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IN ENGINEERING

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GenBot

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Acknowledgments

If any

Acronyms

AGI

Artificial General Intelligence.

AI

Artificial Intelligence.

AIML

Artificial Intelligence Markup Language.

ANI

Artificial Narrow Intelligence.

ANN

Artificial Neural Networks.

BD

Big Data.

DL

Deep Learning.

DM

Data Mining.

DNN

Deep Neural Networks.

FAQ

Frequently Asked Questions.

ICT

Information and Communications Technologies.

IR

Information Retrieval.

ML

Machine Learning.

Acronyms

MRU

Master Research Units.

NLP

Natural Language Processing.

NLU

Natural Language Understanding.

Sci-Fi

Science Fiction.

Abstract

In the scope of this deepening project, and as the technology of NLP is in constant evolution, we will be focusing on the exploration of the word embedding algorithm Word2Vec, which is, at the beginning of 2019, commonly used as a foundation for DNN Chatbots. As a result to this project, the student is demonstrating what is the Word2Vec technology, its extensions, and its applications.

Keywords: Word Embedding, Word2Vec, Natural Language Processing (NLP), Natural Language Understanding (NLU), Machine Learning (ML), Data Engineering, Conversational Agent, Chatbot, Generic

Chapter 1

Introduction

Beginning of 2019, chatbots are everywhere but very limited to narrow tasks, and are, in most cases, sequences of if-else conditions resulting in a very weak Artificial Intelligence (AI). Indeed, hard-coded connections are requiring an infinite amount of human power to create generic Chatbots able to maintain a conversation at a human level. However, the progress in the field of ML is demonstrating that providing large corpora to an unsupervised algorithm is enough to maintain a passive conversation with users, which results into a shifting of the human power into data engineering. Multiple algorithms and technics are emerging monthly, which are demonstrating promising conversational performance improvement; however, they are all still narrow AI. Indeed, even if they are getting better at providing meaningful sentences, they are still not able to generalize all tasks linked to a conversation, such as, understanding the context, search and learn for missing information, initiate conversation in a meaningful manner, be intuitive, and more. The generalization of those features would allow a significant step forward into general Chatbots.

1.1 Aim of Study

In harmony with the author interest, the goal of this deepening semester project is to suggest and demonstrate strategic approaches as a premise to the AGI and getting a step closer to general Chatbots, which can initiate and maintain human-like conversations in a pro-active manner.

1.2 Scope and Study Borders

As a red line for this deepening project, the focus will be on the Word2Vec technology, from a research perspective. Indeed, this technology is seen as a foundation for the modern NLP and DNN Chatbots, which makes it an exciting vector of study about its current usage, its extensions, and potential evolution.

1.3 Industrial Interest

iCoSys, the Institut of Complex Systems at University of Applied Sciences and Arts at Fribourg, Switzerland, is interested into the result of this project as a study for their AI-News project, whose goal is to provide a chatbot as a tool to reader, to help them narrow their interests and deliver the right information. AI-News is in collaboration with

Chapter 1. Introduction

the Swiss Innovation Agency from the Swiss Confederation, and La Liberté, the daily newspaper from Fribourg.

Chapter 2

Questions

To help the student to find a red line to focus its research on, he was required work on the subject "What should be the initial questions to asks to start making AGI Chatbots" as preliminary study before the beginning of deepening project itself and to write down the outcome as a set of questions related to his interests and the field of AGI Chatbots.

2.1 Initial and Broad Questions

As a result to the preliminary study, the following question were produced. Please take into account that those questions were not meant to be answered as part of the project itself, but as part of the process of appropriation of the field of study.

