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| **Empirical Study of Dimensionality Reduction Methodologies for Pose Comparison problems using Computer Vision** | |
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Ficha del Trabajo Final

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| **Abstract (Spanish)** | |
| Esta investigación investiga la viabilidad de incorporar técnicas de reducción de dimensionalidad en problemas de comparación de posturas dentro del campo de visión por computadora. Esta investigación aborda la brecha en la literatura existente al investigar la viabilidad de incorporar técnicas de reducción de dimensiones en problemas de comparación de posturas dentro del campo de visión por computador y determinar las dimensiones clave que definen la correctitud de la postura. Para abordar estas limitaciones, esta investigación emplea técnicas como PCA, Random Forest y ANOVA. Se utiliza un conjunto de datos de Esqueleto 3D que contiene movimientos realizados por varios sujetos para comprender la correctitud de los movimientos entre los sujetos.  Se emplea la metodología CRISP-DM para llevar a cabo las diferentes fases de esta investigación. Los resultados demuestran una reducción exitosa del conjunto de datos de más del 80% al tiempo que conservan información significativa sobre la correctitud de los movimientos. Además, se entrenan dos modelos CNN distintos para clasificar la correctitud de los movimientos. El modelo entrenado con el conjunto de datos reducido muestra un tiempo de procesamiento un 45% más rápido y una mejora del 5% en precisión en comparación con el modelo CNN entrenado con el conjunto de datos completo.  Estos hallazgos resaltan la eficacia de incorporar técnicas de reducción de dimensiones en problemas de comparación de posturas dentro del campo de visión por computadora, ayudando a crear sistemas más eficientes, reduciendo el uso de recursos y producción de CO2. Las aplicaciones prácticas de esta investigación se extienden a campos como deportes, rehabilitación e interacción humano-computadora. La identificación de dimensiones clave que definen la correctitud de la postura puede mejorar la precisión de los modelos de estimación de postura existentes. El trabajo futuro implica la implementación de diferentes técnicas de selección y extracción de características como Kendall, LDA, t-SNE, el desarrollo de modelos Transformer o LSTM para mejorar la clasificación y la expansión de conjuntos de datos para incluir una gama más amplia de datos. | |
| **Abstract (English)** | |
| This research investigates the feasibility of incorporating dimensionality reduction techniques in pose comparison problems within the computer vision field. This research addresses the gap in existing literature by investigating the feasibility of incorporating dimensionality reduction techniques in pose comparison problems within the computer vision field and determining the key dimensions that define pose correctness. To address these limitations, this investigation employs techniques such as PCA, Random Forest, and ANOVA. A 3D Skeleton dataset containing movements performed by various subjects is utilized to understand the correctness of movements across subjects.  The CRISP-DM methodology is employed to carry out the different phases of the research. The results demonstrate successful reduction of the dataset by over 80% while retaining meaningful information regarding movement correctness. Additionally, two distinct CNN models are trained to classify movement correctness. The model trained with the reduced dataset exhibits a 45% faster processing time and a 5% improvement in accuracy compared to the CNN model trained with the complete dataset.  These findings highlight the effectiveness of incorporating dimensionality reduction techniques in pose comparison problems within computer vision, resulting in more efficient systems that reduce resource usage and CO2 production. The practical applications of this research extend to fields such as sports, rehabilitation, and human-computer interaction. The identification of key dimensions defining pose correctness can enhance the accuracy of existing pose estimation models. Future work entails implementing different feature selection and extraction techniques such as Kendall, LDA, t-SNE, developing Transformer or LSTM models to enhance classification, and expanding datasets to include a broader range of data. | |

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# Introducción

Esta plantilla se concibe como una guía para el/la estudiante. Se puede adaptar a las necesidades de cada trabajo, siempre que el tutor/a del trabajo esté de acuerdo.

Pose estimation is a fundamental enables the identification of object positions and orientations through joint angle measurements. Pose comparison, on the other hand, involves assessing the similarity or difference between object poses. This research aims to investigate the definition of pose correctness by applying dimensionality reduction techniques to extract key attributes and improve accuracy and efficiency in pose estimation models.



Figure 1 Pose comparison example [1]

## Contexto y justificación del Trabajo

Punto de partida del trabajo (¿Cuál es la necesidad a cubrir? ¿Por qué es un tema relevante? ¿Cómo

se resuelve el problema en el momento de comenzar el trabajo?) y aportación realizada (¿Qué resultado se quiere obtener?)

Pose estimation is an important part of Computer Vision [7]. We are able to identify the position

and orientation of objects in an image or video by measuring the angles of joints. On the other hand, pose comparison involves comparing the poses of two or more objects in order to determine the similarity or difference of those objects. During the last years we had significant advancements in the field, but our models still have some limitations in terms of accuracy and efficiency [8]. The question we are trying to answer is what defines pose correctness or equality, as for different tasks the factors which are of critical importance vary.

Through the application of different dimensionality reduction techniques, we want to try to find in

the data the attributes that give us the most important information about the pose, keeping them in our dataset. For this, it is important to explore and understand the data we are working with in order to apply the correct dimensionality reduction techniques.

Implementing dimensionality reduction algorithms in pose estimation and comparison tasks offers

significant advantages. It enhances computational efficiency, improves accuracy by focusing on informative features, prevents overfitting, enables data visualization, and aids in interpretability and insight generation. By reducing the complexity of high-dimensional data, these techniques lead to faster processing times, reduced resource requirements, as well reducing the CO2 footprint, and improved model performance. Additionally, the visualization of reduced-dimensional data provides valuable insights, while uncovering underlying structures helps in understanding key factors influencing pose correctness or similarity.

## 1.1.1 Motivación Personal

My personal motivation comes from a personal experience and passion for sports. I have practiced

for many years different sports, from karate, to boxing or football and I have often wondered if computer vision could be used to help people to improve their movements and techiniques without relying 100% on a trainer or coach [6]. By reducing the dependence on trainers or coaches, we could empower the people to learn and improve on their own movements and techniques, reducing the risk of injury during the physical activitites. I hope we can contribute to the field of sports and computer vision, reducing injuries, which can seriously reduce people’s quality life.

## Objetivos del Trabajo

Listado de los objetivos del trabajo

With this research we would like to achieve the next objectives:  
  
**General Objective**:

The implementation of dimensionality reduction techniques into comparison problems is the main

goal of our investigation. The implementation of these techniques allow us to reduce the complexity of the data and to keep in our dataset only the most important information, enabling the detection of the key dimension and improving the accuracy and efficiency of the existing pose estimation models. The approach we are presenting here has practical applications in several fields, like sports or rehabilitation [2], where accuracy and efficiency are crucial. By proving that dimensionality reduction has positive results when estimating a person's pose in terms of accuracy and efficiency, we can make great contributions to the field of computer vision.  
 **Specific Objectives**:

- Investigate the feasibility of implementing dimensionality reduction techniques in pose comparison problems in computer vision.

- Develop a deep learning-based model for pose comparison and evaluate its performance and accuracy.

- Identify the key dimensions in the dataset that enable accurate and efficient pose comparison.

- Identify certain specific conditions and correlations of a pose, within the selected body part.

- Explore and understand the data to be able to apply the correct dimensionality reduction technique.

- Contribute to the improvement and understanding of best techniques for pose comparison in computer vision.

- While this research focuses on the techniques to improve pose comparison, it does not seek to develop the best possible pose recognition model.

## Impacto en sostenibilidad, ético-social y de diversidad

Esta sección debería **identificar los impactos positivos y/o negativos del TF en las tres dimensiones de la competencia transversal UOC “Compromiso ético y global”.** La Guía transversal sobre la Competencia Ética y Global os ayudará a redactar estos apartados.

This section aims to analyze the project's ethical and global impact in alignment with the United

Nations' Sustainable Development Goals for 2030. The University of the Open University (UOC) upholds a strong commitment to sustainability, social responsibility, ethical behavior, and the promotion of human rights and diversity in both academia and professional practice.

The UOC recognizes the significance of sustainability across all its operations and endeavors. This

entails minimizing the university's environmental footprint, advocating for renewable energy usage, and supporting initiatives that contribute to a sustainable future.

Furthermore, the UOC places great importance on social responsibility and ethical conduct. This

involves considering the potential impacts of its actions on the local and global communities and adopting a responsible approach to research and decision-making.

In line with its dedication to human rights and diversity, the UOC ensures that every member of its

community is treated with respect and dignity, while promoting equal access to opportunities and resources. The university takes an active role in addressing issues of inequality and discrimination, striving to foster an inclusive and diverse environment.

In summary, the UOC is committed to being a responsible and ethical global entity, leveraging its

knowledge and expertise to contribute meaningfully and sustainably towards improving the world we live in.

