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AnHALytics: a Workflow for Text Mining

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RESUMO

AnHALytics é um framework para mineração de dados de documentos técnicos e científicos oriundos de repositórios de grande porte. AnHALytics recupera, extrai dados importantes, e enriquece esses arquivos usando informação sobre o próprio artigo, além de outras bases de dados (por exemplo, a Wikipedia). O workflow de AnHALytics é executado de forma manual, o que causa alguns problemas relacionados com a falta de tolerância a falhas e de um fluxo de execução mais flexível, além da dificuldade para manter e garantir a reprodutibilidade científica. Para prover uma solução para esse problema, um estudo sobre os principais sistemas de workflow e como eles iriam se comportar com uma aplicação como AnHALytics foi realizado. No final desse estudo, um desses sistemas foi selecionado, e sobre ele foi executada uma simulação de performance em uma aplicação similar à AnHALytics, onde foi observado seu comportamento em comparação a uma solução por scripts. Os resultados dessa simulação mostraram que esse tipo de aplicação pode ser significativamente melhorado com a integração de workflows científicos. Como os resultados da simulação mostraram, workflows científicos — criados inicialmente para aplicações no domínio das biociências — também podem ser utilizados em aplicações de mineração de dados, e apresentam resultados similares, dando à aplicação significantes melhoras quando comparado com a versão em script, manualmente executada, do workflow.

Resumo estendido

Este é um resumo estendido em português para a Universidade Federal do Rio Grande do Sul do trabalho original que segue. O trabalho de conclusão original, em inglês, foi apresentado na escola ENSIMAG do Institut National Polytechnique de Grenoble através do programa de dupla diplomação UFRGS - Grenoble INP.

1 INTRODUÇÃO

O projeto descrito neste trabalho foi desenvolvido durante um estágio de fim de estudos para o curso de Ciência de Dados do mestrado em pesquisa (MoSIG) da universidade francesa ENSIMAG, parte do Grenoble INP. O estágio se deu no laboratório de pesquisa francês INRIA Alpes. O principal objetivo do projeto foi verificar se sistemas de gerenciamento de workflow poderiam ser usados em uma aplicação de mineração de dados chamada AnHALytics.

AnHALytics é uma plataforma que extrai, analisa e gera dados sobre artigos científicos de grandes plataformas online, como HAL e Istex. AnHALytics é composta por três componentes principais: GROBID, *grobid-quantities*, e NERD.

Durante o projeto, foram estudados dois paradigmas de sistemas de workflow: workflow de negócios (*business workflows*) e workflows científicos (*scientific workflows*), comparando as características de cada uma dessas modalidades de acordo com vários critérios previamente estabelecidos e de considerável importância para um sistema do estilo de AnHALytics. Com esse estudo comparativo, foi possível verificar que workflows científicos apresentam funcionalidades que correspondem mais às necessidades do sistema em questão, quando comparados a workflows de negócios.

Tendo definido que workflows científicos seriam uma solução mais interessante para o problema, foi realizado um estudo comparativo dos principais sistemas de workflows científicos, avaliando-os segundo alguns critérios pré-estabelecidos (quantitativos e qualitativos). Com base nessa avaliação, um desses sistemas – o que foi melhor avaliado segundo nossos critérios – foi escolhido para a implementação de uma simulação, onde um cenário simplificado da execução das principais tarefas do AnHALytics foi implementado usando i) o sistema escolhido e ii) um *script* Python. O objetivo dessa simulação é verificar se e em que medida um sistema como o AnHALytics poderia se beneficiar de ser executado em um sistema de gerenciamento de workflows. Os resultados obtidos indicam que o uso de um sistema que gerencia o fluxo de execução pode trazer várias vantagens, especialmente para aplicações que fazem uso extensivo de dados, como a plataforma estudada.

O restante deste resumo está organizado como segue: na seção 2, a plataforma AnHALytics é descrita de forma mais detalhada. Na seção 3, um estudo sobre os dois principais paradigmas de workflow é apresentado, junto com um comparativo desses paradigmas de acordo com algumas características do AnHALytics. Na seção 4, são apre-

sentados os principais sistemas de gerenciamento de workflows científicos, que serão avaliados segundo critérios importantes para a plataforma AnHALytics. Na seção 5, um cenário de simulação é apresentado, bem como seus resultados. Por fim, a seção 6 apresenta as conclusões deste trabalho.

2 ANHALYTICS

AnHALytics ¹ é uma aplicação de mineração de dados cujo objetivo é facilitar o acesso e organização de repositórios de documentos científicos para a comunidade científica.

O workflow de AnHALytics é composto pelos seguintes processos:

- GROBID: é o processo principal do workflow, responsável pela recuperação dos textos a partir da base de dados.
- *grobid-quantities*: responsável por adicionar informações extras relativas a diversas medidas nos textos.
- NERD: responsável pela anotação e desambiguação dos dados obtidos e tratados com os processos GROBID.

2.1 Problemas com a solução atual

O principal problema da solução atual da plataforma AnHALytics é o fato de que suas tarefas devem ser executadas manualmente, pois não há uma sincronização automática da execução das tarefas. Isso acarreta em algumas dificuldades, como por exemplo uma grande sensibilidade da plataforma a falhas durante a execução, o que leva à necessidade de reexecutar um fluxo de execução desde o início se algum erro ocorrer durante a execução de alguma tarefa do workflow. Por esse motivo, a possibilidade de executar todas as tarefas que compõem o sistema AnHALytics de forma automatizada e com capacidade de lidar com esse tipo de falha é uma ideia interessante, que foi explorada neste trabalho.

¹<http://anhalytics.readthedocs.io>

3 WORKFLOWS

Um *workflow* é a automatização de um processo, contendo uma sequência bem definida de tarefas a serem executadas, bem como de controle de fluxo, fluxo de dados, e participação de usuários nessas tarefas. Sistemas que automatizam workflows já existem há quase meio século. Os dois principais paradigmas de workflow são *workflows de negócio* e *workflows científicos*.

3.1 Workflows de Negócios

O domínio de estudo de workflows de negócio teve início entre os anos 70 e 80 com a automação de sistemas daquela época. Workflows de negócio tem foco no controle de fluxo de eventos e na automação de processos organizacionais.

3.2 Workflows Científicos

Workflows científicos têm como objetivo resolver problemas relacionados à pesquisa científica e *e-science*. O principal objetivo de workflows científicos é poupar ciclos de trabalho humanos e de máquina.

3.3 Comparativo entre os modelos

Workflows de negócio e workflows científicos têm muitas semelhanças, porém se diferenciam em alguns pontos muito importantes. As principais diferenças entre eles são relacionadas aos seguintes critérios:

- **Propósito geral**

O objetivo principal de workflows de negócio é estabelecer um conjunto de regras de negócio e interações entre os papéis de cada usuário do sistema. O principal objetivo de workflows científicos é automatizar algum processo científico.

- **Fluxo de dados**

Em workflows de negócio, apenas dados simples de controle de fluxo são utilizados. Já em workflows científicos, os dados normalmente são complexos e extremamente

importantes para a execução do processo.

- **Fluxo de controle**

Sistemas para workflows de negócios normalmente disponibilizam várias estruturas básicas de controle de fluxo, que em geral são suficientes para descrever a maioria dos workflows desse tipo. Workflows científicos necessitam de estruturas de controle mais complexas, que sejam capazes de expressar concorrentemente a execução de dados e de controle de fluxo.

- **Objetivos do usuário**

O objetivo do usuário de workflows de negócio é saber quais tarefas podem ser otimizadas para reduzir custos. O objetivo do usuário de workflows científicos é conhecer os detalhes do processo científico que levam ao resultado final (por exemplo, dados de tarefas intermediárias).

Decidiu-se, com base no comparativo, que workflows científicos seriam mais apropriados para o sistema AnHALytics. Na seção seguinte são apresentados os principais sistemas de gerenciamento de workflows científicos, os quais serão analisados para que obtenhamos o melhor candidato para ser usado junto à plataforma AnHALytics.

4 SISTEMAS DE GERENCIAMENTO DE WORKFLOWS CIENTÍFICOS

Um estudo sobre os principais sistemas de workflow científicos foi realizado para decidir o sistema mais apropriado para uso em um sistema de mineração de dados.