- Is the Artificial Neural Networks (ANN) approach appropriate to represent the world?
- Can agents be made exclusively from a language?
- Can agents able to experience an environment?
- Is a narrative environment be enough to understand an environment?
- Is the language able to provide to an agent an understanding of the world?
- Is the knowledge of the language syntax enough to gain an understanding?
- Is the result of unsupervised learning enough to discover all nuances?
- Is the unsupervised learning sufficient to make sense to an environment?
- Is a descriptive explanation of the world be expressed in a language?
- Is the description good enough to catch all the nuances?
- Is the language good enough to explain?
- Can we augment or make a semantic language?
- Can we create a common symbolic language?
- Is the language multi-dimensional?
- How many dimensions are needed for a complex language?
- Is it possible to give a word equivalence to machines for human-specific words?
- Are all emotions describable into words?
- Are emotions altering language descriptions?
- Is an approximation of the real world enough to understand the environment?
- Would a the simulated world be a good approximation of the real world?

Chapter 2. Questions

2.2 Narrowed Questions

In a second time, the student was asked to narrow the initial questions above into potential fields of study.

- Common human-machine language
 - Is it possible to create a multi-dimensional human-machine language, which includes a common semantic, symbolic, and emotion definition.
 - Is it possible to create an abstract world for machines to understand human symbolic based on a real world, and define fundamentals for machine representation of the language.
- Machine intuition
 - Is it possible to provide to machines an human-like intuition (inside voice), which would help to keep a long term context and specialize in specific fields.
- Evaluate human-machine communication
 - Is it possible to provide a protocol to test the communication skills and machine understanding.

2.3 Potential Red lines

From the potential fields above, the following suggested red lines were proposed.

- How to verify and quantify a chatbot understanding?
- What is the premise to make chatbots general with today's technology?
- How chatbot can be proactive?
- How to simulate human-like intuition in chatbots?

2.4 The Deepening Project Question and Red line

Based on reflective work and discussions, the concluding red line and question for this deepening project is:

- What is Word Embedding and how is it useful for chatbots?

Chapter 3

Plan

3.1 Constraints

Timeframe: 15 weeks

Starting date: 18.02.2019

Ending date: 31.05.2019

3.2 Initial Plan

As an initial milestone for the deepening project, the student were required to create an initial plan, with the purpose to help the student and the teacher to visualise the project main red line.

3.2.1 Tasks

1. Initial research about general chatbots
2. Determine the project target
3. Play with the subject
4. Explore the Word2Vec methodology
5. Explore the Word2Vec extensions
6. Combine and test ANN algorithms with Word2Vec
7. Explore ANN algorithm topology for the chatbot
8. Analysis of the chatbot intuition with parallel algorithms
9. Analysis of a protocol to evaluate proactive chatbots
10. Profile-based initiatives
11. Analyze and experiment profile nurturing
12. Analyze and experiment with chatbot initiatives with no profiles
13. Overall improvements
14. Autonomous data gathering
15. Make suggestions
16. Determine possible continuation and future outcomes for the project

Chapter 3. Plan

3.2.2 Milestones

1. Initial deepening project plan and specification document
2. Basic multi-dimensional word embedding space
3. Basic conversational agent
4. Basic proactive chatbot
5. Deepening project report

3.2.3 Sprints

18.02.19 to 08.03.19 (3 weeks)

- Do the initial research about general chatbots
- Determine the project target
- Play with the subject
- **DELIVERABLE:** Plan and Initial Specification document

11.02.19 to 29.03.19 (3 weeks)

- Explore the Word2Vec methodology and its extensions
- Combine and test ANN algorithms with Word2Vec
- **MVP:** Basic multi-dimensional word embedding space

01.04.19 to 19.04.19 (3 weeks)

- Explore ANN algorithm topology for the chatbot
- Analysis of the chatbot intuition with parallel algorithms
- Analysis of a protocol to evaluate proactive chatbots
- **MVP:** Basic conversational agent

22.04.19 to 10.05.19 (3 weeks)

- Profile-based initiatives
- Analysis and experiment of the profile nurturing
- Analyze and experiment with chatbot initiatives with no profiles.
- **MVP:** Basic proactive chatbot

13.05.19 to 31.05.19 (3 weeks)

- Overall improvements
- Autonomous data gathering
- Make suggestions
- Determine possible continuation and future outcomes for the project
- **DELIVERABLE:** Report + Sources

3.2.4 Gantt chart

Figure 3.1 represents the visual gantt chart for the initial plan.