**Sustainability**:

In addition to the aforementioned commitments, the UOC acknowledges the importance of

**sustainability** in machine learning projects. Such projects can potentially have adverse environmental impacts, and it is crucial to address these concerns.

Some of the key sustainability considerations in machine learning projects include:

* **Energy consumption**: Training and running machine learning models can require substantial amounts of electricity, contributing to greenhouse gas emissions.
* **Data storage:** The collection and storage of large datasets used in machine learning projects can consume significant energy and resources, potentially leading to e-waste and other environmental challenges if not managed responsibly.
* **Algorithmic bias:** If the training data used in machine learning models is biased, it can result in biased predictions and decisions, negatively affecting marginalized groups and the environment.
* **Unintended consequences:** Machine learning models may produce unintended outcomes that can be detrimental to the environment.

To address these concerns, it is essential to consider the environmental impacts of machine

learning projects and take proactive measures to minimize any negative consequences. This includes adopting energy-efficient practices, implementing responsible data management strategies, addressing algorithmic biases, and actively monitoring and mitigating unintended consequences. By integrating sustainability considerations into machine learning projects, the UOC aims to ensure a more environmentally conscious and responsible approach to research and development.

In this project, we have discovered the potential of machine learning in assessing the correctness

of poses during training or exercise, which can significantly reduce the risk of injuries and have wide-ranging economic and health implications. Moreover, machine learning techniques have the ability to positively impact not only the sports domain but also the medical field. By providing posture correction during rehabilitation exercises, machine learning can aid patients in their recovery from physical injuries.

Furthermore, we have conducted an analysis of the carbon emissions associated with our project.

Based on the "ar4" calculation method and the "CCF" emission factor for the "US-GIR" region in 2022, our project's estimated carbon footprint amounts to approximately 0.001 kg CO2e. Although this is considered a minimum footprint, we are committed to further reducing it by utilizing energy-efficient equipment, incorporating renewable energy sources, and optimizing resource usage during training to minimize waste (ACTUALIZAR CON EL CODECARBON)

It is crucial to recognize the potential long-term impacts of a machine learning project. While the

emissions linked to training and deploying a model may constitute only a fraction of the total emissions incurred throughout its lifespan, we acknowledge the importance of considering and mitigating these impacts. Understand as well that the dataset used for this research is small and other results should be expected with a bigger dataset, model or scenario.

In addition to addressing environmental concerns, we also emphasize the significance of social

responsibility and ethical behavior within the project. It is imperative to ensure that the development and deployment of machine learning models prioritize fairness, inclusivity, and respect for individual rights and privacy.

By integrating environmental sustainability, social responsibility, and ethical considerations, we

strive to foster a comprehensive approach to machine learning research and development, benefiting both society and the environment.

**Social responsibility and ethical behavior**:

Social responsibility and ethical behavior are integral aspects of our research project. We

conducted a thorough assessment of the potential societal impacts, carefully weighing the benefits in terms of advancements in fields like sports, medicine, rehabilitation among others. By considering the potential implications, we ensured that our project aligned with responsible and ethical practices. We were tranparent in our approach, clearly outlininig the goals, methods, and limitations of the project. Throughout the project, we have strived to align our actions with the principles of social responsibility and ethical correctness. However, we recognize that this is an ongoing process, and we remain dedicated to continuously evaluating and addressing the potential impacts of our research. Our unwavering commitment extends beyond the completion of this project, as we are resolved to always uphold responsible and ethical practices in our future endeavors.

**Human rights and diversity**:

In this project, our analysis focused solely on publicly available 3D Skeleton data, which ensures

that the project is accessible to everyone and respects the principles of openness and inclusivity. It is crucial to acknowledge the existence of biases in the field of machine learning. Machine learning algorithms heavily rely on the data they learn from, and if the data is not representative of the target population, biases may arise based on factors such as gender, age, race, or religion. Therefore, when working with datasets, it is essential to exercise caution and critically evaluate their suitability to avoid potential misleading results. By being aware of these biases, we can work towards developing more equitable and unbiased machine learning models in the future.

## Enfoque y método seguido

Mencionar cuáles son las posibles estrategias para realizar el trabajo e indicar cuál es la estrategia

elegida (desarrollar un producto nuevo, adaptar un producto existente…). Valorar por qué ésta es la estrategia más apropiada para conseguir los objetivos.

In this study, we aimed to understand the feasibility of implementing dimensionality reduction

technique in pose comparison problems, using a combination of feature selection and feature extraction techniques and a deep learning model using a dataset with 3D Skeleton data. The 3DFit dataset, which was generated by fit3D IMAR, was the dataset used. The dataset comprises frames capturing diverse movements performed by multiple subjects. Each frame provides the 3D skeleton coordinates of 25 joints, including the 17 Human3.6m joints.

During the last years, deep learning solutions have demonstrated to outperform classical

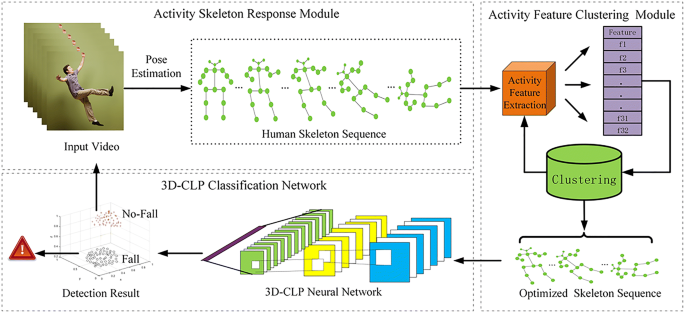
computer vision methods in various tasks such as image segmentation and object detection [4]. Therefore, in this investigation, the CNN model is going to be the approach to use combined with dimensionality reduction techniques. Convolutional neural network are the base of the state-of-the-art methods when designing architectures for object or human pose inference applications. Its local receptive fields and convolutional layers enable it to capture fine-grained details and recognize patterns and relationships between joint  
  


Figure 2 CNN model used in combination with s3CD [3]

Our specific focus lies in analyzing the squat exercise among the various exercises available in

the dataset.

In order to understand the correctness of the squat, we will train two separate models for each

type of [](https://en.m.wikipedia.org/wiki/File:CRISP-DM_Process_Diagram.png)dataset, one with all the dimensions and a second one with the reduced dimensions. These models will not only identify the relevant body parts crucial for categorizing a pose as correct but also discern specific conditions, correlations, or artifacts within the selected body part data that correspond to accurate execution of the movement.

The language program will be Python; therefore we are

going to set up the environment with the necessary libraries and tools.

The methodology selected to carry this investigation is the CRISP-DM methodology.

CRISP-DM is a [data mining](https://en.m.wikipedia.org/wiki/Data_mining) process model used commonly

by data mining experts to tackle problems. This methodology provides a structured approach for carrying out a data mining project. It is a robust, flexible and useful methodology, using analysis to solve problems. The model is a sequence of idealized phases but in truth, many of the phases can be solved in any order and very often it will be necessary to repeat many of them or backtrack to previous tasks in order to contrast improvements in the analysis process. Phases such as modeling, preparation of the data or understanding of the data will be usually repeated more than once as we have experience in this project. This methodology can be applied to any of the projects used regardless of the area to which it belongs, business, medicine, automotive, etc. It is possible to find several guides explaining this methodology online [88]. It breaks the process of [data mining](https://en.m.wikipedia.org/wiki/Data_mining) into six major phases:

Figure 3 Process diagram showing the relationship between the different phases of CRISP-DM

**Business Understanding**

In this initial phase, we are going to understand and define which ones are the business problems

that need to be solved and the objectives, everything from a business perspective. With all this information, a data mining problem will be defined and a plan designed to achieve the objective.

This first phase is important because if you do not understand the objectives of the research,

you could invest a lot of time and effort in producing the correct answers for the incorrect questions

Some of the tasks in this phase are:

* **Determine Business Objectives:** It seeks to describe the main objective and plan required from a business perspective, as well as addressing other types of questions or objectives. We are going to set the criteria used to determine if the project has succeeded or not, answering the questions specified in the beginning. Tasks of this phase:
  + Background,
  + Business Objectives,
  + Business success criteria
* **Asses Situations**: We will make an inventory of the necessary resources, as well as people, data, computer resources, and software. Here we list all the requirements of the project, including the complete schedule, the comprehensibility and quality of the required results. The limitations are listed too, and it can be the availability of resources, technological limitations such as the size of the dataset to model when being small, etc. Here we list also the risks that may delay the project or cause it to fail. Finally, in the case of having costs, a small analysis could be done to understand if it would be worth with the benefits that would be obtained. Tasks of this phase:
  + Inventory of Resources
  + Requirements
  + Assumptions and Constraints
  + Risks and Contingencies
  + Terminology
  + Costs and Benefits.
* **Determine Data Mining Goal:** We will determine the criteria to be able to say that the project has been successfully completed, and the results obtained have been as expected. Tasks of this phase:
  + Data Mining Goals
  + Data Mining Success Criteria.
* **Produce Project Plans**: The planned plan for achieving the objectives of the project is described. You must specify the tools considered in the project and the initial techniques to be implemented. The plan made initially for each stage of the project can be shown in a diagram. Tasks of this phase:
  + Project plan
  + Initial Assessment of Tools and Techniques.