As principais programas de workflow científico são:

- Kepler ¹: desenvolvido com foco em biociências, possui diversos operadores para aplicações deste domínio, podendo ser estendido para outros.
- Pegasus ²: sistema executado unicamente por um terminal (sem interface gráfica), desenvolvido especialmente para execução em clusters e grids.
- Taverna ³: desenvolvido com foco em biociências, possui uma plataforma integrada para compartilhamento de workflows entre usuários.
- Triana ⁴: desenvolvido com foco em sistemas de rádio e comunicação.

¹<https://kepler-project.org/>

²<https://pegasus.isi.edu/>

³<https://taverna.incubator.apache.org/>

⁴<http://www.trianacode.org/>

- RapidMiner ⁵: desenvolvido para aplicações de *big data*, possui extensões que implementam algoritmos para processamento de texto e mineração de dados.
- Knime ⁶: desenvolvido para aplicações de aprendizagem de máquina.

Com base no estudo comparativo realizado entre os sistemas de workflow científico, RapidMiner foi o sistema considerado mais adequado quanto aos requisitos do AnHALytics. RapidMiner é uma plataforma desenvolvida especialmente para aplicações de processamento de dados, tendo, portanto, diversas ferramentas que facilitam a manipulação de dados.

4.1 Discussão

Os principais pontos avaliados na simulação são: i) gerenciamento do workflow, ii) execução do workflow, iii) gerenciamento do workflow durante execução, iv) tolerância a falhas, v) reprodutibilidade, vi) adaptabilidade, vii) escalabilidade. Os critérios de avaliação levam em consideração as principais ferramentas necessárias para a automatização do sistema AnHALytics.

5 IMPLEMENTAÇÃO E RESULTADOS

Um dos objetivos no início do projeto era o de implementar a aplicação AnHALytics usando o tipo de sistema de workflow escolhido após o estudo das principais soluções atuais. A complexidade do sistema impediu a implementação durante o período de estágio, portanto foi optado pela realização de uma simulação utilizando um cenário similar ao da aplicação.

5.1 Solução proposta

Foram propostos dois cenários de simulação: i) usando RapidMiner, ii) usando um script Python.

O cenário simula uma versão simplificada do processo de extração de dados oriundos das bases de dados utilizadas (HAL e Istex), o pré-processamento desses dados (to-

⁵<https://rapidminer.com/>

⁶<https://www.knime.org/>

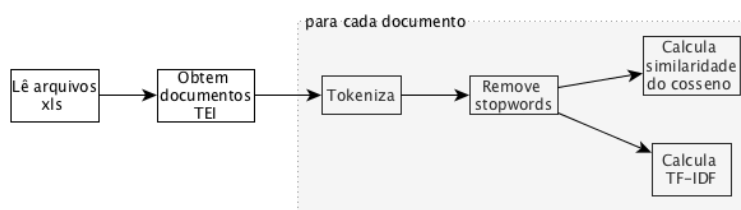
kenização, remoção de *stop words*), bem como a execução de um algoritmo de mineração de dados (TD-IDF). Tarefas semelhantes são executadas pelo subprocesso GROBID, o principal processo do workflow da plataforma AnHALytics.

A seguinte sequência de tarefas é executada na simulação:

1. Ler um arquivo Excel que contem URLs para trinta documentos TEI;
2. Obtenção do conteúdo desses documentos;
3. Extração do *abstract* em inglês;
4. Tokenização e remoção de *stop words*;
5. Cálculo da similaridade do cosseno e TF-IDF do abstract em inglês.

A figura 5.1 representa o cenário de simulação.

Figura 5.1:



5.2 Resultados

A tabela 5.1 apresenta os resultados da simulação.

Tabela 5.1: Resumo dos critérios de avaliação da simulação

CRITÉRIO	CENÁRIO	
	Script	Workflow Científico
Reprodutibilidade	Precisa ser implementado manualmente	Mais fácil de obter, com logs automáticos e portabilidade
Tolerância a Falhas	Precisa ser implementado manualmente	Execução pode ser reiniciada a partir do último ponto
Tempo de Execução	Computação mais lenta (de harvesting + tokenization)	Computação mais rápida (de harvesting + tokenization)
Controle de Execução	Não possui	Possui breakpoints e pause/continua do workflow

5.3 Discussão

Como pode ser visto na tabela 5.1, as principais vantagens da utilização de programas de workflow científicos para o controle de execução de uma aplicação como AnHALytics se dá especialmente em critérios qualitativos, não quantitativos. Embora o tempo de execução tenha diminuído com a execução do cenário utilizando o programa de controle de workflow, essa melhora foi de apenas cerca de 10% em relação à versão executada manualmente. Quanto aos critérios qualitativos, RapidMiner oferece ferramentas para garantir a reprodutibilidade dos workflows, bem como para o gerenciamento da execução.

6 CONCLUSÃO

O projeto desenvolvido teve como base um estudo sobre os principais paradigmas e tecnologias na área de workflows para automatização de tarefas computacionais.

O estudo mostrou que workflows científicos podem ser uma boa alternativa para o gerenciamento da execução de sistemas baseados em mineração de dados. Ainda que boa parte das tecnologias atuais tenha foco principal em aplicações voltadas para as biociências, novas aplicações para diferentes domínios vêm sendo desenvolvidas.

Trabalhos futuros relacionados a este projeto incluem a implementação do sistema AnHALytics com a aplicação estudada, RapidMiner, bem como uma análise mais profunda dos critérios qualitativos avaliados na prática.



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AnHALytics: a Workflow for Text Mining

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Abstract

AnHALytics is a framework for text mining of technical and scientific documents coming from very large repositories. AnHALytics retrieves, extracts important data, and enriches these files using information on the article itself and other knowledge bases (e.g. Wikipedia). The AnHALytics workflow is executed by hand, which causes some issues related to the lack of fault tolerance, of a more flexible workflow execution, and the difficulty to maintain and guarantee. In order to provide a solution to this, we have made a study on the main workflow workbenches and how they would perform with an application such as AnHALytics. At the end of this study, we have selected one workbench in which we performed a simulation of an application similar to AnHALytics and observed its behavior when compared to a scripting solution. The simulation results have shown that this kind of application can be significantly improved with the integration of scientific workflows. As the simulation results have shown, scientific workflows – created at first for applications from the biosciences domain – can also be used with text mining applications and present similar results, giving the application significant improvements compared to the classic scripting version of the workflow.

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Contents

Abstract	i
Acknowledgement	ii
1 Introduction	1
2 AnHALytics	3
2.1 Main processes	5
2.1.1 GROBID	5
2.1.2 grobid-quantities	5
2.1.3 NERD	6
2.2 Executing AnHALytics	7
2.3 Issues with the current solution	7
3 Workflows	9
3.1 Business Workflows	11
3.2 Scientific Workflows	11
3.2.1 Requirements and desiderata	12
3.3 Scientific vs Business Workflows	13
3.4 Discussion	15
4 Scientific Workflow Management Systems	17
4.1 Kepler	17
4.2 Pegasus	18
4.3 Taverna	18
4.4 Triana	19
4.5 RapidMiner	19
4.5.1 Radoop	20
4.6 Knime	20
4.7 Discussion / Comparison	20
4.7.1 Workflow management and deployment	20
4.7.2 Workflow execution	21
4.7.3 Deployment of a workflow while in execution	22
4.7.4 Fault tolerance and error handling	23

4.7.5	Reproducibility	23
4.7.6	Adaptability	24
4.7.7	Challenges when comparing to scripting solutions	25
4.7.8	Scalability	25
4.8	Discussion	26
5	Implementation and Evaluation	29
5.1	Proposed solution	29
5.1.1	Simulation	29
	Script	30
	Scientific workflow	30
5.2	Evaluation	31
5.2.1	Reproducibility	32
5.2.2	Execution Time	32
5.2.3	Execution Management	33
5.2.4	Fault Tolerance	33
5.2.5	Discussion	33
6	Conclusion	35
	Bibliography	37

Introduction

AnHALytics [3] is a platform whose goal is to extract information and enrich scientific documents that are obtained from platforms such as HAL ¹ and ISTEEX ² by using a combination of text mining algorithms. AnHALytics is a complex application that involves several different processes, from gathering documents from a database to obtaining information from a knowledge base. Currently, the AnHALytics workflow is executed by hand, which brings issues, such as difficulty to ensure fault tolerance and reproducibility, and a less efficient use of computational resources. We have investigated different solutions to automate the AnHALytics workflow in a way that it would improve its results both quantitatively and qualitatively. In order to do this, we have studied the state of the art of business and scientific workflows.