3.3 Effective Plan

As expected the initial plan served as an initial model, and evolved iteratively based on the student and teach feedback while exploring the subject.

3.3.1 Tasks

1. Initial research about general chatbots
2. Determine the project target
3. Set the initial plan
4. Make LaTeX report template
5. Explore the Word2Vec subject
6. Explore the Word2Vec algorithm
7. Build a Word2Vec model on the latest english wikipedia dump
8. Explore Word2Vec parameters
9. Explore Word2Vec analogies
10. Explore Word2Vec sentence generation
11. Explore visual representations of Word2Vec vectors
12. Explore Word2Vec applications with chatbots
13. Writing the report

3.3.2 Milestones

1. Initial deepening project plan and specification document
2. Basic Word2Vec Word Embedding Model
3. Conclusions Word2Vec based chatbots
4. Ideas to make chatbots proactive
5. Deliver the report

3.3.3 Gantt chart

Figure 3.2 represents the visual gantt chart for the effective plan.

Chapter 3. Plan

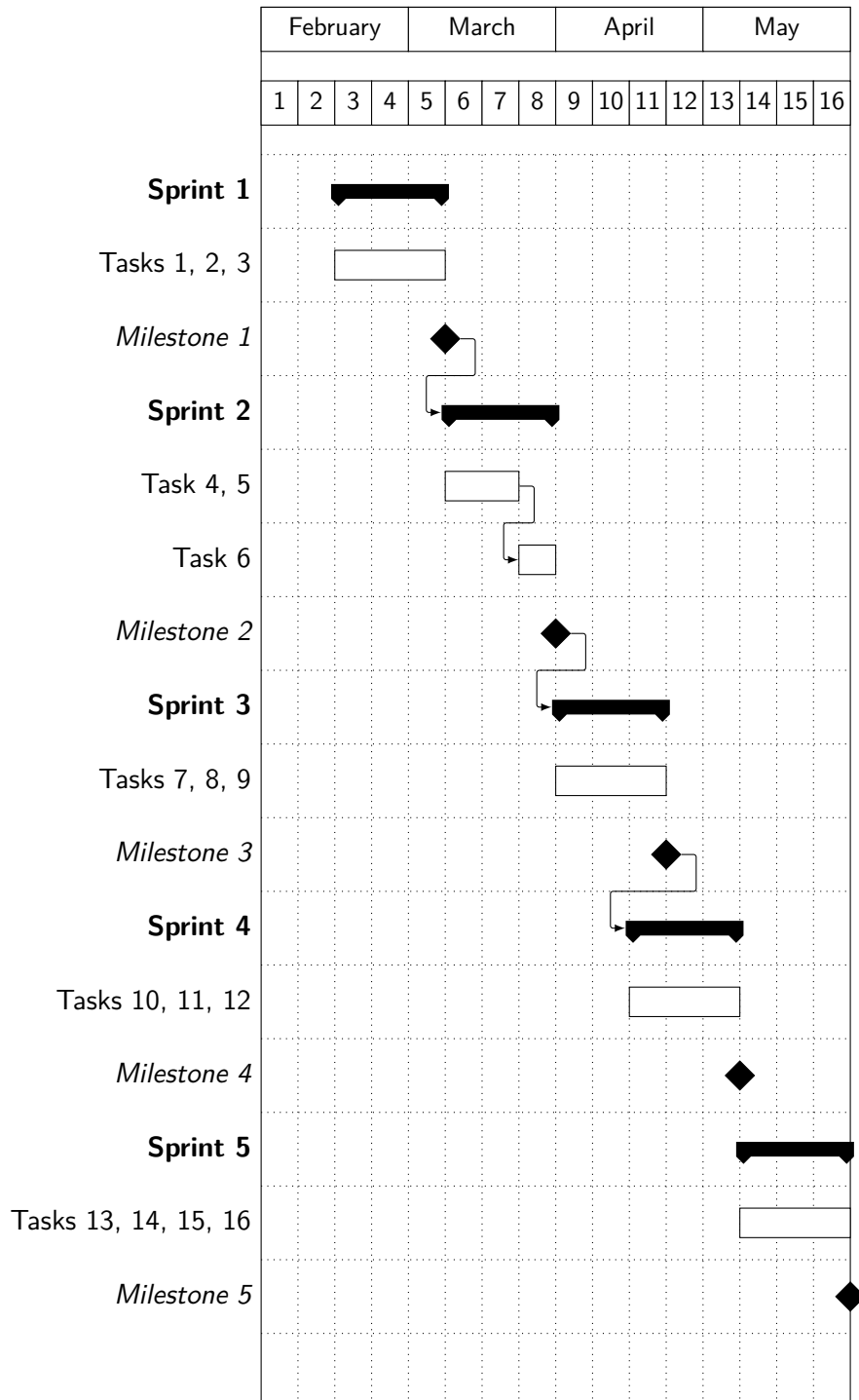


Figure 3.1: Initial Gantt Chart

3.3. Effective Plan

February				March				April				May			
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16

Figure 3.2: Effective Gantt Chart

Chapter 4

State of the art

4.1 Chatbots

From a user point of view, chatbots are trendy nowadays, big companies such as *Google* or *Apple* are pushing to make the technology mainstream. Even if not every lambda people understand the word “chatbot”, they all have at least a mental representation of it. Indeed, they could call it Digital Assistant, Siri, Ok Google, and so on, in the end, they all understood the concept of an artificial intelligence narrowed to more or less human-like conversations.

4.1.1 History of Chatbots

When are they coming from? Not mentioning *Alan Turing* or *Joseph Weizenbaum*, considered as the fathers of AI and chatbots, would not be fair. Indeed, they forecasted in 1950, that computers would be able to use human-like communication and they proposed a test to distinguish humans from machines, called the Turing Test[1]. Where a human is asked to talk to a masked entity, and determine if it is talking to a human or a computer. If the human cannot determine who is the computer, then the machine passed the Turing test, as seen on figure 4.1.