**Data Understanding**

In this phase, we are going to start collecting data, which means we will get the data from

internal or external sources and with specific characteristics including data volume, variety, formats and so on, as well as whether the data is in data files, in the cloud, it is life or stream.

We will identify data quality problems, discover insights into the data, detect if we have

inconsistent in the data or duplicate values, the degree to which data is missing, etc.

Some of the tasks in this phase are:

* **Collect Initial Data:** Here we are going to perform the “Initial Data Collection Report” It will indicate where the data has been acquired, the source, the problems obtained to acquire them and the solution found to acquire them. This will help both the future execution of the project and the creation of similar projects.
* **Describe Data:** Here we are going to perform the “Data Description Report” The properties of the acquired data will be examined. Describing its format, the quantity, identities of the fields and evaluating if the data acquired satisfies our requirements.
* **Explore Data:** Here we are going to perform the “Data Exploration Report”. In this step, we will address data mining questions, directly addressing project objectives, refining the description of data or quality reports and even transforming and preparing data for further analysis.
* **Verify Data Quality:** Here we are going to perform the “Data Quality Report”. We are going to examine the quality of the data, if the data is complete or if we are missing values in the data.

**Data Preparation**

It seeks to prepare the data to be used by machine-learning algorithms. This process involves a

number of tasks including cleaning, filtering, transformation, feature selection or dimensionality reduction. The objective is to improve the set of features eliminating variables which are not necessary and could produce noise or contribute to a poor precision of the algorithms. Feature Engineering is going to be performed here. Some of the tasks in this phase are:

* **Select Data**: Here we are going to perform the “Rationale for inclusion/exclusion criteria”. We decide which data is going to be used for the analysis. These decisions are made based on the goals of our project, the type of data, etc. The selection of the attributes can be both rows and columns. If it is possible, it can be explained why this data is excluded and the reasons.
* **Clean Data**: Here we are going to perform the “Data Cleaning Report”. We will raise the quality of the data to the technical level of the analysis that we have selected. To do this we will select subsets of the data, insert new values or apply techniques estimating missing values through modeling.
* **Construct Data**: By this, we mean construction operations such as the production of derived attributes or transformation of values to existing attributes. The derived attributes will be generated through one or more existing values. On the other hand, new attributes are going to be generated that may not be in our dataset, but after studying it we prove that they would be necessary to achieve our objectives. Tasks of this phase:
  + Derived attributes
  + Generated Records
* **Integrate Data**: Here we are going to perform the “Merged Data”. When integrating data, it is sought to mix or merge information from different datasets or different databases. In this process, the aggregations are made, calculating new values summarizing information from different registers or tables.
* **Format Data**: Here we are going to perform the “Reformatted Data”. We are going to seek the correct format to work with the machine learning algorithms.

**Modeling**

The development of a machine-learning model is based on the calibration and evaluation of

different techniques to obtain the best performance.

These models are used to predict, analyze, or search for patterns, associations, or groups in our

dataset. Different techniques can be used to solve a problem, but it depends on the type of data we are working, so it is recommended to study the dataset first to understand the data and the algorithms that can work properly with it. In case it is necessary we could return to the data preparation phase, to improve our dataset. We will encounter two types of machine-learning algorithms: supervised and unsupervised.

The tasks in this phase are the next:

* **Select Modeling Techniques**: In this section, we will select the techniques of modeling, and it is possible that many of them have changed with the techniques we were supposed to use in the beginning. We must explain the chosen modeling technique and the assumptions we have made to carry them out, for example, all elements must be numbered or that the elements must be normalized. Tasks of this phase:
  + Modeling Technique
  + Modeling Assumptions
* **Generate Test Design:** Here we are going to generate the Test Design. Before creating a model, we will have to prove the quality and the validity of the model.

In a situation like ours, where data mining is supervised to classify different models, certain patterns are used as measures of quality to indicate that a model works correctly or not. So, the dataset is divided into two parts, "test" which is the set to estimate the quality of the final algorithm and "Train", where we train and build our algorithm. We must describe the techniques we used and especially how we have performed this testing process.

* **Build Model**: We are going to run the modeling tools, creating one or more models. We will adjust the parameters for each algorithm, performing small tests checking which parameters work best in which case. It would be helpful to make a description of the resulting models, informing about the interpretation of the models and the problems that we had in order to implement them. Tasks of this phase:
  + Parameter Settings
  + Models
  + Models Description
* **Asses Model**: We must interpret the models with the knowledge that we have of that field and the criteria we have about data mining. After this, we have to discuss with experts in the field such as mathematicians or business analysts the results obtained.

We must classify the models and evaluate them according to the evaluation criteria. We must

consider the goals and understand that it is usual to apply a technique more than once, obtaining results generated by different techniques. The results obtained will be evaluated, enumerating the qualities of the models generated and with relation to each other. Check that the algorithms have been tuned correctly and that the chosen parameters are indeed correct for that model. Tasks of this phase:

* + Model Assessment
  + Revised Parameter Settings

**Evaluation**

After developing a model, we will evaluate if the performance is the expected and we are

predicting the classes correctly. For them, it is recommended to review the steps followed from the beginning. For example, in the case of predictions, we try to evaluate the number of elements that were predicted correctly. After this phase, we must express if the results are satisfactory and determine which models we will use. The tasks in this phase are the next:

* **Evaluate Results:** We will evaluate the results, checking the accuracy obtained from the models. We are going to summarize the results of the evaluation, stating whether or not our model finally met the specified objectives in principle or not. In case we agree with the results obtained, we will give the models as good and we will approve them to use them in a real situation. In case the budget or time allows, other test models with real data can also be evaluated. Tasks of this phase:
  + Assessment of Data Mining Results
  + Business Success Criteria
  + Approved Models.
* **Review Process**: We are going to do a review of the models to verify that we have not forgotten some important task. Questions will be asked to check if the process has been performed correctly. If it is possible we have to remark which activities should be repeated or probably have been missed.
* **Determine Next Steps**: In this part, we can decide how to proceed with the results obtained. In case we have possible potential actions to implement, we should put pros and cons to implement them. Tasks of this phase:
  + List of Possible Action
  + Decisions.

**Deployment**

In the final step, if we are happy with the model we created, now we are going to deploy the

models to run in different environments It does not mean that this one is the end of the project, even if we were just looking to improve the performance of the model, the knowledge we gained have to be organized and presented in a way the customers can understand and use. In many cases will be the customer the one which will carry out the deployment steps, and not the analyst. Tasks in this phase:

* **Plan Deployment:** At this point, it is where we will describe the procedure followed to create the model so that we can use it later.
* **Plan monitoring and maintenance**: Here we are going to deploy the monitoring and maintenance plan. It would be helpful to detail a data mining plan, with the process we are following.
* **Produce Final Report**: Finally, we are going to redact a report, explaining the experiences obtained and making a report. It could be a presentation of the data mining results to Tasks of this phase:
  + Final Report
  + Final Presentation.
* **Review Project:** In the Experience Documentation, we are going to explain what went right and what went wrong, summarizing the experience obtained in this project. At the same time would be helpful to explain any pitfalls we encountered, misleading approaches, etc. for future research.

With this introduction, I wanted to clarify some doubts with the terminologies in this Area and

give an idea about the direction of this Research for those Students interested in this Field.

## Planificación del trabajo

Descripción de los recursos necesarios para realizar el proyecto, las tareas a realizar y una planificación temporal de cada tarea utilizando un diagrama de Gantt o similar. Esta planificación debería marcar cuáles son las metas parciales de cada una de las PEC.

When it comes to a large piece of work like dissertation, managing the time well is essential to stay on track. For this reason, we define a list of milestones, tasks and risk analysis because is a great way to see what we need to do at each stage.

**Milestones:**

Figure 4 Planification of the pecs.

We can see the number of days for each PEC and the start date and end date for each PEC.

**Tasks:**

Next we are going to show the Gantt chart with the tasks that we plan to carry out to carry out this

investigation. Dates may vary as we develop the project.