The use of software workflows for the automation of processes started in the late 70's with the rise of business workflows. These types of workflows were conceived to work with processes that are very heavy on control flow and that use data only as auxiliary to the control flow.

As this type of workflow was not generic enough to all kinds of applications, in the 90's a new type of workflow came into the picture: scientific workflows. The domain of scientific workflows emerged alongside with the ever-growing need of automation of processes coming from specially the life sciences. They come to fill the gap in a very specific context because the user of such workflows is a specialist in his own field but do not necessarily knows how to deal with complex scripting schemes very well.

AnHALytics is a framework aimed at extracting information while at the same time enriching scientific documents in order to improve their indexation and retrieval. AnHALytics is composed of a quite complex workflow that contains text mining processes all linked together to achieve its goal.

This workflow is, at the moment, being manually executed by the user. Our main goal is to find a way to automatize the execution of the AnHALytics workflow, while at the same time obtaining more fault tolerance and the capability of resuming the execution of a faulty workflow.

Given the characteristics inherent to the AnHALytics framework, we can achieve that with the help of scientific workflows, as AnHALytics deals with large amounts of data, and is much more focused on the interactions and processes applied into the data than in a complex control flow.

¹<https://hal.inria.fr>

²<http://www.istex.fr>

We started by studying the most well-known workbenches for scientific workflows, then compared them under several criteria which are important to the context in which AnHALytics is executed. From this comparison, we have decided that the workbench that better suits the AnHALytics platform is RapidMiner [36].

In order to check whether or not scientific workflows would bring improvements to the AnHALytics workflow, we implemented two simulation scenarios to emulate the behavior of AnHALytics under a scientific workflow platform and AnHALytics executed by hand, as its current version.

The simulation results have shown a good improvement in the version that was integrated with RapidMiner. The benchmarks demonstrate a performance gain, with a lower execution time. As for the qualitative results, the reproducibility is easier in the RapidMiner version because of the execution logs provided by default, which make it easier to track and analyze previous executions.

The document is structured as follows. Chapter 2 presents an overview of the AnHALytics platform and its main tasks. Chapter 3 introduces the concept of workflow and the two main types of workflow systems: business and scientific workflows. Chapter 4 presents and compares the most well-known systems for creating scientific workflows. Chapter 5 describes a simulation scenario we used to evaluate the performance of AnHALytics with a scientific workflow, and its results. Finally, Chapter 6 presents our conclusions.

AnHALytics

AnHALytics¹ is a text mining application that aims at facilitating the access and indexing of scientific repositories by the research community. It achieves this by normalizing the scientific documents to a standardized format, as well as adding information to scientific documents in order to enrich them, making the indexation and the retrieval easier and more efficient. This enrichment concerns in particular the key terms and key categories of the document, as well as a process of disambiguation of the author of the article, which improves the retrieval process.

Lopez [23] describes parameters used by AnHalytics to enrich scientific documents:

- **Keyword:** a phrase that is usually selected by the author, and it is generally located in the header of the document.
- **Keyterm:** the most discriminant phrase in a document. Each keyterm is associated to a relevance score, which corresponds to the probability that a reader of the document would select a given keyterm as a key phrase. Keyterms are extracted with grobid-keyterm.
- **Key category:** obtained from the set of Wikipedia categories that are the most relevant to a document given its corpus. These parameters are categories associated with the keyterms (that were extracted with grobid-keyterm), and NERD performs the disambiguation.
- **Concept:** an annotation produced by the NERD component. As NERD has a more semantic approach, it annotates mentions in the text with their concepts.
- **Key concept:** the most discriminant concepts (i.e., Wikipedia article) to characterize a document, given its corpus.

Lopez continues by defining a *term* as being described by three different scores: phraseness, informativeness, and keywordness. The *phraseness* measures lexical cohesion, that is, the degree to which a sequence of words can be considered a phrase. *Informativeness* measures the degree to which a term is representative of a document. This is a very standard measure in document classification, called TF-IDF (Term Frequency - Inverse Document Frequency). Lastly, the *keywordness* measures the degree to which a term is selected as a keyword. It is given simply by the frequency of a keyword in the global corpus.

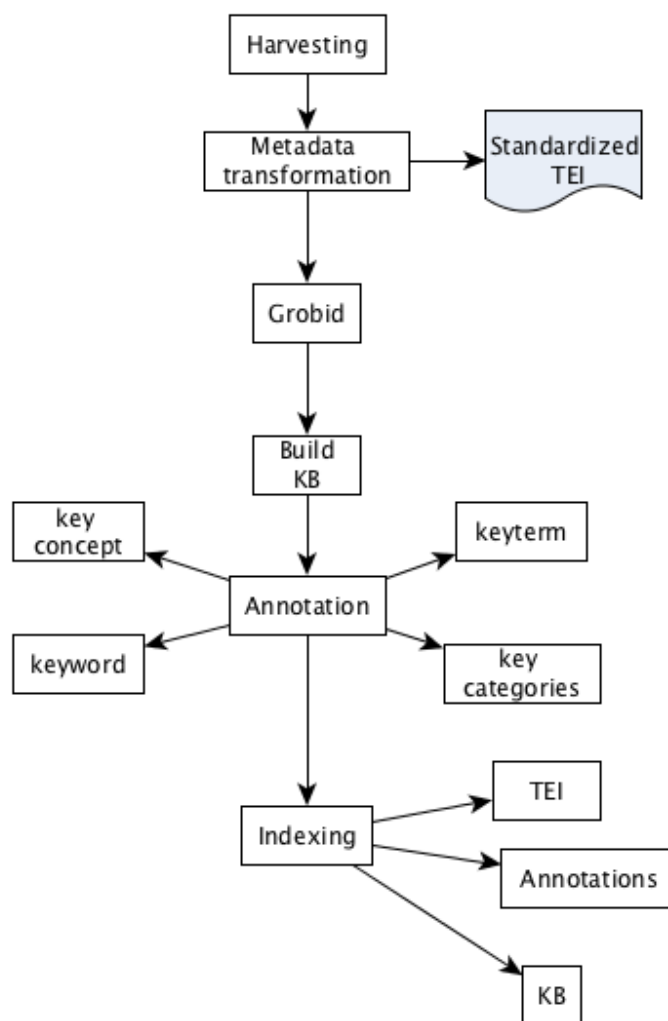
The extraction of these terms and keywords is the responsibility of the *GROBID* process. GROBID has three subprocesses that perform slightly different tasks : grobid-keyterm, grobid-quantities, and grobid-nerd.

¹<https://github.com/anHALytics>

Besides the term extraction and enrichment of the scientific documents, AnHALytics is also responsible for harvesting these documents from their original repositories and storing them in local databases, and for creating a standardized TEI file with all the information added by this enrichment, which will also facilitate the indexing of these files afterwards.

Figure 2.1 shows the AnHALytics execution workflow.

Figure 2.1: AnHALytics workflow



The core processes of the AnHALytics workflow are the GROBID processing and the annotations. We will describe these processes in more detail in section 2.1. In section 2.2 we describe how the execution of AnHALytics takes place. And at last, in section 2.3, we discuss some issues and drawbacks of the current implementation of the AnHALytics execution workflow and some alternatives to solve the problem.

2.1 Main processes

2.1.1 GROBID

GROBID², which stands for *GeneRation Of Bibliographic Data*, is a data extraction algorithm based on conditional random fields (CRF) algorithm. This algorithm allows GROBID to automatically extract and restructure raw and heterogeneous content into a standardized format.

More specifically, GROBID is responsible for the extraction of keywords and the addition of annotations in scientific documents. The subprocess of GROBID that extracts the keywords is called *grobid-keyterm*.

One of the main obstacles of the extraction of information in scientific documents is the fact that these files are not in a standardized format and some of them do not even provide information that can be easily extracted.

GROBID is usually successful in extracting information from documents, but mistakes can happen occasionally. The information extracted is mostly concentrated in the header of the file: the title, the authors and their affiliations, document key words. The header is the main information of a scientific document, as it allows the document to be cited and indexed in library systems.

After the keyword extraction, the documents can also be annotated with GROBID, through *grobid-quantities* and *grobid-NERD*.

2.1.2 grobid-quantities

*grobid-quantities*³ is focused at recognizing expressions of measurements in textual documents. These measurements can be later converted to SI units. The measurements will be grouped according to the different types found in the document (e.g., years, pressure, mass) and will be shown to the user by using different colors to specify these groups.

Figure 2.2 shows an example of the result of executing *grobid-quantities* on a document.

