MULTIMEDIA DATA ANALISYS FOR EMOTION RECOGNITION

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MOTIVATION OF THE WORK

The motivation that has led to the choice of this area of knowledge for the Doctoral Thesis is threefold:

- The communication of emotions is crucial for social relationships and survival (Ekman, 1992), and the voice is possibly one of the main channels for conveying them. Therefore, it is vital to have systems that allow automatic recognition of the emotions of people through this signal, which also have a wide range of aplications including notably:
  - oHuman-computer interface.
  - o It helps human-human communication.
  - o eHealth, especially in the area of mental health.
  - o Managing voice files.

- It is a field of research much less developed than the automatic speech recognition.

- The rapid development in machine learning, especially with regard to the Deep Neural Networks. The possibility of applying these new techniques in the field of automatic recognition of emotions will open many lines of research with promising results.

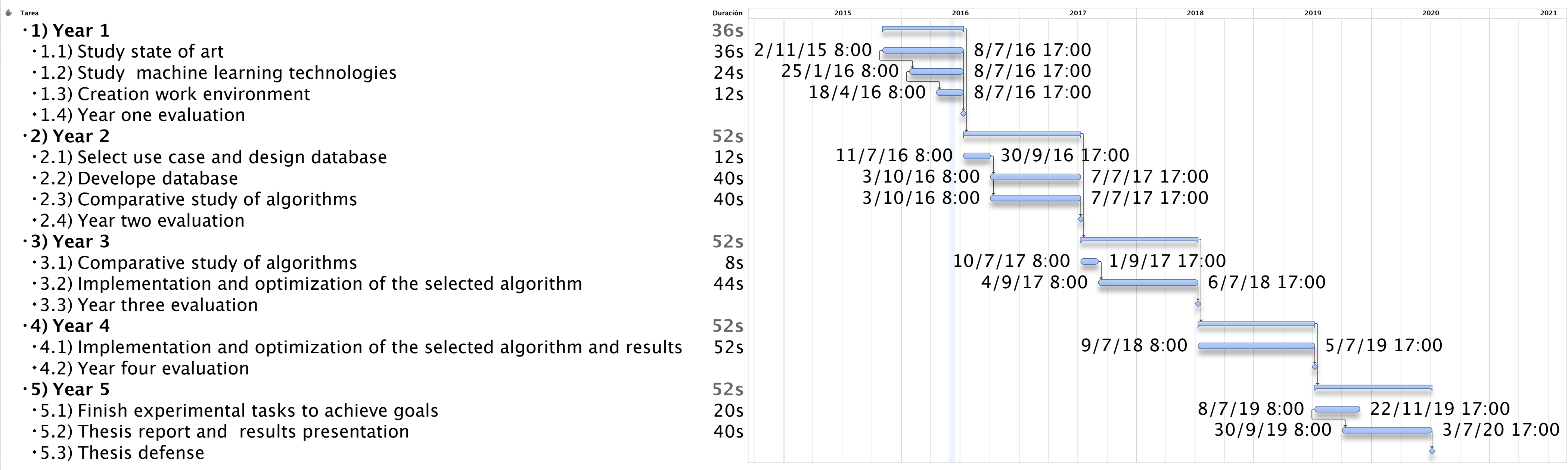
THESIS OBJECTIVES

Develop a methodology that allows to detect the emotions of the people through multimedia data.