The important tasks of the project are:

- Search for resources and read articles related to the investigation

- Identifying an appropriate dataset for the research (labeled dataset)

- Creation of a deep learning-based model for pose-correctness evaluation

- Applying dimensionality reduction techniques to the selected dataset and train the model.

- Evaluating the performance of the proposed model using benchmark datasets.  
- Development of the memory and preparation of the defense.

Figure 5. Tasks to be developed

**Risk analysis:**

A list of the risk that could affect the project:

|  |  |  |  |
| --- | --- | --- | --- |
| DESCRIPTION OF THE RISK | SEVERITY | PROBABILITY | MIGRATION |
| Large scope of the project | High | Low | Although the project is large in scope, there are multiple stopping points. Once we achieve to implement dimensionality reduction in our data and train a model, it is sufficient to compare the pose results. |
| Inconclusive or poor results | High | Medium | We hope to contribute to this field by addressing this problem. The objective can be still be achieve even if the model does not perform well. It is possible to find another dimensionality reduction techniques and train our model, improving the results |
| Time | High | Low | We want to use public available data, so we do not need to collect the data on our own. The team in Cambridge is going to support us to find a suitable dataset. |
| Lack of supervision | High | Low | Working closely with the supervisor of this project is key to answer doubts and questions. Weekly meetings and constant feedback from the supervisor. |

## Breve sumario de productos obtenidos

No es necesario entrar en detalle: la descripción detallada se realizará en el resto de capítulos.

* **Product**: The code and this document can be found in the repository, with a swell other documents that will help readers to understand this research. <https://github.com/danielGOB/TFM/edit/main/README.md>
* **Functions**: Several functions were created to develop this research. These ones can be used and implemented in other projects. Fucntions like sequence\_extractor, alignment\_sequence, get\_sorted\_indices and get\_equally\_spaced\_elements were developed from scratch and solve common problems in the field of computer vision.
* **Pipeline**: The strategy developed to implement dimensionality reduction successfully can be found on the document “Strategy implemented” in the github repository and it is recommended to read it while reading this research, to have a better understanding of the code.

## Breve descripción de otros capítulos de la memoria

Breve explicación de los contenidos de cada capítulo y su relación con el proyecto global.

* Estado de la cuestión: This section describes the various steps taken to carry out the analysis of this dissertation.
* Resultados: This section shows the results obtained after the analysis as well as their discussions.
* Conclusiones y trabajos futuros: This section describes the conclusions drawn from the research, critical reflection of the objectives achieved, as well as the planning and methodology implemented.
* Glosario: Alphabetized catalog of words and expressions from one or more texts that are difficult to understand, together with their meaning or some comment.
* Bibliografía: detailed list of all the sources consulted and cited in a research paper or project.
* Anexos: extra or complementary information that is included at the end of the thesis and that provides data whose purpose is the information about this research.s

# Estado de la cuestión

En estos capítulos, es necesario describir:

* los aspectos más relevantes del diseño y desarrollo del trabajo
* la metodología elegida para realizar este desarrollo, describiendo las alternativas posibles, las decisiones tomadas, y los criterios utilizados para tomar estas decisiones.
* descripción de los productos obtenidos.

**La estructuración de los capítulos puede variar en función del tipo de trabajo.**

En caso de que proceda, se incluirá un apartado de “Valoración económica del trabajo”. Este apartado indicará los gastos asociados al desarrollo y mantenimiento del trabajo, así como los beneficios económicos obtenidos y un análisis final sobre la viabilidad del producto.

We will conduct a comprehensive analysis of the current state of the art in the field of computer

vision and pose comparison, examining four areas I think are key to understand the background

literature.

In this first part of the analysis, we are going to make a review of the current state of knowledge in the field of Computer Vision, with a specific focus on the next four areas: digital human avatars,

biomechanics of the human body, correctness of a movement – pose and dimensionality reduction

methodologies for pose comparison problems. Pose comparison is an important task in computer

vision, that has significant applications in areas like sports, rehabilitation or human computer

interaction. When we speak about pose comparison, we speak about the task of identifying the

difference or similarity between two observed positions of bodies or objects. In particular, the

comparison of human skeletal poses is useful for analyzing movements.

In this context, dimensionality reduction methodologies have emerged as a promising method to

reduce the complexity of pose comparison problems by identifying the key dimensions that define

pose correctness.

# 2.1 Digital human avatars, representation and comparison

In recent years, digital human avatars helped us to understand better human movement through the creation of virtual representations of the human body. This provides us with a tool potentially accurate when representing the human body and its movements, which can be used to better understand and analyze poses and movements.

Several studies highlighted the potential of using human avatars to improve human movement analysis. For instance, researchers at Meta’s Artificial Intelligence Research Lab and the University of Twente, have co-developed an open-source framework called “MyoSuite”, which combines advanced musculoskeletal models with advance artificial intelligence to create “digital humans” that mimic complex movements. With this tool they can analyze the biomechanics of movement and evaluate the effectiveness of a robotic therapy beforehand, optimizing it for a patient and delivering a truly personalized and cost-effective treatment [10]. In sport science, digital human avatars have been used to analyze the movement in athletes and understand better potential injuries [11].

Several challenges and limitations must be faced at the moment of using digital human avatars. How we obtain accurately the movements and gestures is one of the main challenges. To achieve that, we need to use high-quality motion tracking techniques, as well as data analysis [12].

The use of digital human avatars for human analysis is an early noninvasive technology, that has the potential to help us understand the human movement better, with a lower cost and fully capturing its complexity. However, it is necessary to solve first the current limitations of this technology

# 2.2 Biomechanics of the human body

Biomechanics of the human body is a critical area in the study of human movement. Biomechanics is the study of the mechanical principles of living organisms, especially the human body. It involves understanding how the various systems and structures in the body, such as muscles, bones, and joints, work together to produce movement. Biomechanical analysis can be used to understand and improve movement patterns in sports, physical therapy, and other areas.

The description of the biomechanics of the human body can be achieved through different approaches. For example, understand and capture the joint constraints of the human body using markerless motion capture techniques, that rely on computer vision algorithms, allow us to understand better the biomechanics of the anatomy of a person, improving the accuracy at the moment of stating a pose [13]. This first approach has the potential to be the best cost-effective and accessible option, but currently faces challenges in accurately capture the subtle nuances of human movement.

Another approach uses motion capture technologies, which help us to understand more accurately the biomechanics of the body but increments the effort when processing and analyzing the data because of its complexity. Both approaches help us to understand better how to reduce the physical overload of the body during certain activities. Understanding which joints and muscles have a bigger impact is key, when developing better guidelines for certain activities and movements, helping us to prevent potential injuries [14].

There are several challenges and limitations in the field of biomechanics and movement analysis, including the need for more robust and accurate algorithms, better understanding of the complex interactions between the different components of the human body during movement or the lack of datasets with training data [15].

Understanding the biomechanics of the human body is crucial for developing accurate and robust computer vision systems for pose comparison, and ongoing investigations in this area have a strong potential to achieve promising results in the field.

# 2.3 Correctness of a movement - pose

When we analyze human movement, one of the toughest part is to define a movement or a pose as correct. This can vary depending on the use case, such as sports performance, physical therapy or biomechanical research. We can find several investigations that attempt to define what constitutes a correct movement or pose based on biomechanical principles and the opinion from experts.

For example, one study by David W Meister and Amy L Ladd was trying to determine the biomechanical factors that may influence golf swing power generation [16]. This study identified biomechanical factors highly correlated to golf swing power generation. Similarly, a review by Kyle R Barnes and Andrew E Kilding try to identify and determine the biomechanical factors that determine or influence the Running Economy [17].

However, determining what constitutes a correct movement or pose can also involve subjective factors, such as aesthetics and cultural norms. A study done by Lurlynn Maharaj-Pariagsingh and Phaedra S. Mohammed presented a prototype intelligent dance tutoring system, DanceTutor, for coaching students. Evaluation done by three experienced professors from different countries of the prototype revealed the highly subjective nature and cultural biases of evaluating the quality of a dancer’s technique [18].

Ultimately, determining what constitutes a correct movement or pose requires a combination of objective biomechanical analysis and subjective expert opinion. Advances in computer vision and pose comparison techniques have enabled more precise and objective analysis of movement, but subjective factors cannot be ignored.

# 2.4 Dimensionality reduction techniques

Dimensionality reduction methods help us to analyze large datasets by reducing their dimensionality while retaining the most important information. For example, dimensionality reduction methods with motion data allow us to extract key features and patterns in the movement, retaining the most important information and providing the models with cleaner data. This data can improve the results of our models, giving more accurate results when comparing different movements, as the data used to feed them has less dimensions, therefore lower noise.

