain MRI and propose a model based on this research.

Data Understanding : we should research the data sources as IXI[1], data quality and we should explore the data and its characteristics.

Data Preparation : Data should be cleaned, filtered, selected and integrated if necessary.

[1] https://brain-development.org/ixi-dataset/

We could carry out tasks like preprocessing T1 weighted brain MRI or realize data augmentation. I will be explained in-depth in section 6.2.

Modeling : Specify the model to use and the architecture, parameters, etc. Maybe running several model architecture and hyper-parameter optimization to reach the most powerful model. So in can be an iterative process.

Evaluation : We must evaluate models properly to get meaningful conclusions. There are many techniques of model evaluation and it should be made carefully.

Deployment - Publication : As our main goal is academic research, this phase would be *Publication*. The tasks are: review the project and generate the final report.

Chapter 4

Theoretical concepts

4.1 To Be Done

Chapter 5

Techniques and tools

5.1 To Be Done

Chapter 6

Project development

6.1 To Be Done

6.2 Data Life-cycle

- Capture: download from web.
- Storage: Locally.
- Preprocessing:
  - Cleaning and filtering: clean corrupted data, filter no-needed data.
  - MRI needed preprocessing (FreeSurfer in [13]).
  - Feature engineering: Normalize, downsampling.
  - Data augmentation: Noise addition, crop parts, ¿Rotations?
- Analysis: create autoencoder
- Visualization: Optional - Make some visualizations from results, layers or behavior of the autoencoder.
- Publication.

Chapter 7

Related works

7.1 To Be Done

In later stages, we will replace here the summary of papers and state of art.

Chapter 8

Conclusion and Outlook

8.1 To Be Done

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