SECUNDARY OBJECTIVES

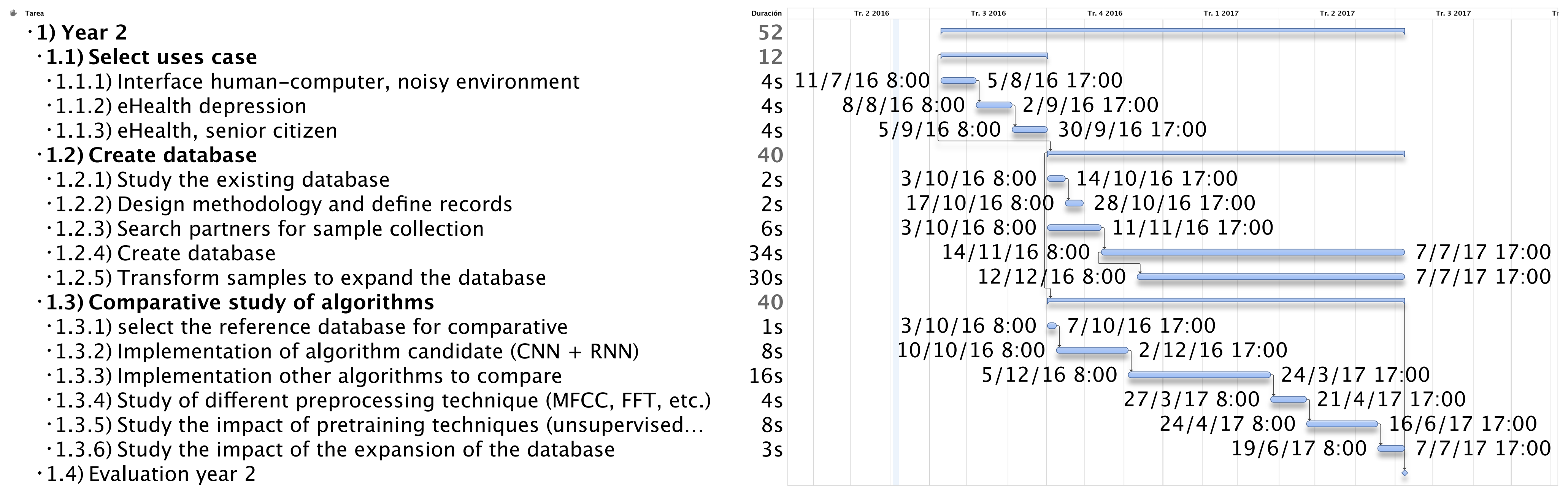
- Detect cases of use in which emotion recognition have an application of interest.
- Select multimedia records that they are interesting for the resolution of the problem: voice, image, movement records, etc.
- If it is necessary, we will create a new database enabling us to innovative results.
- Detect those algorithms and/or methodologies that they have the better behavior to solving the problem.
- Improve, if it is possible, the behaviour of the selected algorithms.
- Define an architecture that enables in real-time to solve these problems.