One of the most common dimensionality reduction techniques that have been used in the analysis of motion data for example is principal component analysis (PCA). PCA has been widely used for motion analysis, for example at the moment of estimate hand pose. Experiments demonstrate that the implementation of PCA methods achieves better accuracy in hand pose recovery compared to state-of-the-art baseline methods [19].

Other dimensionality reduction techniques that have been used in the analysis of motion data include linear discriminant analysis (LDA). Depending on the technique we use, the strengths and weaknesses of each method must be considered. For example, in the investigation of Nojun Kwak and Sang-II Choi, a modified version of LDA is used with regression problems to estimate head pose and compare the performance with other conventional extraction methods [20].

The use of dimensionality reduction methods aims at finding the transformation from the original feature space to a low dimensional subspace that retains most of the discriminative information. In this research we can find how different dimensionality reduction algorithms were applied when inferring 3D human poses from monocular videos, obtaining better results, proving the effectiveness of the proposed methods [21].

Overall, dimensionality reduction techniques are a powerful tool for analyzing motion data and skeletal movement, allowing us more efficient processing and analysis of large datasets. While there are many different techniques available, each with its own strengths and weaknesses, researchers must carefully consider the specific requirements of their analysis when choosing the most appropriate technique.

# 2.5 Conclusion

In this state-of-the-art review, we have explored four areas: digital human avatars, biomechanics of the human body, what defines a movement - pose as correct on a conceptual level, and dimensionality reduction techniques applied to skeletons or motion data.

Digital human avatars have the potential to be powerful tools for analyzing and improving human movement in fields such as sports science and physical therapy. However, there are still challenges and limitations to be addressed in the field, such as accurately capturing subtle movements and gestures.

The biomechanics of the human body provide a framework for understanding how different poses and movements are produced and can be described. This knowledge allows us to more accurately track and analyze movements for a wide range of applications. Defining what constitutes a "correct" movement or pose on a conceptual level is a challenging task, and one that may depend on specific use cases.

Finally, dimensionality reduction techniques can be applied to skeletal and motion data to reduce complexity, providing us with more efficient processing and analysis. This research has important implications for fields such as sports science and physical therapy, where large amounts of movement data must be processed and analyzed. We expect to be able to understand how to implement dimensionality reduction algorithms on 3D Skeleton data and in the case we obtain positive results, provide a strategy to be able to reduce the dimensions successfully.

Overall, the intersection between computer vision and human movement analysis is an evolving and exciting area of research, with a wide range of potential applications across multiple fields. Exploration and refine of these four areas are key to unlock even more possibilities for improving human movement and understanding the complexities of the human body.

# Experiment design

Two different experiments were performed, one for the dataset with the reduced dataset and one for

the dataset with all the dimensions.

Additionally, results obtained for the accuracy and lost of each classification are shown and a graphic,

as well as the confusion matrix for each pair “Classification Model-Reduction algorithm”.

The next diagram in Figure 6 [9] explains briefly the procedure followed, according to the CRISP-DM

methodology:

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Figure 6. CRISP-DM phases followed to understand the experiment.

**3.1 Business Understanding and Data Understanding**

In the phase Business Understanding, we determined as requirements would be needed a student

with knowledge of the subject and a phd student as cotutor of the Cyberhuman Lab from the University of Cambridge to carry out this project. We will also need a computer to work with a minimum of 16 Gb Ram and a core processor M2 Pro working on a macOs system.

As a programming language, Python 2.7.13 has been chosen and the necessary software is:

* Anaconda 23.3.1 for 64-bit
* scikit-learn, tensorflow, scipy, libraries
* iTerm Terminal
* Jupyter Lab

CRISP-DM was chosen as the methodology to be followed in this project, because it is a robust,

flexible and useful methodology, using analysis to solve problems.

Speaking about the data, a dataset would be needed (in this case a dataset with 3D Skeleton data)

with the intention of applying dimensionality reduction techniques on the subject for classification pose problem for a given sport movement. Since this kind of datasets are not common, it will be difficult to acquire it, spending a lot of time searching one with the quality and information necessary to analyze the data. Speaking of quality, we refer to the information of the data and the facility to understand what is expressed in the dataset. This at first delayed us quite a lot, since it was not easy for us to find the right one with the movements required from our supervisor, and when found, the information was not clear and the creators of the dataset had to be contacted.

Another problem we encountered was the amount of data to analyze since it was not large enough,

we had to use data mining techniques to perform acceptable algorithm training. The lack of larger datasets with this specific data was a big challenge and delayed the research critically.

At the beginning of this project, a diagram was given where we can find the different stages

proposed for this project. It is expected that after finishing this project, a better understanding of the different dimensional reduction algorithms will be obtained.

The dataset utilized in this study is the 3DFit dataset, generated by fit3D IMAR. It consists of frames capturing a variety of sport movements performed by multiple subjects. Each frame includes the 3D coordinates of 25 joints, including the 17 Human3.6m joints.

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Figure 7. Dataset included in the fit3D Dataset

The dataset created from the fit3d Dataset treats mainly sport movements, focusing on the squats, but in the original dataset, we can also find other movements and types of data with information from other movements, videos from the movements, camaras information and types of data to store movement.

During the first few weeks, the experiment was anchored in this point, since other datasets were initially considered but did not meet the objectives described in phase 1. Datasets like the SportsPose dataset, UCF101 dataset or the MPII Dataset were select at the beginning for consideration. Reason like the complexity to understand the content of the dataset or the lack of information, incomplete codebook, lack of 3D Skeleton data and low quality of the dataset were decisive to reject them and use the fit3D dataset. Therefore, it is recommended to have an agreement with an institution, which provides us the data, or if possible in any other case, obtain such data by oneself. We were creating data using the Optitrack System, but the complexity of the results obtained, and the lack of time were reasons to decide to don’t implement the data obtained in this research, but use it in future work.

**3.2 Data Preparation and Modelling**

This part of the experiment will show the technique used after understanding which one would be the most correct and suitable for this problem, so it could vary depending on the focus that is being sought to achieve the goals and does not follow always a constant pattern.

The core of this project focuses on the feature engineering, which will be carried out in the data preparation phase. By means of feature engineering, a new dataset was created from the original, having a certain number of features after a detailed study of which one of the features would give us greater information, and eliminating those whose weight was smaller or contained redundant information. After this, the squat movement features were selected to create the new dataset, and the correctness as the target, as it is the topic we would like to understand, what describes better the correctness of a movement. We selected the squat movement because its complexity, as it involves upper and lower body parts in the movement.

Finally a total of 105 columns were selected to be implemented dimensionality reduction, containing the main coordinates for all the different landmarks, the angles between the different landmarks and as well the correctness label. To achieve this, a great deal of time was invested in applying different combinations of techniques, both processing and modeling, moving between these phases again and again until the best technique combination was found, thus obtaining the best performance for our algorithms (even when this project was not intended). It was considered that it would be important to show a correct processing of the dataset for future research, therefore this process is shown below.

**3.2.1 Preliminary Steps**

First of all, we assume that all the different elements are normalized and are numbers. The original dataset had a json format, therefore we had to transform the json file into a dataframe, using the functions process\_json\_files and calculate\_angles.

A screenshot of a phone

Description automatically generated with medium confidence

Figure 8. Raw data transformed into a dataframe with own defined functions.

With the dataframe obtained, we can verify whether the dataset is imbalanced. Since the subject S08 is the trainer, the data related to this subject was selected as correct, and as a first approach, the rest of the data was defined as incorrect.

**3.2.1.1 Imbalanced dataset**

The dataset exhibits an imbalance due to having only one trainer among a total of eight subjects. This observation highlights the need to address the issue of class imbalance. Considering the trainer's movements as the reference for correctness, it is noteworthy that only 11.51% of the total rows are classified as correct in this initial analysis.

To tackle this challenge, we will employ various techniques such as error calculation using MJPE (Mean Joint Percentage Error) and MAPE (Mean Angle Percentage Error), as well as oversampling of the minority class. These approaches aim to mitigate the impact of class imbalance and enhance the effectiveness of the subsequent analysis.

A red and blue bar graph

Description automatically generated with low confidence

Figure 9. Imbalanced dataset.

Therefore, for a correct operation of the algorithms, the dataset had to be treated and for that purpose resampling techniques were applied. It will be done through oversampling techniques, to obtain a better performance of our classification algorithms in the moment of fitting the model.

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Figure 10. Dataframe treated with imbalanced data using own defined funtions

After the creation of synthetic data, the discriminated class was oversampled, obtaining a 20.64% of data for the correct data. Even though the dataset is still imbalanced, it is consider slighlty imbalanced. We will continue working on this problem when we are able to understand the error. To understand how to calculate the error, first we need to understant the problem with the lengths of the videos.