In 1966, Joseph Weizenbaum wrote Eliza, a computer program simulating a psychotherapist, seen as one of the first well-known attempts to make a chatbot passing Turing test. Note that due to technical restrictions, Eliza is not performing well at all time. As it is for today, it is possible to play with it at on a dedicated website. [12]

Since Eliza, a lot of progress has been made, indeed, to only cite a few noticeable chatbots: *Parry*[11] (1972), *Jabberwack*[17] (1988), *Dr. Sbaitso*[6] (1991), *A.L.I.C.E*[15] (1995), *Smarterchild*[16] (2001), *Watson*[10] (2006), *Siri*[3] (2010), *OK Google*[9] (2012), *Alexa*[2] (2014), *Cortana*[13] (2014), Facebook Bots[7] (2016), and *Tay*[14] (2016), which where all part of the Chatbot history [8]. For more informations about chatbots history and up to today, Chatbot.org[5] is a great reference.

From IF-ELSE, Artificial Intelligence Markup Language (AIML), up to ML with ANN and Deep Neural Networks (DNN), the improvement in the field of chatbots increased drastically over the years. At every iteration, the algorithms are becoming more sophisticated and better at using the human language, which is now called the field of the NLP and NLU.

Chapter 4. State of the art

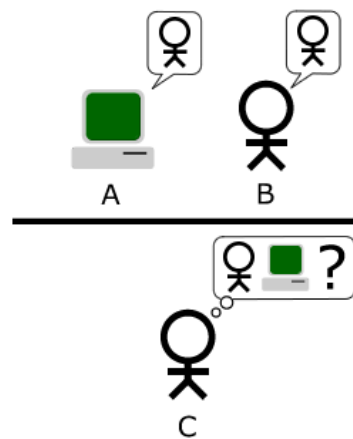


Figure 4.1: The "standard interpretation" of the Turing Test, in which player C, the interrogator, is tasked with trying to determine which player - A or B - is a computer and which is a human. The interrogator is limited to only using the responses to written questions in order to make the determination. [4]

4.1.2 Narrow

Once again, chatbots are almost everywhere nowadays. Indeed, it became a common tool for companies of any size to communicate with their customers and a toy for users. However, most of the time, Chatbots are not understood by their users and is leading to a high level of frustration. Even if they are becoming increasingly mainstream and sophisticated, people do not realize their limits. Today's chatbots are often mistaken for AGI in Science Fiction (Sci-Fi) and are expected to do much more than they can do. Indeed, making ANI chatbots implies a specialization into a specific field.