Figure 2.2: A *grobid-quantities* example

Badrul Sarwar et al. [4] explored Item-Based Collaborative Filtering technique to produce high quality recommendations. They first analyzed the user-item rating matrix to identify the relationship between different items, and then used these relationship to directly compute recommendations for the users by using Item-based technique. They applied Matrix Factorization model SVD to reduce the dimensionality of a ratings matrix. Using the MovieLens dataset, they selected 943 users to form a (943 × 1682) matrix each user on average rates 5% of the 1682 movies i.e., 95.4% sparse. They first fill missing values using user and movie rating averages, and then apply SVD. For this large dataset Item-Based technique provide optimal accuracy with significantly faster and high quality online recommendations than user-user (k-Nearest-Neighbor) method.

Goldberg et al. [8] proposed an approach to use Principal Component Analysis (PCA) in the context of an online Joke Recommendation System. Their system, known as Eigentaste [8]. In Eigentaste they addressed sparseness using universal queries, which insure that all users rate a common set of k-items. So, resulting sub-matrix will be dense and directly compute the square symmetric correlation matrix and then did linear projection using Principle Component Analysis (PCA), a closely-related factor analysis technique first described by Pearson in [190]. Like SVD, PCA reduces dimensionality of matrix by optimally projecting highly correlated data along a smaller number of orthogonal dimensional subspace such as the variance retained is maximized and the least square reconstruction error is minimized.

Royi Ronen et al. [9] proposed a project Sage, Microsoft's all-purpose recommender system designed and developed as an ultra-high scale cloud service. The main focus of project Sage is on both state of the

Atomic value
raw value: 5
raw unit name: %
normalized value: 0.05
normalized unit name: one
quantified (experimental): raw: the 1682 movies
normalized: the 1682 movies

²<https://github.com/kermitt2/GROBID>

³<https://github.com/kermitt2/grobid-quantities>

2.1.3 NERD

Named Entity Recognition and Disambiguation (NERD) is the part of the AnHALytics workflow that deals with entity disambiguation by using knowledge bases, more specifically, wikipedia. NERD is a process that gives semantical meaning to the terms that were extracted with GROBID. It uses Wikipedia data to train the examples and then supervised machine learning algorithms to perform the disambiguation.

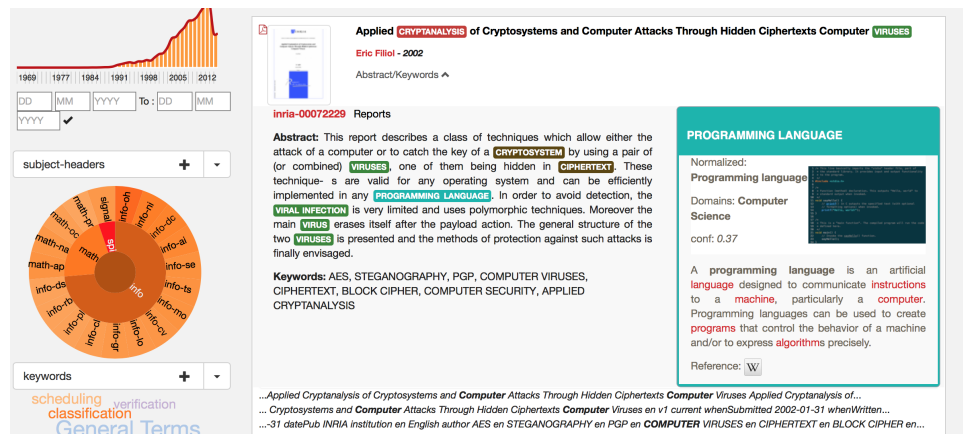
A browser accessible NERD console is also available, and it takes a PDF file or raw text as an input. Entities are recognized and displayed in different colors according to their types, which can be several different things, such as personal names, cities and countries, chemical elements, etc. The training is performed with Wikipedia articles.

NERD performs the following tasks:

- Entity recognition and disambiguation against wikidata and wikipedia in a raw text, partially annotated segment.
- Entity recognition and disambiguation against wikidata and Wikipedia at document level, for example a PDF with layout positioning and structure aware annotations.
- Search query disambiguation - below disambiguation of the search query "concrete pump sensor" in the service test console.
- Weighted term vector disambiguation (a term being a phrase).
- Interactive disambiguation in text editing mode.

Figure 2.3 shows an example of the result of executing NERD on a document.

Figure 2.3: A grobid-NERD example



But the tool does not always get the context right. Figure 2.4 shows a case in which the meaning extracted by the knowledge bases of NERD is not the same as the one used by the author of the article.

Besides the term extraction and enrichment of the scientific documents, AnHALytics is also responsible for harvesting these documents from their original repositories, storing them in local databases, and creating a standardized TEI file with all the information added by this document enrichment, which will also facilitate the indexing of these files.

Figure 2.4: A grobid-NERD example – different context

The screenshot displays the AnHALytics web interface. At the top, there's a search bar with date filters (1969-2012) and a 'subject-headers' dropdown. A circular navigation menu is visible, with 'info' highlighted. Below it, a 'keywords' dropdown shows terms like 'scheduling', 'verification', 'classification', 'General Terms', 'Keywords₃', 'optimization', 'simulation', 'Algorithms', and 'Scheduling'. The main content area shows a document titled 'Applied CRYPTANALYSIS of Cryptosystems and Computer Attacks Through Hidden Ciphertexts Computer VIRUSES' by Eric Filiol (2002). The abstract discusses techniques for catching keys of cryptosystems using viruses. A detailed view of the 'VIRUSES' entity is shown on the right, including its normalized text, domains (Biology), confidence score (0.79), and a reference to a 1982 article by Dmitri Ivanovsky.

2.2 Executing AnHALytics

From the point of view of the execution, the AnHALytics framework is divided in two parts: the AnHALytics-core and the AnHALytics-frontend. The AnHALytics-core is the server part; here, documents are harvested and analyzed by GROBID. The frontend part is the client side of the framework, where a user can control the execution that happens in the backend.

A user can access the AnHALytics-frontend through his web browser, where he can then search documents from main scientific databases. These documents are annotated and separated in categories that were learned by executing the AnHALytics server on the database.

2.3 Issues with the current solution

One of the main problems of the AnHALytics platform at the moment is that all the processes that we described in this chapter are manually executed, which takes a great deal of human time and makes the platform more susceptible to errors and mistakes. Besides, by manually executing the whole AnHALytics workflow, the platform is also not capable of providing fault tolerance, error handling, or workflow resuming/restarting. One of the possible solutions for this issue is the use of automated workflows.

Automated workflows are capable of executing the processes in an automatic fashion, which means that there is less user interference during the execution. Usually automated workflow applications will also provide some level of fault tolerance and of resuming a workflow process after a failure. The two most well known types of automated workflows are business and scientific workflows.

We will describe these two in more detail in chapter 3.

Workflows

A workflow [6, Chapter 5] is the automation of a process, containing a well-defined sequence of tasks, control flow, data flows, and participation of users. The design of a workflow is usually achieved by using a workflow system.

There were traditionally two types of workflows systems [10] – one focused on *business* processes and other for *functional* style computation of data. Later on, *scientific* workflows came as a third option that lies in between the two traditional ones, with properties for both data and control flows, which are characteristics of functional and business workflows, respectively.

The most known and broadly used type of workflow is the business workflow. Even the workflow management coalition [16], one of the main references in the domain, defined workflows in terms of business workflows, as *the automation of a business process (BP), in whole or part, during which documents, information or tasks are passed from one participant to another for action, according to a set of procedural rules*. This definition does not exactly apply for scientific workflows, as they are not usually focused on participants and actions but rather on activities and data flow.

One of the reasons to use workflows is that they present several advantages when compared to other common solutions. Workflows can, for instance, automate and manage processes that were being controlled by a script.

Ludascher et al. [25] cite some advantages of using workflows over scripting approaches: (i) scripting languages lack built-in provenance recording facilities, and (ii) it is difficult to use a single script to automate a process spanning multiple computer nodes, heterogeneous communication.

Workflows are much more scalable than scripts, and they also provide functionalities such as fault tolerance and management on the fly of the execution.

Scaling Workflows are dealing with growing amounts of data, so the scalability of a workflow is very important.

The following metrics need to be scaled: (i) data, (ii) number of workflows, (iii) number of resources involved, and (iv) number of participants

Workflow requirements and desiderata According to McPhilips et al. [28], a workflow should provide:

- Well-formedness: Workflow systems should make it easy to design and validate workflows.