RESEARCH PLAN



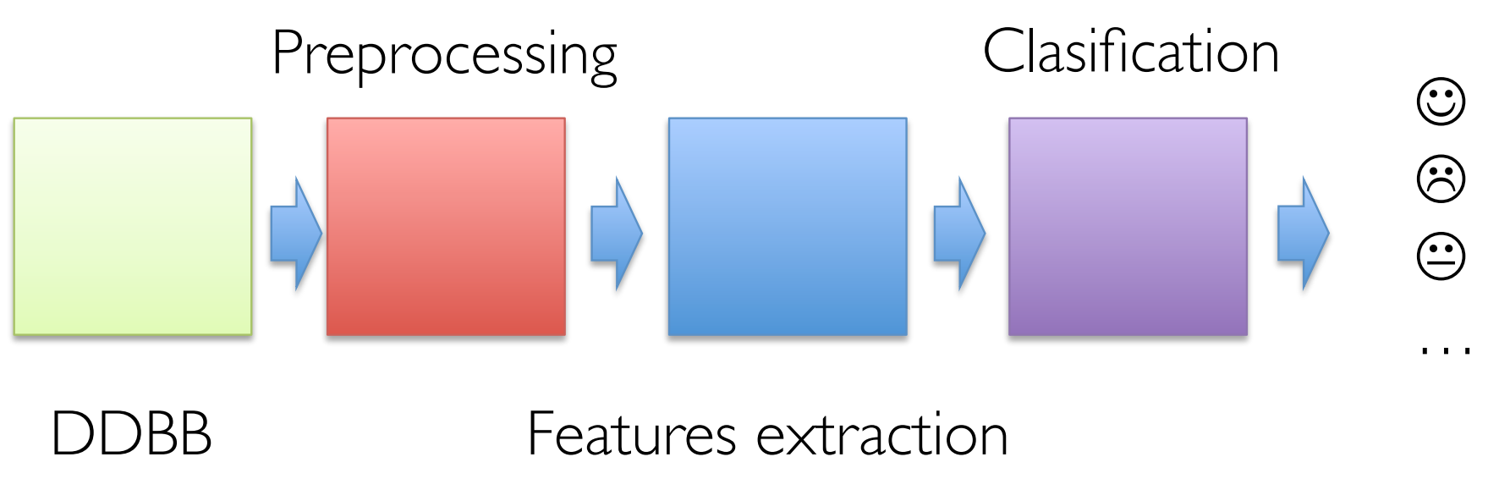
Tarea	Duración		
1) Year 1	36s		
1.1) Study state of art	36s	2/11/15 8:00	8/7/16 17:00
1.2) Study machine learning technologies	24s	25/1/16 8:00	8/7/16 17:00
1.3) Creation work environment	12s	18/4/16 8:00	8/7/16 17:00
1.4) Year one evaluation			
2) Year 2	52s		
2.1) Select use case and design database	12s	11/7/16 8:00	30/9/16 17:00
2.2) Develope database	40s	3/10/16 8:00	7/7/17 17:00
2.3) Comparative study of algorithms	40s	3/10/16 8:00	7/7/17 17:00
2.4) Year two evaluation			
3) Year 3	52s		
3.1) Comparative study of algorithms	8s	10/7/17 8:00	1/9/17 17:00
3.2) Implementation and optimization of the selected algorithm	44s	4/9/17 8:00	6/7/18 17:00
3.3) Year three evaluation			
4) Year 4	52s		
4.1) Implementation and optimization of the selected algorithm and results	52s	9/7/18 8:00	5/7/19 17:00
4.2) Year four evaluation			
5) Year 5	52s		
5.1) Finish experimental tasks to achieve goals	20s	8/7/19 8:00	22/11/19 17:00
5.2) Thesis report and results presentation	40s	30/9/19 8:00	3/7/20 17:00
5.3) Thesis defense			

NEXT YEAR PLANNING



Tarea	Duración		
1) Year 2	52		
1.1) Select uses case	12		
1.1.1) Interface human–computer, noisy environment	4s	11/7/16 8:00	5/8/16 17:00
1.1.2) eHealth depression	4s	8/8/16 8:00	2/9/16 17:00
1.1.3) eHealth, senior citizen	4s	5/9/16 8:00	30/9/16 17:00
1.2) Create database	40		
1.2.1) Study the existing database	2s	3/10/16 8:00	14/10/16 17:00
1.2.2) Design methodology and define records	2s	17/10/16 8:00	28/10/16 17:00
1.2.3) Search partners for sample collection	6s	3/10/16 8:00	11/11/16 17:00
1.2.4) Create database	34s	14/11/16 8:00	7/7/17 17:00
1.2.5) Transform samples to expand the database	30s	12/12/16 8:00	7/7/17 17:00
1.3) Comparative study of algorithms	40		
1.3.1) select the reference database for comparative	1s	3/10/16 8:00	7/10/16 17:00
1.3.2) Implementation of algorithm candidate (CNN + RNN)	8s	10/10/16 8:00	2/12/16 17:00
1.3.3) Implementation other algorithms to compare	16s	5/12/16 8:00	24/3/17 17:00
1.3.4) Study of different preprocessing technique (MFCC, FFT, etc.)	4s	27/3/17 8:00	21/4/17 17:00
1.3.5) Study the impact of pretraining techniques (unsupervised…	8s	24/4/17 8:00	16/6/17 17:00
1.3.6) Study the impact of the expansion of the database	3s	19/6/17 8:00	7/7/17 17:00
1.4) Evaluation year 2			