**3.2.1.2 Sequence alignment**

In our dataset, we have multiple subjects performing movements at different velocities, in our dataframe we can appreciate it with the number of the rows or frames. To accurately compare and evaluate the correctness of these movements, we need to align the frames between subjects. This alignment is crucial for calculating error metrics such as Mean Joint Percentage Error (MJPE) and Mean Angle Percentage Error (MAPE). Our strategy focuses on preprocessing the data, detecting sequences, and aligning them to ensure consistent frame comparisons.

We detect the sequences by identifying the moments when a subject performs a squat. By analyzing the angles, we locate the frames with the lowest angles for the connections between the hip, knee, and ankle. These frames represent the lowest points of each squat sequence.

To align the sequences, we determine the highest angle before and after the lowest angle frame for each sequence. These points mark the start and end frames of the sequence. However, since sequences may vary in length due to different subject velocities, we standardize the sequence length to ensure fair comparisons.

To achieve consistent sequence lengths, we extract a fixed number of rows for each half sequence. By using the function linspace, we calculate the jump size, which determines the frames to be extracted. This approach guarantees that each half sequence will have the same length, regardless of the original number of frames.

We repeat this alignment process for all subjects, including trainers and trainees. For the training dataset, we aim to obtain five aligned sequences per subject, with each sequence comprising 32 frames (16 frames per half sequence).

With the aligned sequences, we can now calculate the MJPE and MAPE by matching frames on a 1-to-1 basis between the trainer and each trainee at corresponding moments. These error metrics provide quantitative measures of the correctness of movements, allowing us to assess the accuracy of trainees compared to the trainer and to define different level of correctness of a movement based on the error.

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Figure 11. Aligned sequences calculated from balanced dataframe

**3.2.1.3 Calculating Errors**

To assess the accuracy of movements, we employ error metrics such as Mean Joint Percentage Error (MJPE) and Mean Angle Percentage Error (MAPE). These metrics allow us to calculate the discrepancies between the trainer's movements and those of each trainee on a frame-by-frame basis. By comparing the errors, we can categorize each frame as correct, nearly correct, or incorrect based on predefined thresholds. This classification provides insights into the accuracy of trainees' movements in relation to the trainer's, enabling us to evaluate their performance and identify areas for improvement.

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Figure 12. Calculate errors and merge dataframes

Now that we have obtained the necessary attributes in our updated dataframe, we can proceed with the classification of each frame based on the errors. By analyzing the errors, we can determine whether a particular frame is classified as correct or incorrect, providing valuable insights into the level of correctness at different moments or executions. We coud as well now identifiy a new level for classification, almost correct.

To establish meaningful thresholds for classification, we will plot the errors per subject.

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Figure 13. Distribution of Angle and Coordinate Errors per subject

After carefully evaluating the errors and their relevance to our analysis, we have come to the realization that relying solely on the coordinates may not be the most effective approach for determining the correctness of a movement. Upon closer examination, we have observed that the SInter, which represents synthetic data generated from a correct movement, exhibits remarkably low angle errors.Additionally, we have identified Subject S07 as the closest match to the correctness defined by the trainer, suggesting that their movements can also be classified as correct.

**3.2.1.4 Production extra synthethic data**

As we are lacking data and we can realise that the production of synthethic data is working properly, we are going to generate three more synthetic elements. Observing the graphic we are going to take the s04, s05 and s07 because the difference in the error between them can be easily appreciated. This will help us, at the moment of testing our model.

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Figure 14. Steps 2, 3 and 4 are implemented on S04, S05 and S07.

**3.2.1.5 Update correctness**

In light of these findings, we have updated our classification groups as follows:

* Angle error between 0 and 10: Correct
* Angle error between 10 and 20: Almost correct
* Angle error greater than 20: Incorrect

By incorporating angle errors into our classification criteria, we aim to provide a more comprehensive and accurate assessment of movement correctness.

We will now visualize the distribution of our data through a graph to assess if the error analysis has resulted in a more balanced dataset. The dataset has undergone necessary preprocessing steps to ensure its suitability for algorithmic analysis. Our goal is to examine if the distribution of different correctness groups has improved, indicating a more balanced representation of the data and enhancing the performance of the algorithms.

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Figure 15. Correctness on the data updated

**3.2.2 Model 1**

Before proceeding feeding the models and implementing feature selection, it is important to define the criteria for determining the importance of dimensions. In this case, our objective is to identify the parts of the body that are important for the squat movement. Therefore, we can exclude certain dimensions that are unlikely to provide us with this specific information.

For example, dimensions such as "Subject" or "Errors" may not directly contribute to identifying the joints or body parts involved in the squat. These dimensions are more related to other factors, such as the specific individuals performing the squat or the errors in the movement calculation.

By dropping these dimensions, we can focus on the dimensions that directly represent the angles and coordinates of different movements, which are more likely to capture the information we need to understand the importance of different body parts in the squat.

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Followint the use case 1 in the research, a CNN model is going to be developed and trained to calculate the correctness with the whole dataset.

CNNs are a type of artificial neural network that are primarily used for image recognition and processing, but they can also be used for other types of data, such as audio, video, and text. For example, you can use a CNN to classify text data, such as in natural language processing tasks like sentiment analysis or language translation. Additionally, you can use a CNN to process and analyze time series data, such as sensor data or financial data. The key is to represent the non-image data in a way that the network can understand and process, such as converting audio to spectrograms or text to word embeddings.

The CNN defined was trained and executed for a total of 100 epochs. The results will be explained in the next chapter.

**3.2.3 Dimensionality Reduction**

Dimensionality reduction is a technique used in machine learning and data analysis to reduce the number of input features or variables in a dataset. The high dimensionality of data can often lead to challenges such as increased computational complexity, overfitting, and difficulty in visualization.

Dimensionality reduction methods aim to transform the original dataset into a lower-dimensional representation while preserving important information or patterns present in the data. These methods can be broadly categorized into two types: feature selection and feature extraction.  
  
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Description automatically generated

Figure 16. Image showing a briefly explanation of Dimensionality Reduction

**3.2.3.1 Feature Selection**

Feature selection is the process of reducing the number of input variables when developing a

predictive model. Statistical-based feature selection methods involve evaluating the relationship

between each input variable and the target variable using statistics and selecting those input variables that have the strongest relationship with the target variable.

Before exploring the relationship between the dimensions and the target dimension, we need to transform the "Correctness" dimension in our dataset into numerical values. This conversion is necessary to facilitate the analysis and understanding of the data.

To begin, we will utilize the concept of feature importance, which helps us determine the significance of each dimension in predicting the target variable. Specifically, we will employ the feature importance scores obtained from tree-based models. By training a decision tree on our dataset, we can extract these importance scores, which are tailored specifically for classification tasks. These scores provide insights into which dimensions carry the most information and have the strongest influence on predicting the correct class.

In addition to the feature importance approach, we will also utilize analysis of variance (ANOVA) as a second method to gain insights into the variance within the dataset. ANOVA enables us to assess the statistical significance of the relationships between the dimensions and the target dimension. It helps us determine if there are any significant differences in the means of the dimensions across different classes of correctness.

By combining these two methods, we can gain a comprehensive understanding of the importance of different dimensions and their impact on predicting the correctness of the target dimension. This analysis allows us to make informed decisions about feature selection and prioritize the dimensions that contribute the most to the prediction task.

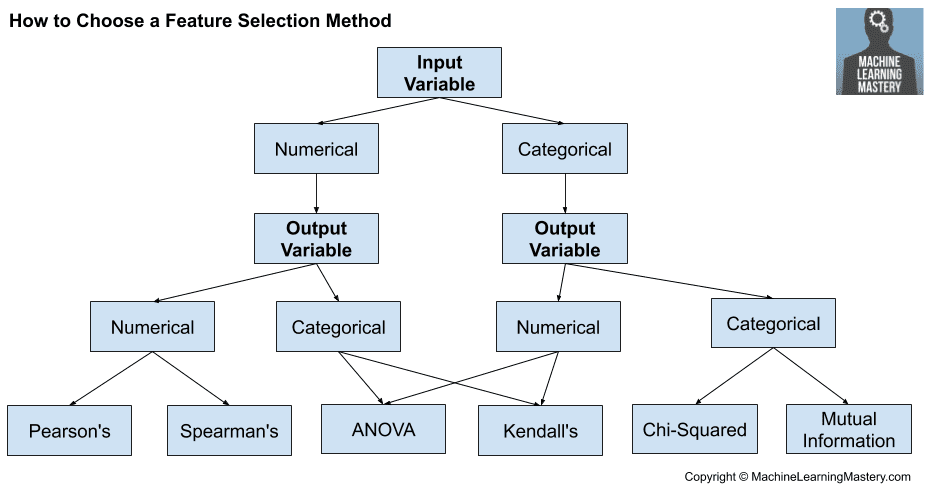


Figure 17. How to choose feature selection methods

**3.2.3.1.1 Random Forest**

In tree-based models, feature importance is a measure of the contribution of each feature in the model's decision-making process. It helps identify which dimensions are most informative or influential in predicting the correct class or target variable.