- Clarity: Workflow systems should make it easy to create self-explanatory workflows.
- Predictability: Purpose of products of workflow are easy to see and understand.
- Recordability: The system should make it easy to see what a workflow did when it ran.
- Reportability: Workflow systems should make it easy to see if a result makes sense scientifically.
- Reusability: Workflow systems should make it easy to design new workflows using existing workflows.
- Scientific data modeling: Workflow systems should provide data modeling schemes that let users represent their data in terms that are meaningful to them
- Automatic optimization: Workflow systems should take responsibility for optimizing workflow performance

Gil et al. [14] describe some workflow application requirements:

- Collaborations: with the ever growing computation of large amounts of data in distributed locations, these resources usually belong not to an individual, but to several, hence collaboration is necessary.
- Reproducibility: allowing scientists to reproduce the method used to obtain a result is at the core of the scientific method. Reproducibility is highly dependent on provenance information.
- Flexible environments: scientists must be able to perform both common analysis as well as be able to set up their own methods in the workflow.

Abstract and Concrete workflows Yu et al. [46] state that when it comes to resource allocation, workflows can come in two different models (also called *specification*): *abstract* and *concrete*.

In the abstract model, the workflow is described in abstract form, without specifying grid resources. In the concrete model, the workflow is described in concrete form, allocating tasks to specific resources.

An abstract workflow is a workflow in which the activities are independent of the physical resources used to execute them. As this workflow is just an abstraction and not linked to anything tangible, it is also said to be portable. Usually the resources will be allocated to a workflow on the fly, dynamically, as these resources are shared among several users and are difficult to allocate to a given process ahead of time.

The concrete workflow is the executable workflow, that is, a workflow with all the necessary resources allocated and mapped to specific grid or cluster unities to run their tasks, as well as all the necessary data movement that happens between the workflow activities

In the following sections we will get into more detail on business and scientific workflows. In section 3.3 we present some important differences between business and scientific workflows. Finally, in section 3.4 we discuss how the characteristics of these workflow types could be used in the context of the AnHALytics workflow process.

3.1 Business Workflows

The field of business workflows have its origins traced back to the 70's and 80's with the office automation systems of that time [24]. Today they are mostly used in web services for service choreography.

Business workflows are focused on control-flow and events and on automation of organization processes [44]. These processes usually involve different roles that manipulate resources and are mainly control flow-driven. Data flowing through a business workflow is usually lightweight control data, so this type of workflow is more suited for dealing with complex control flow than with data flow.

As these types of workflows are very focused on control flow and participation of each role, so they provide branching primitives such as loop and iteration by default.

The user of a business workflow is usually a computer science expert, and he is the one that builds the workflow according to the needs of his client, the person or company interested in the results of the workflow execution.

The main goal of a business workflow is to check which processes can be automated in order to save resources – which could be human time, computation time, physical resources, and money.

The most famous business workflow platforms is Business Process Management (BPM). Van der Aalst et al. [40] define BPM as supporting BP processes using methods, techniques, and software to design, enact, control and analyze operational processes involving humans, organizations, applications, documents and other sources of information.

Business workflows are usually represented by using Petri nets. Petri nets are a basic model for representing parallel and distributed systems. According to Peterson [32], the structure of a Petri net is defined by its places, transitions, input function, and output function. A Petri net graph is a representation of a Petri net structure as a bipartite directed multigraph. Van der Aalst et al. [39] give three reasons why it is a wise choice to select Petri-net-based workflow: (i) formal semantics (despite graphical nature), (ii) state-based instead of event-based, and (iii) abundance of analysis techniques.

3.2 Scientific Workflows

Scientific workflows are workflow frameworks aimed at solving the problems of scientific research and e-science. The term *e-science* was coined to describe computationally and data intensive science. The use of workflows in this domain is growing because it is difficult to manage computationally heavy processes by hand, without automation.

According to Ludascher et al. [25], the main goals of scientific workflows are to save "human" cycles and to save machine cycles. This means that scientific workflows need the hard work to be performed by the machines rather than by the users. A user of a scientific workflow wants to automate a scientific process and not be concerned about how this process takes place.

Zhao et al. [47] state that scientific workflow systems are engaged and applied to the following aspects of scientific computations:

- Describing complex scientific procedures
- Automating data derivation processes

- High performance computing to improve throughput and performance
- Provenance management

Ludascher et al. [25] also define some scientific workflow concepts and system features:

- Integrated workflow environment
- Workflow preparation and execution support (parameter seeds to simplify multiple runs)
- "Smart reuse" is desirable
- Runtime monitoring
- Fault tolerance ("smart resume"), with checkpointing or logging, for instance.

These features are usually very similar for any kind of workflow, but are of great importance in scientific workflows.

Life cycle The scientific workflow life cycle consists of the following steps: (i) workflow design (usually reuse pre-existing workflows or refine them), (ii) workflow preparation (selection of sources and setting parameters), (iii) workflow execution (input data is consumed), and (iv) post-execution analysis (evaluate data products and interpret results)

Reproducibility According to Gil et al. [14], one of the most important aspects of scientific workflows is that they should easily allow the reproduction of the steps to obtain the final results. Scientific reproducibility implies that someone can follow the general methodology, relying on the same initial data, and hopefully obtain equivalent results.

3.2.1 Requirements and desiderata

Ludascher et al. [24] describe some requirements and desiderata of scientific workflows:

- Seamless access to resources and services: remote execution of jobs and access to databases.
- Service composition and reuse, and workflow design: how to design actors to perform simple tasks and how to reuse these actors in other workflows.
- Scalability: workflows can deal with a large number of nodes to execute a task or with large amounts of data to process or analyze.
- Detached execution: workflows should be able to run in the background on a remote server and not need to be connected to the user application during all the execution time.
- Reliability and fault tolerance: workflows should be made more reliable by using fault tolerance mechanisms.
- User-interaction: users might be required to interact with workflows at several steps of the execution, like choosing where to run a task or to resume the execution in a certain node after a failure occurred.

- Smart re-runs: allows to change a parameter in an actor without the need to re-execute the workflow from the beginning, only re-execute the nodes affected by this change. Smart re-run also comprises checkpointing, so the workflow can be executed from the last checkpoint if a failure occurs.
- Smart (semantic) links: a scientific workflow workbench should assist the design by suggesting which components fit together and datasets that might be fed to each actor. a scientific workflow system has to be able to capture some sort of semantics within the data it is dealing with
- Data provenance: an experiment run in a scientific workflow should be reproducible. so it is important to keep track of what has been done / executed in a workflow, such as its results and which actors were and in what sequence. In this context comes data provenance, that comprises information of what has been run in the workflow. Data provenance gives semantic information about data (because it can track down how it was produced and why).

3.3 Scientific vs Business Workflows

Scientific and business workflows share a lot of similarities, but they also differ on several aspects. We will discuss the points where these two workflow standards differ and where they coincide in this section. Most of the points raised in this section were based on evaluations made by Yildiz et al. [44] and Barga et al. [4].

General purpose The goals, concerns and the nature of scientific and business workflows are intrinsically different. While in business workflows the main goal is to have a set of business rules and interactions between the roles, the goal of a scientific workflow is to facilitate a scientific process by automating it. Business workflows usually focus on the roles of several actors and how they interact with each other and the activities they have to perform, while scientific workflows usually only have one "actor" (the scientist), and it is more focused on dealing with data

The processes of the scientific field are much more dataflow-driven and rely on the analysis of the data generated by the execution of the workflow (which is inherently much more complex than the data in business workflows) rather than in the overall control / coordination dependency scheme that is common in business workflow scenarios.

As it is more focused on data, the user of a scientific workflow needs to run a given workflow multiple times, changing the input data in some of its tasks. This is the main difference of business and scientific workflows: how they deal with data.

Data flow Business workflows deal mainly with lightweight control data, so the data flow is not a very important aspect for this type of workflow.

Scientific workflows usually deal with large amounts of complex data. The data that results from each step is important (because it contains intermediate results), and should be correctly processed and stored.

Control flow Business workflows provide basic control flow methods such as sequence, branching and choice.

A scientific workflow is usually represented by a directed acyclic graph (DAG), which makes it more difficult to represent these simple primitives, as DAGs do not allow loops in the basic structure.

In scientific workflows, the control flow is modeled in a (mainly) dataflow environment. This makes dataflow and control-flow "entangled" in scientific workflows, which makes then harder to design and to understand.