Not to forget that the primary purpose of chatbots is to provide a conversational service to the user from text to vocal or even visual format. However, its purpose can derivated in an almost unlimited amount of solutions such as Health, Weather, Customer Service, Games, and much more.

4.1.3 IR

Most of the time used by Frequently Asked Questions (FAQ) chatbots, which are probably the most common type of chatbots, its goal is to answer specific questions, based on a specific keyword. Indeed, the communication skills are limited to pre-made sentences and a question/answer database, which often results in the best case scenario in a perfect match, or the worst case scenario would be the return of something unexpected.

Technically speaking, IR is part of the Data Mining (DM) in the field of ML. It is well suited for search engines, as it works in a query mode. Indeed, the algorithm tries to find the best match to the submitted query in its database, usually with pattern extraction and a rank.

Sequential

"If he says this, then say that, then do so." This sentence is a good example of the concept of sequential chatbots. From a communication point of view, it does not have to talk to accomplish its purpose; it is indeed usually based on a keyword detection technic to determine what pre-made action to do. However, as the whole system works on

4.1. Chatbots

pre-made actions, the development of such algorithms requires a lot of brain power from the developers. Indeed, as all actions result from anticipated specific keywords, and even specific order of keywords, the complexity can quickly increase, which most of the time, makes sequential chatbots seen as command line terminals instead of conversational chatbots.

Forwarder

Often used by companies for customer service, it has become the most popular type of chatbots and seen as a hybridization of the IR and sequential chatbots. Its goal is to simulate an agent that is available 24/7 to help the customer. Indeed, it will try its best to answer the most popular questions based on its FAQ database and forward the user seamlessly to a human agent if its knowledge is getting limited. In the best case scenario, it is greatly appreciated by the user as the transition from chatbot to human is not noticeable.

Learning

As ML evolves at an incredible rate and boosted by DNN, new NLP algorithms emerges, and most of the time leaves the previous generation far behind. Modern learning chatbots algorithms are what comes closer to human-like conversations. Leaving the algorithm alone progress through iterations on a large dataset or commonly named Big Data (BD) of real conversations, it will learn patterns by itself. However, the output generated by the trained model is dependent on the data the training occurred on. The most well-known example is *Tay*[14] (2016), the Twitter chatbot from Microsoft, that was influenced by the 4chan community to make it speak like a Young Racist Girl. However, it is essential to take note that learning chatbots are exciting for a long time now. *A.L.I.C.E*[15] had already basic learning skills, as AIML was taking care of saving variable on the run, such as the first name of the user. Even if this methodology could be seen archaic if compared to new Deep Learning (DL) algorithms such as LSTM, it is still used today likewise the AIML technology.

Proactivity

“Hey, I saw that you are on the website for some minutes now, do you need some more dedicated information?”. It is almost impossible that someone never received a message alike. Indeed, proactivity is not new in the field of chatbots, mimicking an interest from the chatbot to initiate conversations has become a standard in marketing and customer support chatbots. However, the limitations are hit fast, beyond asking general questions, not much progress has been made until now.

True proactive chatbots are implying that the algorithm is capable of initiating conversations from a human-like perspective, initiating the conversation or asking information in a meaningful manner based on the user, the context and the relationship with the user. The state-of-the-art search could not find any evidence of existing real proactive chatbots as described.

Examples

As a help to get a feeling about narrow chatbots, a none-exhaustive list of applications is available below:

Chapter 4. State of the art

- Receive relevant information about a trip, book flights, and hotels, and get updated on the boarding and weather conditions at the airport.
- Keep track and order coffee remotely at the office.
- Monitor customer's satisfaction.
- Convert potential customer into paying customers by interacting with them at the right moment.
- Personal assistant on-the-go, get the schedule and the next meetings.
- Relay for people on hold at a service.

