Dark matter halo shapes in the AURIGA Milkiway-like simulations

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1 Introduction

Nowadays, the nature of Dark Matter (DM) remains unknown and is one of the biggest puzzles to understand the fundamentals that constitute our universe. As it is assumed by the nature of its discovery that it does not posses electromagnetic interactions, observing DM directly is practically impossible. However, due to its strong gravitational effect on the surrounding vissible matter, (acceleration curves, weak lensing), its presence can be sensed and furthermore, its density field can be constrained.

In this context, it is of much interest to probe the density field of the DM that clusters (DM halo) around the Milkyway as it can shed light in this fundamental puzzle having implications in many areas of physics. Specifically, the complete density field of the DM halo of our host galaxy is strong evidence to deduce many features of its formation history and evolution.

Many methods have been developed to constraint the shape of the Milkyway's DM halo, ranging from the use of Jean's equations [?] to the satellite systems such as the Sagittarius stream and the Large Magellanic Cloud [?, ?, ?]. However, due to the difficulty in the observation of some specific sensitive details of our galaxy and its surrounding systems, many assumptions have to be done over these models, producing considerably different results between each other. Then, it is safe to say that the constraints on the density field of the DM halo of the Milkyway is still an open research topic in astronomy.

Recently, with the growth of computational power and the improvement of numerical models, the performance and further study of realistic simulations which trace the non-linear interactions of DM and baryonic components has been possible [?, ?, ?]. These simulations can reproduce important features of our observable universe in a wide range of scales, from the cosmic star formation rate density and galaxy luminosity function in cosmological simulations as [?] to more specific features of Milkyway-type galaxies [?, ?] such as its stellar mass, rotation curves, star formation rates and metallicities. These simulations are an important field of study that complements observations and theory due to its freedom and control over the state of the systems and its observables.

In this context, the analysis of realistic Milkyway-like galaxies, which has only been possible until very recently [?], is of great importance to complement and perhaps give clues about details to have into account when probing the DM density field in observations regarding our galaxy. However, realistically reproducing the features of our Miklyway galaxy is not an easy task. It requires producing the correct initial conditions and not only having a sophisticated full-physics model to reproduce observables, but to very carefully tune the free parameters of these models such as the ones associated to the many dissipation and feedback processes of baryonic matter.

This is why, before the arrival of realistic Milkyway-like simulations such as Aquarius, there was a generation of DM-only simulations which used the final state of the evolution of DM to reproduce the statistical features of the observable universe. These type of simulations have substantial information to analyze in this field of study, but may be biased in aspects regarding the historical relation between DM and baryonic matter, such as the main question related to the probe of our galaxy's DM density field. The task of incorporating baryonic matter in these type of simmulations is in fact so difficult that, even with the most correct prescriptions of that date, Aquarius is a set of just six Milkyway-like galaxies. This can make any study performed on these simulations of low statistical significance.

More recently, with the deveolpment of the latest and most accurate hydrodynamical code AREPO [?] and the improvements of the physical numerial models regarding baryons, it has been possible the simulation of thirty Milkyway-like galaxies in the project AURIGA [?]. This code AREPO conciles the advantages and solves the flaws of the two paradigms of cosmology-oriented numerical hydrodynacs models namely Smoothed Particle Hydrodynamics (SPH) and Eulerian hydrodynamics with Adaptative Mesh Refinement (AMR). Furthermore, it can simulate magnetic fields, which is a novel feature in this type of simulations.

The objective of this monography would be then to use the results of the AURIGA project to study the halo density field of these thirty galaxies and obtaining statistically significant results, compare our study with state-of-the-art observations. Specifically, we will study the shape of the DM halo in terms of its radius and its history according to the guidelines stablished in a previous and similar study over the Aquarius simulations by Vera-Ciro et al [?].

2 Objetivos Generales

Estudiar el comportamiento de las redes neuronales desde un enfoque físico para verificar si el mecanismo de su aprendizaje es verificable por medio de modelos teóricos.

3 Objetivos Específicos

- Desarrollar redes neuronales simples para familiarizarse con su diseño
- Estudiar a fondo las técnicas computacionales de diseño de redes neuronales, así como los problemas técnicos a los que se pueden enfrentar
- Elegir entre las diferentes aplicaciones de redes neuronales una que sea versátil para el estudio de los modelos físicos asociados
- Estudiar qué posibles modelos físicos y estadísticos pueden ser aplicados a la red neuronal elegida para poder obtener conclusiones acerca de su funcionamiento
- Verificar las aplicaciones de estos modelos sobre la red elegida.
- Verificar la generalización de estos modelos para redes neuronales con diseños diferentes

4 Metodología

El estudiante realizará la investigación y el desarrollo de los temas individualmente, con el apoyo periódico del director por medio de las reuniones del grupo de Astrofísica. En estas obtendrá retroalimentación del desarrollo de su trabajo y se decidirá si en algún momento requiere de mayor asesoría por parte del director.

La metodología propuesta tiene un componente computacional fuerte relacionado con el desarrollo de varias redes neuronales y el monitoreo de su proceso de aprendizaje para la verificación de las conclusiones teóricas a obtener. A lo sumo, para agilizar los procesos de cómputo, se necesitará acceso al Cluster. Para el desarrollo de la parte teórica será necesaria la revisión de bibliografía especializada sobre el tema.

5 Cronograma

- Tarea 1: Desarrollo de redes neuronales simples
- Tarea 2: Investigación del diseño y funcionamiento de redes neuronales

Tareas \ Semanas	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	X	X	X	X	X	X										
2	X	X	X	X	X	X	X	X	X							
3								X	X	X	X	X	X	X	X	X
4												X	X	X	X	X
5										X	X	X	X	X	X	X
9					X	X	X	X	X				X	X	X	X
Tareas \ Semanas	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
4	X	X	X	X	X	X										
6			X	X	X	X	X	X								
7						X	X	X	X	X	X					
8									X	X	X	X	X			
9	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

- Tarea 3: Investigación de modelos teóricos sobre redes neuronales
- Tarea 4: Desarrollo de intuiciones o modelos verificables sobre el funcionamiento del aprendizaje de las redes
- Tarea 5: Preparación de la presentación de avance
- Tarea 6: Verificación de las conclusiones de los modelos anteriores sobre las redes neuronales artificiales específicas
- Tarea 7: Ampliación a redes neuronales más complejas
- Tarea 8: Desarrollo de resultados y conclusiones del trabajo
- Tarea 9: Escritura del documento final

6 Personas Conocedoras del Tema

- Juan Manuel Pedraza (Universidad de los Andes)
- Alonso Botero (Universidad de los Andes)
- Juan Gabriel Ramírez (Universidad de los Andes)

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Firma del Director

Firma del Estudiante