Scientific workflows might need a more expressive control flow mechanism compared to business workflows in order to express both data and execution concurrency.

User Goals Users of business workflows want to know which tasks can be optimized in order to reduce costs, while users of scientific workflows (that is, scientists) want to know details about the scientific process that generates the final results.

Process modeling Scientific workflows usually model process using dataflow information, while business workflows usually aim at expressing a certain order of the execution of the tasks (control flow).

Dependency In business workflows, dependency is related to the partial order between two tasks in the workflow. In short, the dependency in business workflows is related to the control flow.

On the other hand, in scientific workflows the dependency is related to the data relationship (data dependency) between two tasks in the workflow, but can also depend on the control flow, because data and control flow are entangled in scientific workflows.

In conclusion, in business workflows the dependencies between activities are dependencies in the control flow, while in scientific workflows dependencies are related to control flow, data flow, or both.

Model of computation In business workflows, the model of computation is similar to imperative programming. This is a very rigid approach, that couples modeling and execution. This is not the best way to describe all processes, so approaches that allow a more flexible modeling have been proposed too. In these approaches, the modeling is a mixture between imperative programming and declarative programming.

In scientific workflows, the model of computation is dataflow oriented, so the execution of a task is data-driven. A task is "activated" and will execute only when its input data is available. This model does not impose an order of execution between the tasks, only data dependency. However, some control structures might be needed, for instance to express conditionality.

Data and control flow The main difference between business and scientific workflows lies in how they deal with data. Because it is more focused on data, it is common that a scientific workflow needs to be run a given workflow multiple times, with different data in some of its tasks.

Who builds the workflow Business workflows are generally constructed by professionals in information technology, while scientific workflows are build by scientists themselves, who are usually not experts in that domain.

Provenance Information In business workflows, the goal is to know the parts of the process that can be optimized in order to reduce costs. In scientific workflows, there is much more concern about the intermediate steps, that are data resulting of a scientific process.

Comparison Table 3.1 shows the comparison between business and scientific workflow.

Table 3.1: Differences between Scientific and Business Workflows

CHARACTERISTIC	WORKFLOW	
	Business	Scientific
Implementation vs modeling	Process	Executability
Goals	Outcome is known since the beginning	Outcome may confirm or invalidate hypothesis
Users and roles	Responsible for distributing work to human actors	Largely automated, requiring little to no human intervention
Dataflow vs control flow	A \rightarrow B represent control flow	A \rightarrow B represents data flow (A produces data and B consumes it)
Reusability	Does not allow	Allows (and encourages)
Computation	Service innovation	Dataflow computations
Models of computation	Petri nets	Varied (can be job or dataflow oriented)

3.4 Discussion

In chapter 2, we discussed the AnHALytics platform and some issues with its current implementation. We argued that a possible solution would be to use a workflow system to automatize the processes that are currently executed by hand. In this chapter, we talked about the two most well known types of automated workflows: business and scientific, pointing out their characteristics and for which applications they are more suitable.

Knowing that AnHALytics is a platform that focus mainly on the processing of *data*, and analyzing the pros and cons of each type of automated workflow, it is clear that the most appropriate type of workflow for automatizing its processes is a scientific workflow.

The field of scientific workflows has been gaining a lot of attention in the last decade, and several different workflow systems have been proposed, each with its own characteristics and aimed at different types of scientific applications. In the next chapter we will describe the most well known workflow systems and compare them according to some criteria in order to find the one that would be most adapted for AnHALytics' needs.

Scientific Workflow Management Systems

Workflow management systems aim to automate the execution of processes [44]. The automation of a process involves the scheduling, control and monitoring of the tasks that comprise it. A workflow system provides means to model, re-engineer and automate the execution of processes.

In chapter 3, we described the standards for business and scientific workflows and their differences and similarities. In this section, we will present some of the most well known systems for creating and managing scientific workflows. For each of them, we will provide a brief description and at the end of the chapter we included a section in which they are compared based on some characteristics that are fundamental for our application.

Yildiz et al. [45] stated that *the main advantage of workflow management systems is the modeling capabilities that allow users, who may not be specialized in programming, to implement their processes using the comprehensible design primitives such as activities, dependencies, and control structures.*

Our goal is to find the workflow system that is more adapted to our application needs.

4.1 Kepler

According to Zhao et al. [47], Kepler¹ is a scientific workflow framework based on Ptolemy II, which is a framework to design heterogeneous and concurrent systems. Kepler uses *cinema* as a metaphor for how it sees the components of a workflow: each workflow has a director and several actors. Directors specify when an event occurs while actors specify what occurs. There are different types of directors, each of them more specified to work in a different scenario.

Curcin et al. [10] classify Kepler's core directors in four different types:

- SDF (synchronous data flow): it has fixed rates for token production and consumption. The order of execution is statically determined from the model.
- PN (process network): it is a derestricted version of SDF, where the actor is invoked only when the data arrives, although there is no need to have all data to invoke the actor. This leads to a more dynamic environment, where actors can be executing in parallel.
- CT (continuous time): it introduces the notion of timestamps on tokens and it is usually described in terms of differential equations to approximate functions and schedule the executions.

¹<https://kepler-project.org/>

- DE (discrete event): it also uses timestamps on the tokens to measure average waiting times.

Kepler does not have a functional composition – it is the director that controls the order in which the actors will execute. Each director can be classified as strict, loose or loosest, based on the semantics. Embedding in Kepler are allowed only when an inner director is at least as strict as an outer director.

In order to give a semantic meaning to what an actor does, the actor has to be directed. It is the director that controls, for instance, how many times an actor is to be executed or if it can be executed in parallel with other actors.

Some highlights of Kepler: (i) web service extensions, (ii) grid and other extensions, and (iii) actor-oriented modeling

4.2 Pegasus

Pegasus (Planning for Execution in Grids) ², as its name implies, is a tool designed to map workflows onto grid resources that can execute them. Pegasus does not provide a GUI, so workflows must be created by describing their scheme in the DAX (Directed Acyclic Graph XML) language. Pegasus provides libraries to DAX generators in Perl, Python, and Java. This DAX description is portable and it does not depend on local files or information to execute. The workflow created with the DAX language is only an abstract form of the workflow.

According to Deelman et al. [11], to map an abstract workflow into a concrete (executable) one, three things have to be found: resources to execute the tasks, data used in the workflow, and the necessary software.

Pegasus is also capable of performing workflow reduction when mapping an abstract workflow into its concrete form. For instance, if a file is the input to a task and it has been already computed, Pegasus will use this file and not recompute the task that created it (and for which the file is an output).

The concrete workflow produced by Pegasus can be executed by DAGMan. It generates a submit file that contains information about the allocation of tasks to resources and the order in which the tasks should be executed.

According to Ludascher et al. [24], Pegasus is (at that moment) semi-dynamic, because abstract workflows are mapped to concrete workflows only when they are given to Pegasus.

Pegasus uses three different information catalogs:

- Site catalog: description of the sites where each workflow job is going to be executed
- Transformation catalog: description of the executables used by the workflow (location, operating system, etc)
- Replica catalog: description of the location of each input file used in the workflow

4.3 Taverna

According to Wolstencroft et al. [41], Taverna is designed to combine distributed webservices and local tools into complex analysis pipelines, which can be executed in clusters, grids, etc or

²<https://pegasus.isi.edu/>

even on the local machine. Taverna is composed [10] by the Taverna workbench, the SCUFL language and the FreeFluo enactment engine.

The workbench is composed of the graphical user interface and several components that the user can use (by dragging and dropping into the workflow canvas) to build his workflow. The workflow a user builds is going to be stored in the SCUFL representation language. The workflow is represented as a DAG. When the user wants to run workflows he has build, they will be run with the Freefluo engine. SCUFL, the language in which Taverna workflows are represented has some limitations. SCUFL is a dataflow language with only some control flow primitives. The only control structure Taverna has is a conditional construct, similar to the case construction. Loops can be achieved only in a limited form.

Usually Taverna workflows are composed from a mixture of distributed web services, local scripts and other services (for instance, R scripts). The biggest advantage of using distributed systems is that all the computation overhead of the execution happens in a remote location, and not the local machine, so there is no need to install any tools locally. This is specially evident for the execution in the cloud, where the cloud server can easily provide the user with all the tools he needs to execute his workflow from the start.