4.1.4 General

Before going further into the world of general chatbots, it is required to understand the following two axes of AI defined by Tasks and Knowledge. Indeed, narrow chatbots are limited by the range of tasks they can accomplish and the knowledge they can use. However, most of the time, they are very good at a particular task for a particular knowledge requirement. 4.1

Tasks Talk, FAQ, Remote Control, Customer, or Placing orders are just a few tasks that a chatbot could accomplish.

Knowledge Health, Weather, Customer Service, or Games are just a few knowledge examples chatbots could excel at.

General Chatbots

Much effort is being made to get chatbots able to perform well simultaneously in various tasks and knowledge. Indeed, general chatbots should not be limited to previously learned tasks and subjects; they should also be able to learn and relearn. Those type of chatbots have not been found during the state of the art phase, and are probably by this mean either non-existent at the moment or hidden in laboratories, far from public knowledge. However, big companies like Amazon are providing to the public a feel of general chatbots with *Alexa*[2]. Users can converse with it, command their smart houses, use it as a personal assistant, and even program it to perform custom actions. However, it is not yet able to learn by itself and generate out of the blue non-programmed skills. Note that general chatbots could be scary for lambda people if it starts mimicking human being too well, as in the user mind, talking to a machine should be differentiable from talking to humans. Admittedly, in the case of the *Turing Test*[1], the human does not know if it is talking to a human or a machine, which makes it probably more comfortable to accept than talking to a machine directly. Sci-Fi is conditioning people to believe that human-like performing machines are dangerous for the human species.

4.1. Chatbots

Tasks	Knowledge	
	Expert in a specific Field Expert at all Tasks	General Chatbots Expert in all Fields Expert at all Tasks
	Narrow Chatbots Expert in a specific Field Expert at specific Task	Expert in all Fields Expert at specific Task

Table 4.1: Tasks versus Business Knowledge in the field of AI and Chatbots

4.1.5 From ANI to AGI

On a side, even if it is not part of the deepening project. It is interesting to write a few lines about AI. New incredible algorithms outperforming the previous one, and experiments reports are emerging almost every month and redefining the standard of AI. Paradigms are shifting and technologically speaking; we are entering a new era of computer-assisted humankind.

ANI More than a sequential algorithm, narrow artificial intelligence in modern terminology is the definition of “being good at something”. ANI has been made possible with the huge progress in ML, the arrival of the DL, and the need for humans to store data about everything (BD). In medicine, for instance, it is sometimes performing so well, that humans, who spent years studying are left behind by an algorithm trained large datasets for a few days.

AGI The next step into the field of AI, when supervision has been banned as a teaching method for algorithms as the human interaction is inputting more errors than machine themselves if unsupervised. In addition to teaching themselves, algorithms are teaching each other, and improve over the iteration with auto corrections and optimizations. They are excelling at all tasks requiring repetition, precision, and safety. Besides, they are also all able to retrieve any available information and use it for their need. “In the future, machines will be able to understand and do everything, much more efficiently than humans.”