When a decision tree is built, it makes a series of splits at each internal node based on different features. The splits are chosen to maximize the separation or purity of the target classes in the resulting subsets. The feature that contributes the most to reducing impurity or increasing purity at each split is considered more important.

The feature importance scores can be normalized to sum up to 1 or scaled to a specific range, depending on the implementation. These scores help you understand which dimensions have the most significant impact on the model's predictions. Features with higher importance scores are considered more influential in determining the correct class, as they contribute more to the overall predictive power of the model.

By analyzing the feature importance, you can gain insights into the underlying relationships between the input dimensions and the target variable. It allows you to focus on the most relevant features and potentially improve the model's performance by selecting a subset of informative dimensions or by prioritizing feature engineering efforts.

However, it's important to note that feature importance scores from tree-based models should be interpreted with caution. They reflect the model's internal decision-making process and may not capture complex interactions or dependencies between features. That's the reason, the results will be compared with the results from ANOVA to compare if we have similar importance dimensions.

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Description automatically generated

Figure 18. Random Forest implemented and most relevant features selected.

The results reveal that the top features predominantly consist of angle measurements, specifically those related to the joints in the upper body. Notably, the angles involving the arms, shoulders, upper and lower back, and the connection between the neck, head, and head top exhibit significant importance in determining the correctness of the squat.

**3.2.3.1.2 ANOVA**

ANOVA (Analysis of Variance) is a statistical test used to compare the means of two or more groups to determine if there are statistically significant differences between them. It assesses whether the variation between group means is larger than the variation within each group.

ANOVA helps us to understand if there are significant differences in the means of certain dimensions (features) across different levels of the "Correctness" variable (target dimension). ANOVA will help us identify which dimensions have a strong relationship with the target variable, indicating their importance for predicting correctness.

Our results are sorted in descending order of the F-statistic and ascending order of the p-value to prioritize dimensions with larger F-statistics and lower p-values, indicating stronger relationships and statistical significance. The sorted results are printed, showing the dimensions with their corresponding F-statistics and p-values.

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Figure 19. Anova implemented and most relevant features selected.

The ANOVA results reinforce the significance of angles in determining the correctness of movements. The top features obtained from ANOVA, similar to the previous feature importance results, predominantly consist of angles. This consistency indicates that angles play a crucial role in identifying the correctness of movements. By extracting the common features from both lists, we can further explore and analyze their impact on determining movement correctness.

The results indicate that the angles play a crucial role in understanding the correctness of the movement. The top features are primarily concentrated in the upper body region, including the shoulders, elbows, wrists, and the connections between them. Additionally, the angles related to the spine and hip are also significant. Notably, the coordinates of the body parts align with the angles, emphasizing the importance of the top part of the body and spine, with a notable exception for the right toe. Therefore, we will focus on selecting the top angles from the ANOVA and Random Forest results to proceed with the PCA analysis.

A screenshot of a computer program

Description automatically generated with low confidence

Figure 20. Top elements from both resulst are selected

**3.2.3.1 Feature Extraction**

Feature extraction is a crucial step in data analysis and machine learning tasks. It involves transforming raw data into a representative set of features that capture the essential information and patterns within the data. These features serve as inputs to machine learning algorithms for training and prediction. Feature Extraction algorithms, which are a little bit more complex in comparison with feature selection, but at the same time are the proper ones if we are trying to discriminate values in a dataset with the intention of classifying. With Feature Extraction, we build combinations of the variables, solving the dimensionality problem, and still describing the data with sufficient accuracy.

**3.2.3.1.1 PCA**

Principal Component Analysis is a dimensionality reduction technique that transforms the original dimensions into a new set of uncorrelated variables called principal components. These components capture the maximum variance in the data, allowing you to represent the data with fewer dimensions. Generally speaking, we are going to search the bigger variance between our points. Most of the variance in your dataset would be explained by a small number of components, usually in 10% of the data can we find 95% of the variance.

Once we have obtained the dataframe with the selected features from the feature selection process, the next step is to normalize the data. Normalization is important to ensure that all the features are on a similar scale and have a similar range of values. Normalization can be achieved by applying a scaling technique such as standardization. Standardization transforms the data to have a mean of 0 and a standard deviation of 1.

After normalizing the data, we can proceed with applying PCA to generate the synthetic dimensions. In our case, we will generate three principal components using PCA. These components will be added to the original feature set, resulting in an expanded feature matrix. Each sample in the dataset will now be represented by the original features as well as the values in the three PCA dimensions.

By incorporating the PCA dimensions into the input data for the CNN, we provide the model with a more comprehensive representation of the data. The CNN can then learn to extract meaningful features from the combination of original features and synthetic dimensions, enhancing its ability to understand the correctness of the squat movement.

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Description automatically generated

Figure 21. PCA dimensions and feature selection subset is merged.

BBy observing the plot, we can make some observations about the separation between the classes:

* There is some overlap between the "Correct" and "Almost correct" classes, as we can see areas where the green and blue points are close to each other. This suggests that these two classes share some similarities in their PCA dimensions.
* The "Correct" class appears to be more distinct and separate from the other two classes. We can see regions where the red points are relatively isolated from the green and blue points.
* The distribution and arrangement of the data points in the 3D space provide insights into the relationship between the PCA dimensions and the correctness labels. It appears that certain combinations of PCA values are more associated with a specific correctness label.

We can realise that the PC dimensions, created from the feature selection, help us to understand and recognise correctnes. These dimensions are going to be added to the angles dataframe with the selected features and will be used to train the CNN model.

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Description automatically generated

Figure 22.PCA dimensions showing the separation between classes.

**3.2.4 Model 2**

A second model is going to be trained to process the information with reduced data and compare the results with the results obtained with the first model. The normalized data is going to be used to train our model as we did in the first part of the research. The results from the cnn models is going to be explained and analysed in the chapter results.

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Figure 23. Trained second model with reduced data

**3.2.5 Deployment**

In our case are the results obtained will be explained in the next section. The files used in this experiment will be attached with this Project. This phase is going to be developed in the next block.

# Resultados

This block will focus on explaining the results obtained in this experiment for each of the two use cases implemented. As it is a classification problem the appropriate techniques to measure are the Accuracy, F1-score and Confusion Matrix.

* Accuracy simply measures how often the classifier correctly predicts. We can define accuracy as the ratio of the number of correct predictions and the total number of predictions.
* F1 Score: explains how many of the actual positive cases we were able to predict correctly with our model. It is a useful metric in cases where False Negative is of higher concern than False Positive. It *is important in medical cases where it doesn’t matter whether we raise a false alarm but the actual positive cases should not go undetected.*
* Confusion Matrix: *Confusion Matrix is a performance measurement for the machine learning classification problems where the output can be two or more classes. It is a table with combinations of predicted and actual values.*

Other parameters were used to understand the learning process of the models was the Loss. We could go deeper in this field, but it is not the aim of the experiment.

# 4.1 Use Case 1: Base case no Dimensionality Reduction Applied

As we need to compare our results to measure the performance, the first situation we are going to find is the base case without performing any Dimensionality Reduction algorithms.

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Figure 24. Accuracy and loss for the base use case

In figure 24 we can appreciate the results for the model 1 trained with the dataset with all the dimensions. Our model needed 3.07 seconds to train with the whole dataset. All the coordinates and angles were used, in total 100 columns. The results are good and we can see how the model learns to classify the correctness of the different frames. Around the epoch 20 achieves a 0.8 accuracy and reaches 0.88 after 80 epochs. We can realize that the model is improving its accuracy gradually until it reaches the 80 epochs, then it doesn't achieve a better score. The loss as well gradually decrease until it reaches the bottom as well around 80 epochs. After testing the model, the accuracy obtained is 0.891 accuracy and 0.902 f1 score.