4.4 Triana

Cursin et al. [10] describe Triana ³ as being a visual workflow-based problem solving environment developed at Cardiff university. A workflow component in Triana is called *unit*, and units can connect with each other by directed cables.

Triana is a dataflow system, but can provide support for control flow by using some special messages that can trigger control between units. There are also special nodes for branching and looping, and they can be combined with other functional units to build more sophisticated forms of control flow.

One of the main disadvantages of Triana is that it has not had any recent updates. The GitHub repository that hosts the Triana development code was last updated almost three years ago, with the last stable version launched more than four years ago.

4.5 RapidMiner

RapidMiner is a data science / data mining platform. Its workbench is called RapidMiner Studio, and it offers the users a very modern GUI in which they can build their workflows. It provides several tools to work with the data and to create workflows that focus on the relationships and the transference of data.

Jungermann et al. [17] described the information extraction in RapidMiner ⁴ as being a plugin that converts documents containing natural language texts to machine-readable form in order to extract interesting information and relationships between them.

The process-view in RapidMiner presents a modular view of the experiment. it usually consists of four stages: (i) input stage, (ii) preprocessing stage, (iii) learning stage, and (iv) evaluation stage.

³<http://www.trianacode.org/>

⁴<https://rapidminer.com/>

4.5.1 Radoop

One of the issues with Hadoop is that it is not very user-friendly because it lacks a graphical user interface.

Prekopcsak et al. [34] developed Radoop, an extension to RapidMiner which allows it to work with Hadoop.

Radoop aims at dealing with the problem of big data (and for that, distributed computation) while hiding the complexity of data analytics through a high level framework such as RapidMiner.

4.6 Knime

Knime⁵ [5], also known as Konstanz Information Miner, is an environment for the interactive execution of a data pipeline. It allows the user to create (and visualize) the analysis flow by building blocks connected through pipes that represent the data flow between those blocks.

The user can model and visualize workflows. A workflow consists of nodes and connections between these nodes; the nodes process data and the connections carry the data among the nodes.

A node in Knime processes all its data before forwarding it. This means that the process can be stopped and easily resumed and also that new nodes can be added to the workflow scheme after the node in execution and it will not be necessary to rerun the previous nodes of the workflow again.

Workflows in Knime are directed acyclic graphs (DAGs). Besides the nodes that compose the workflow *per se*, there is also the workflow manager. The workflow manager holds the power to allow (or not) the addition of new nodes and connections between nodes in the workflow schema.

Besides the built-in nodes provided by Knime, a user can also create his own workflow nodes by using Knime plugins. New nodes are created by extending one of the abstract classes for nodes, so the user must know how to code in order to build new nodes from scratch.

A workflow in Knime is represented by a DAG, and for this reason, loops cannot be represented. To overcome this problem, Knime provides two special nodes: loop start and loop-end. These nodes, unlike regular nodes, are not reset when the loop executes and they can exchange information with each other.

4.7 Discussion / Comparison

In this section we will present a comparison study between the scientific workflow systems previously described in this chapter. This comparison takes into account some important criteria to the execution of an application such as AnHALytics, mainly focusing on a distributed scenario.

4.7.1 Workflow management and deployment

Kepler Kepler has a monitor manager that, for each element of the workflow, allows the user to indicate the style and the events to be monitored [19]. This is, however, a experimental

⁵<https://www.knime.org/>

module and might not work perfectly.

Pegasus In Pegasus, the management of the workflow being run is done with logs, which can be of three different types [38]:

- Pegasus mapper log
- DAGman log
- Job logs (aka kickstart records)

DAGman writes a log file in near real time during execution. This log file contains the status of each job in the workflow, as well as the scripts associated with it.

Taverna Taverna workflows can be annotated (by the user or configurable to be automatically annotated). However, Taverna does not capture provenance of a workflow definition, and assumes that the scientist is managing this through versioning (names, git, etc). Each time a workflow is changed, an internal identifier it has also changing, which allows the user to keep track of these changes and workflows that have the same ancestry [35].

Triana Triana can be used alongside stampede to provide better management and deployment tools. Besides that, Triana does not have any kind of logging or management tools or information [38].

Knime Knime does not have a logging scheme *per se*, but it has some tools that can store some intermediate execution information about the nodes of a workflow.

RapidMiner RapidMiner has a log table which can store all kinds of information, such as parameters, execution time, etc. The information stored in the log table can also be analyzed in form of graphs in RapidMiner's result workspace [21].

4.7.2 Workflow execution

Kepler Kepler supports multiple levels of distributed execution, on the workflow, subworkflow and atomic actor levels. It supports master-slave, map/reduce, and grid distributed execution, among others [33].

Pegasus Pegasus can run, from the point-of-view of the user, workflows across multiple heterogeneous resources distributed in a wide area, while at the same time shielding the user from the grid specific details [12]. Both data storage and the workflow execution itself can be distributed.

Taverna Taverna workflows can be executed in distributed web services, using services on a grid or on a cloud [41].

Triana Triana is mainly focused on executing workflows on the grid or as web services. It has two distribution policies: parallel and pipeline, as well as two modes of execution: dynamic and static [8]. In the dynamic approach, the workflows are sent to services that can execute any subworkflow and communicate with other Triana services they are connected to. In the static approach, a user can chose to launch a group unit as a specific remote service, so Triana units or groups may be deployed as Web services.

Knime Knime has no free option for distributed execution. It has three main frameworks, Knime Cluster Executor, Knime Server, and Knime Spark Executor, but they are all commercial products [42].

RapidMiner RapidMiner has an extension called Radoop which allows it to be integrated with the Hadoop framework more easily. The main method of distributed execution in RapidMiner is by using Radoop to run tasks on Hadoop, which is the most well known platform for distributed execution focused on the map/reduce model, very efficient in distributing the execution of big data applications [34].

4.7.3 Deployment of a workflow while in execution

Kepler Kepler has an execution monitoring that keeps track of all the activities performed in a workflow as well as the data it is using [19].

Pegasus Pegasus has a monitoring framework called NetLogger that runs under Stampede (Synthesized Tools for Archiving, Monitoring Performance and Enhanced DEbugging). The goal of Stampede is to enable real-time debugging and performance and behavior analysis of workflows [38].

Taverna During a workflow execution, Taverna displays status information. For each SCUFL processor, the last event is displayed alongside with detailed information (if any), which can include the progress through an iteration and retry information. This status information also provides more details about intermediate inputs and outputs [30].

Taverna also has a workflow monitor web application that performs periodic monitoring of workflow activities and provides information about their current status [43].

Triana Triana can be extended to use Stampede Monitoring, just like Pegasus. When integrating Triana and Stampede, each task within a task graph is run locally [38].

Knime Knime has a monitoring tool called NodeMonitor. Using the debug feature of NodeMonitor allows the user to check the execution times for each node of a workflow.

RapidMiner Logging and Monitoring are utilities available for RapidMiner + Radoop. Monitoring contains information on the cluster's status, health, version, etc. It provides detailed information on the applications and jobs running in the cluster, as well as logs and information about the MapReduce jobs. These utilities are also available whenever RapidMiner is used with the spark web UI. If the user wants to execute jobs on the cloud, RapidMiner also provides a tool called CloudMonitor that monitors the jobs executing on the cloud [22].

4.7.4 Fault tolerance and error handling

Kepler Kepler has some specialized actors to deal with errors and exceptions, such as the so called "exception catching actors". Kepler also has the rerun capability based on the provenance of the information collected by the system [1].

Pegasus Pegasus provides the following fault tolerance mechanisms [13]:

- Job retry: jobs and data transfers are automatically retried in case of failures.
- Data movement reliability
- Failed workflow recovery / rescue DAGs: the workflow will restart from the point of failure
- Workflow re-planning: in case of workflow failures, users can re-plan the workflow and continue the computation using a different resource

Taverna Taverna provides fault tolerance mechanisms such as dynamic service substitution and retry [30].

Triana Triana provides fault tolerance (prevention and recover capabilities) at task level, workflow level and user level. It can also easily detect faults on hardware level, but not so much on the OS level [9].

Knime Knime provides try/catch nodes and basic error handling. Its mechanisms for fault tolerance are not as sophisticated as the ones of some other workflow management systems.

RapidMiner Using only RapidMiner, in order to restart from an intermediate step, the user needs to save the data to the disk, which can be done through the GUI. Using Radoop alongside RapidMiner allows to use the fault tolerance provided by Hadoop [34].