Chapter 4. State of the art

4.2 Word2Vec

4.2.1 What is Word2Vec

4.2.2 Gensim

4.2.3 Frameworks

4.3 Word Embedding Alternatives

4.3.1 FastText

4.3.2 Glove

4.3.3 Word2Vec-f

4.3.4 Wang2vec

4.4 Sentence/Document Embedding Alternatives

4.4.1 Doc2vec

4.4.2 Skip-thought

4.4.3 Smooth Inverse Frequency

4.4.4 RNN

4.5 Datasets

Chapter 5

Analysis

5.1 Natural Language Processing

5.2 Pipeline

5.3 Word2Vec

5.3.1 Bag of Words VS Skip-Gram

5.3.2 Dimensions

5.3.3 N-Grams

5.3.4 Epochs

5.3.5 Lemmatization

5.3.6 Normalization

5.3.7 Distance and Cosine Angle

5.3.8 Training

5.3.9 Retrain Model

5.3.10 Memory Issues

5.3.11 Analogies

5.3.12 Proverbs

5.3.13 Evaluation

5.3.14 Visual Representation

5.3.15 Benchmarks

5.3.16 CPU VS GPU

5.3.17 Datasets

5.4 Chatbot

5.5 Proactivity

Chapter 6

Experiments & Results

6.1 Environments

6.1.1 Jupyter Notebook

6.1.2 Local Machine

6.1.3 Amazon Web Services

6.1.4 iColab-gpu2

6.1.5 CPU Dedicated Machine

6.2 Gensim Framework

Errors Memory allocation with multi-core. The problem is occurring during the merge of the cores. Indeed, my current machine has 128GB ram, and the dataset weights about 16GB in the memory, and each core during merging is processing at least the same amount, plus the processed informations.

```
2019-03-25 08:31:18,867 : INFO : PROGRESS: pass 0, dispatched chunk #34 = documents up to #70000/4614519, outstanding queue
size 31
Exception in thread Thread-1:
Traceback (most recent call last):
  File "/usr/lib/python3.5/threading.py", line 914, in _bootstrap_inner
    self.run()
  File "/usr/lib/python3.5/threading.py", line 862, in run
    self.target(*self.args, **self.kwargs)
  File "/usr/lib/python3.5/multiprocessing/pool.py", line 366, in _handle_workers
    pool.maintain_pool()
  File "/usr/lib/python3.5/multiprocessing/pool.py", line 240, in _maintain_pool
    self.repopulate_pool()
  File "/usr/lib/python3.5/multiprocessing/pool.py", line 233, in _repopulate_pool
    w.start()
  File "/usr/lib/python3.5/multiprocessing/process.py", line 105, in start
    self._popen = self._Popen(self)
  File "/usr/lib/python3.5/multiprocessing/context.py", line 267, in _Popen
    return Popen(process_obj)
  File "/usr/lib/python3.5/multiprocessing/popen_fork.py", line 20, in __init__
    self._launch(process_obj)
  File "/usr/lib/python3.5/multiprocessing/popen_fork.py", line 67, in _launch
    self.pid = os.fork()
OSError: [Errno 12] Cannot allocate memory
```

Figure 6.1: Error 1

6.3 Materials

6.4 Products

Chapter 6. Experiments & Results

```
2019-03-25 08:31:18,867 : INFO : PROGRESS: pass 0, dispatched chunk #34 = documents up to #70000/4614519, outstanding queue
size 31
Exception in thread Thread-1:
Traceback (most recent call last):
  File "/usr/lib/python3.5/threading.py", line 914, in _bootstrap_inner
    self.run()
  File "/usr/lib/python3.5/threading.py", line 862, in run
    self.target(*self.args, **self.kwargs)
  File "/usr/lib/python3.5/multiprocessing/pool.py", line 366, in _handle_workers
    pool._maintain_pool()
  File "/usr/lib/python3.5/multiprocessing/pool.py", line 240, in _maintain_pool
    self._repopulate_pool()
  File "/usr/lib/python3.5/multiprocessing/pool.py", line 233, in _repopulate_pool
    w.start()
  File "/usr/lib/python3.5/multiprocessing/process.py", line 105, in start
    self._popen = self._Popen(self)
  File "/usr/lib/python3.5/multiprocessing/context.py", line 267, in _Popen
    return Popen(process_obj)
  File "/usr/lib/python3.5/multiprocessing/popen_fork.py", line 20, in __init__
    self._launch(process_obj)
  File "/usr/lib/python3.5/multiprocessing/popen_fork.py", line 67, in _launch
    self.pid = os.fork()
OSError: [Errno 12] Cannot allocate memory
```

Figure 6.2: Error 2

Chapter 7

Discussion

7.1 Next steps?

Chapter 8

Conclusion

- 8.1 Word Embedding: Word2Vec**
- 8.2 Framework: Gensim**
- 8.3 Word2Vec Chatbots**
- 8.4 Proactive Chatbots**

Lausanne, May 27, 2019

Romain Claret

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Appendix

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.0.1 Appendix

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