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Description automatically generated

Figure 25.Confusion matrix for base use case

We can see that the results fort he incorrect elements is pretty accurate, with only 4 errors.for the almost correct element is as well pretty accurate, with 101 elements correctly classified and 3 wrong classified. In contrast the correct elements ist the class with less accuracy. A total of 100 element were properly classified, but 29 classified wrong classified, with 21 classified as incorrect. From our perspective, as we are trying to find the correctness in the movements and apart of sports this tool can be used as well in medical environment, the consideration that a movement incorrect is classified more accurate as incorrect, is more important that a correct movement classified as incorrect. In the case a patient would be doing a exercise incorrect and getting a feedback as correct, could lead to a wrong recovery for example. In the other case a correct movement classified as wrong is not dramatically and the patient could ask for assistant. The same situation could be applied in sports. We expect in a future this problems to be solved.

# 4.2 Use Case 2: Use case with Dimensionality Reduction Applied

The second part of the experiment was implemented with the reduced dataset and a new CNN model.

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Description automatically generated

Figure 26. Accuracy and loss for the experimental use case.

The training process of the model was completed in approximately 1.70 seconds for 100 epochs. During this period, we observed that the model exhibited a gradual improvement in minimizing the difference between the predicted and actual values. This can be seen in the decreasing trend of the loss values over the epochs, indicating that the model is learning and becoming more accurate in its predictions.

Notably, the accuracy of the model also showed significant progress throughout the training. After the initial phase, the accuracy steadily increased, reaching its highest and lowest points around the 10th epoch. This suggests that the model is continuously improving its performance and becoming more adept at correctly classifying the data.

When comparing this model with the one trained using all dimensions, we observed a remarkable difference. The model trained with the selected dimensions achieved its highest accuracy of 0.9 in just 10 epochs, while the model using all dimensions required 90 epochs to reach a similar accuracy level. Additionally, the training time for the model with selected dimensions was notably faster, taking only 1.70 seconds compared to the 3.07 seconds of the model with all dimensions, which means that the second model trained 45% faster. This implies that by choosing the appropriate dimensions, we can significantly enhance both the training speed and accuracy of the model.

The second model shows slight improvements in accuracy and F1 score compared to the first model. The accuracy and F1 score remain the same at 0.943, while we had 0.891 accuracy and 0.92 f1-score with the model containing all the dimensions, indicating a 5% improvement.

# 

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Figure 27.Confusion matrix for the experimental use case.

The confusion matrix also reflects these improvements, with higher accuracy for the correct and nearly correct classes, but slightly lower accuracy for the incorrect class. Overall, the results demonstrate better performance than the first model, suggesting the potential for implementing these algorithms in future research endeavors and confirming the potential that dimensionality reduction algorithms have implemented with 3D Skeleton data.

# Conclusiones y trabajos futuros

Este capítulo debe incluir:

* Una descripción de las conclusiones del trabajo:
  + ¿Una vez se han obtenido los resultados qué conclusiones se extrae?
  + ¿Estos resultados son los esperados? ¿O han sido sorprendentes? ¿Por qué?
* Una reflexión crítica sobre la consecución de los objetivos planteados inicialmente:
  + ¿Hemos alcanzado todos los objetivos? Si la respuesta es negativa, ¿por qué?
* Un análisis crítico del seguimiento de la planificación y metodología a lo largo del producto:
  + ¿Se ha seguido la planificación?
  + ¿La metodología prevista ha sido suficientemente adecuada?
  + ¿Ha sido necesario introducir cambios para garantizar el éxito del trabajo? ¿Por qué?
* De los impactos previstos en 1.3 (ético-sociales, de sostenibilidad y de diversidad), evaluar/mencionar si se han mitigado (si eran negativos) o si se han logrado (si eran positivos).
* Si han aparecido impactos no previstos en 1.3, evaluar/mencionar cómo se han mitigado (si eran negativos) o qué han aportado (si eran positivos).
* Las líneas de trabajo futuro que no han podido explorarse en este trabajo y han quedado pendientes.

This research highlights the significant impact of dimensionality reduction algorithms, such as Random Forest and PCA, on 3D skeleton data analysis. By effectively reducing the number of dimensions, these algorithms not only improve training time but also yield remarkable enhancements in accuracy, training time and use of resources. We were able to prove that the dimensionality reduction algorithms can be implemented on 3D Skeleton data, detecting the important dimensions to understand the correctness of specific movements, improving the accuracy for DNN models when classifying correctness and reducing the use of resources. Random Forest provides insights into the influential dimensions for predicting correctness, while ANOVA helps identify dimensions with strong relationships to the target variable. Moreover, PCA transforms the original dimensions into uncorrelated variables that capture maximum data variance, effectively representing the data with fewer dimensions.

As well we understood how important is to follow a proper methodology like CRISPDM to carry out machine learning projects. Using the methodology, we could understand how important is to preprocess properly the data and a big part of the time invested in this research was used in the initial phases “Business Understanding”, “Data Understanding”, “Data Preparation” and “Modelling”.

As expected, we have obtained pretty good results, but as well we have discovered the huge challenge that is working with this kind of data. Not only the complexity of working with data in 3D space, preparing the data to be able to work it and calculate the errors between the same frames for videos with different lengths consumed several weeks of our work. As well the implications of other areas like biomechanics, showed us that future researchers should have to understand the biomechanics of the body or if possible, count with an expert in the area when working in the field of computer vision and sports. Additionally, the generation of synthetic data plays a vital role in addressing dataset imbalances and augmenting training sample sizes. Through interpolation techniques, synthetic data creation effectively enhances model performance by ensuring a more balanced representation of the target classes.

We have successfully reached the goals defined at the beginning of this project:

* A deep learning based model like CNN for pose comparison was developed and we have evaluated its performance and accuracy, in compare with a second CNN model.
* We have identified the key dimensions in the dataset that enable accurate and efficient pose comparison.
* Certain specific conditions and correlations of a pose, within the selected body part were found. In this case, detected the importance of the upper body parts and spine with hips when doing squats.
* We have explored and understood the data to be able to apply the correct dimensionality reduction techniques.
* A strategy and best techniques were developed and implemented to improve and understand pose comparison.

Throughout the course of this research, we encountered several challenges and complexities. One of the primary issues we faced was the scarcity of 3D Skeleton data available. While various datasets exist, they often lacked quality, documentation, or specific information required for our project, particularly for movements like the squat exercise. As a result, we had to generate our own data to ensure accuracy and relevance. Despite these hurdles, we successfully completed the project by adapting our methodology along the way.

One significant modification we made was focusing on a single model for pose comparison, specifically using CNN. Initially, we had intended to explore the use of Transformers or LSTM to better understand movement sequences and spatial relationships between points.

As well because of lack of time we were not able to implement other types of dimensionlaity reduction techniques like LDA or Pearson.

Through this research, we have successfully reduced resource consumption and mitigated the negative environmental impact associated with AI technologies, particularly in terms of CO2 emissions. The implementation of these technologies not only benefits the environment but also has a positive social impact by improving systems that support human health preservation and improvement. The dataset used in our study consisted of diverse subjects, including individuals of different genders, heights, and body types. However, for future research, it is recommended to obtain more diverse datasets that include subjects from various races and backgrounds to minimize biases. It is important to note that all subjects in the dataset were represented by numerical identifiers, ensuring the privacy and anonymity of their personal information.

This research serves as a stepping stone for future investigations in several directions. Exploring alternative models holds promise in comprehending the underlying sequential patterns of movement sequences, going beyond the limitations of frame-level analysis. Additionally, the alignment and sequence extraction algorithms employed here can be harnessed for other projects requiring video sequence normalization, providing the basis for further analysis and comparisons across diverse movement sequences.

I hope future students and researchers can use this code and that the research helps them providing a solid framework to build upon. By improving the existing models, refining the code implementation, and delving into additional functions, there is ample room to advance the field.

# Glosario

Definición de los términos y acrónimos más relevantes utilizados en la Memoria.

# Bibliografía

Lista numerada de las referencias bibliográficas utilizadas en la memoria. En cada lugar donde se utilice una referencia dentro del texto, debe indicarse citando el número de la referencia, por ejemplo: [7].

Es muy importante incluir **todas** las referencias utilizadas y citarlas apropiadamente, es decir, incluyendo toda la información necesaria para identificar la referencia. La información mínima a incluir según el tipo de referencia es:

* **Libro**: Autores, Título, Edición (en su caso) Editorial, Ciudad, Año.
* **Artículo de revista**: Autores, Título, Nombre de la Revista, Número de Página inicial y final, Número de la revista / Volumen, Año.
* **Web**: URL y fecha en la que se ha visitado.

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# Anexos

Listado de apartados que son demasiado extensos para incluir en la memoria y tienen un carácter autocontenido (por ejemplo, manuales de usuario, manuales de instalación, etc.)

Dependiendo del tipo de trabajo, es posible que no sea necesario añadir ningún anexo.