RESULTS



Preprocessing

Clasification

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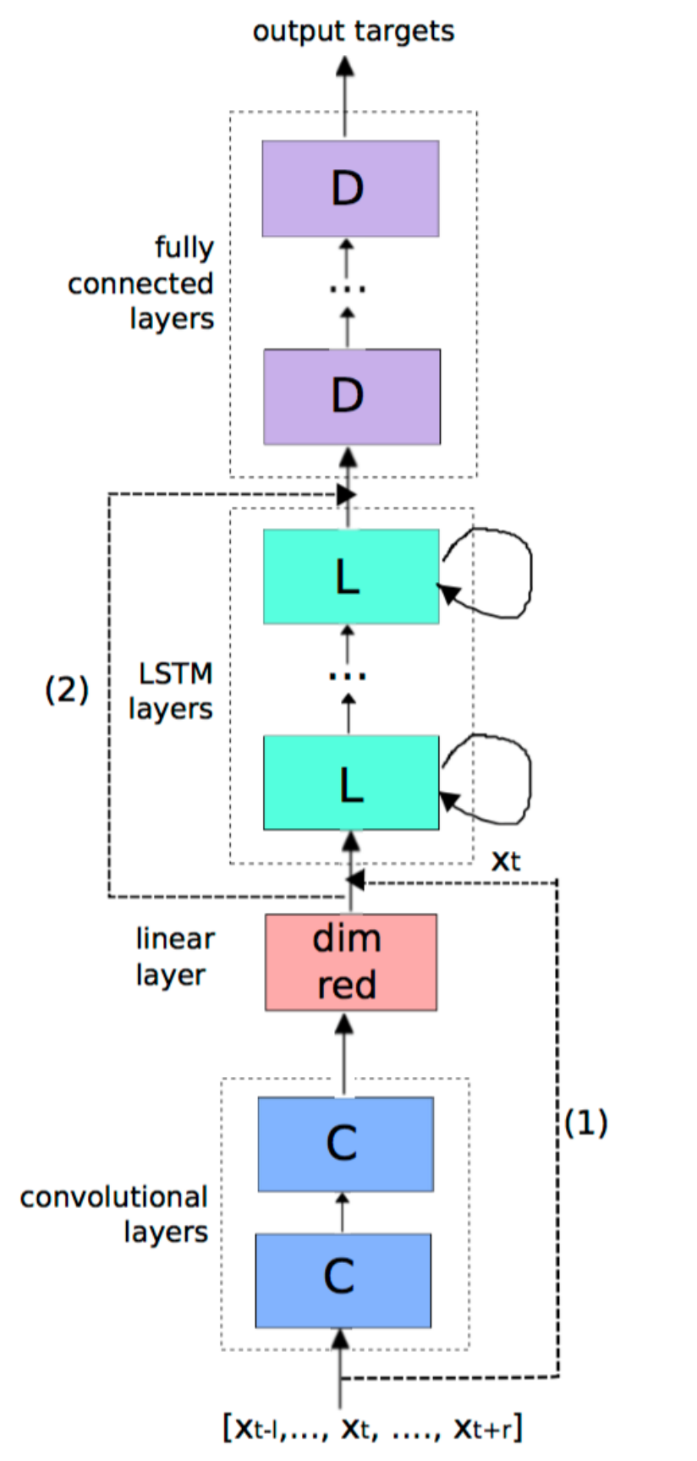
☹
😐
…

DDBB

Features extraction

DDBB: Extend with transformations and adding noise
Preprocessing: FFT, Mel scale, log transformation, multiwindow.
Features extraction: Pretrainning (autoencoder), choose pooling, activation, architecture, Inception, optimization algorithm,…
Clasification: choose architecture, optimization algorithm,….



CLDNN Architecture [12]

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