4.7.5 Reproducibility

Most workflow management systems provide reproducibility through data provenance. To obtain data provenance, these systems log each step of the workflow with great detail, in order to make that workflow easily reproducible by anyone, thus asserting scientific reproducibility.

For scientific workflows, provenance can be of three different types [35]:

1. Provenance of the workflow definition
2. Provenance of a workflow run
3. Provenance of data

Each workflow system might capture a different set of these provenance types.

Kepler Kepler has an add-on module that allows the user to record a workflow execution history. It is a button in the GUI which the user can activate and deactivate as he sees fit. Whenever a user changes some parameters of an actor, the workflow might be able to perform a smart re-run, which takes data dependencies into account and only executes the parts of the workflow that were affected by the changes [29].

Pegasus Pegasus keeps track of what has been done (provenance) including the locations of data used and produced, and which software was used with which parameters. By default, all jobs in Pegasus are launched using the Kickstart wrapper that captures runtime provenance of the job and helps in debugging. Provenance data is collected in a database, and the data can be queried with Pegasus specific tools or directly using SQL [31].

Taverna The Taverna Engine (workbench + command line) enacts the workflows and collects the provenance of workflow runs, including individual processor iterations and their inputs and outputs. It is also able to provide some level of provenance of workflow data through some tools in myGrid, such as annotations [18].

Triana Triana provides data provenance through workflow annotation, which can happen manually (user annotates the workflow) or automatically. Provenance data recorded includes: date and time composed, date and time of the execution, details of the resource on which a service was executed, and intermediate data products generated [26].

Knime At any point of the workflow, the user can inspect data, model, etc., which provides intermediate results of the workflow. Knime also provides logging which is divided in several levels such as DEBUG, INFO, WARN and ERROR. The verbosity of this log can be controlled by the user beforehand [20].

RapidMiner In RapidMiner, there is little built-in support for recording and accessing the information of how data outputs have been produced by different versions of a flow. Most logging is focused on logging the Radoop extension in order to access and monitor the cluster's web interfaces [15]. RapidMiner also provides a log operator that can be used to store the values a user has chosen.

4.7.6 Adaptability

Most workflow management systems allow the execution both locally and on distributed environments (be it a cluster, a grid, or a cloud). Generally, this is not transparent to the user; the user needs to state his or her preference for where the workflow is going to be run.

Kepler Extensions allow Kepler to be executed in a distributed environment, such as clusters, grids, and clouds. Kepler is not targeted to a particular distributed execution requirement. The distributed execution in Kepler can happen at the workflow level, subworkflow level, director level or actor level. Because of these wide variations, this is not transparent to the user.

Pegasus In Pegasus, user created workflows can be easily run in different environments without alteration. Pegasus currently runs workflows on top of Condor, grid infrastructures, and clusters. The same workflow can run on a single system or across a heterogeneous set of resources.

Taverna In Taverna, the distributed execution happens in the form of webservices. A workflow (or subworkflow) is seen as a service. Taverna also provides local and distributed pipeline execution. In order to use Taverna's distributed resources, the user needs to be using Taverna Server.

Triana The user needs to select the resources for execution. A user will, for example, select a group of tasks he wants to execute in parallel. The main unit of Triana distributed execution are those group tasks; data is distributed accordingly.

Knime Knime only allows distributed execution with the help of a paid extension, which means that the open source and free version does not allow / adapt to distributed environments, only single user machine.

RapidMiner RapidMiner has the Radoop extension, so the behavior for execution (be it distributed or not) will be similar to using Hadoop while using this extension. The user has to describe the available machines in a file, and any tasks that can be distributed are going to be allocated to each of these machines. Without this extension, RapidMiner can only execute the workflows locally.

4.7.7 Challenges when comparing to scripting solutions

The design and implementation of a solution using a scientific workflow can be more difficult than using scripts. This happens because while using scientific workflows, one needs to think in terms of actors/operators to execute a task, instead of functions and classes as in usual programming languages. After this first step, it can be actually easier to develop new features and manage the execution while using a workflow management platform than while using scripts.

4.7.8 Scalability

All of the workflow systems we studied are said to scale well in distributed environments, being able to deal with up to thousands of workflow elements.

Kepler Kepler has specialized actors to deal with grid architectures / environments and can also be integrated with Hadoop and Spark [2].

Pegasus Pegasus can easily scale well to both the size of the workflow and the resources. Pegasus can run workflows ranging from just a few computational tasks up to one million tasks. The number of resources involved in executing a workflow can scale as needed without any impediments to performance [31]. Among the workflow systems we have considered, Pegasus is the best for distributed execution.

Taverna Taverna was build to be scalable through the SCAPE project, aimed at building a scalable platform for planning and executing workflows. The workflows are deployed on a large scale (using Hadoop) and executed over large, distributed and heterogeneous objects [37].

Triana Triana workflows can be executed on the grid and in P2P by selecting resources for execution, so it scales well for the number of nodes. Triana can also be executed on the cloud if an appropriate extension is used in the workflow [26].

Knime The Knime distributed execution module is paid, and the system does not scale well with local execution (limited ram, processors, and disk space).

RapidMiner RapidMiner uses Radoop, an extension that allows users to use Hadoop inside of RapidMiner very easily; so, in theory, it should scale as well as Hadoop [26]. However, the distributed version of RapidMiner is paid, so in the free version only one thread is used to run the workflow.

4.8 Discussion

In chapter 2, we discussed the AnHALytics platform and how automatizing its processes could improve the overall performance of the framework. In chapter 3 we presented the two most used and well known types of automated workflow types, and we argued that scientific workflows would be a better fit for the automation of AnHALytics, according to its characteristics and general needs. In this chapter, we presented some of the most well known and widely used scientific workflow platforms and compared them using some criteria that is of great importance in the context of the AnHALytics application.

Table 4.1 shows a comparison between the systems studied regarding the most important criteria analyzed.

Among the workflow systems described in this chapter we believe that the AnHALytics framework would work better with RapidMiner.

Taverna and Kepler could also be good fits for AnHALytics, but they are focused applications for the biosciences. Implementing data mining algorithms in these workbenches would be a lot more expensive in terms of time and work than with RapidMiner. Besides the domain, RapidMiner is also the workbench with the best documentation among all of those we have studied and the one that is more often updated.

RapidMiner provides operators that implement data mining algorithms, fault tolerance, process logging, and easy execution management. However, only its core is free and open source. Distributed execution is not available in the free version, so the criterion of scalability should not be the first priority when using RapidMiner. Even with this drawback, we consider that it is a good fit for AnHALytics.

In the next chapter we discuss how we can use this scientific workflow system to improve the AnHALytics workflow process.

Table 4.1: Comparison between workbenches

CRITERION	WORKFLOW SYSTEM					
	Kepler	Pegasus	Taverna	Triana	Knime	RapidMiner
Focus	bio-sciences	bio-sciences	bio-sciences	signal processing	data-driven appl.	data science
Open-source	✓	✓	✓	✓	✗	✗
Reproducibility	✓ (prov.)	✓ (prov.)	✓ (prov.)	✓ (annot.)	✓ (log/ inspection)	✓ (log)
Fault Tolerance	job retry	job retry, try-catch actors	job retry WF re-plan	job retry	try-catch	job retry
Monitoring/ logging	✓	✓	✓	✗	✗	✓
Workflow management (pause, stop)	✓	✓	✓	✓	✓	✓
Distributed execution	cluster, grid	cluster, grid	webservices	grid, p2p	hadoop (paid)	cluster, grid (paid)

Implementation and Evaluation

At first, we had planned to implement the AnHALytics framework over one of the workflow workbenches, but we underestimated the complexity of this task.

Because of the nature of the scientific workflow systems we have studied so far, implementing a large application such as AnHALytics over one of these workbenches is going to require a lot of technical work, possibly with the need of redesigning the whole application.

As time was an important factor during an internship, we decided it would be best to implement a simulation using two different scenarios instead. These scenarios aim to reflect the behavior of the execution of the AnHALytics platform in its current form (with all the processes being executed by hand) and the execution of AnHALytics being managed by a scientific workflow system.

5.1 Proposed solution

As stated in the previous section, the process of integrating AnHALytics with scientific workflow workbench goes beyond the scope of this internship, as it deals with a lot of technicalities and would require more time to redesign the system. Two scenarios are proposed in order to simulate the behavior of the AnHALytics platform in its current state and with a scientific workflow. These two implementation are presented in more detail in the next subsection.

5.1.1 Simulation

The simulation scenario is composed by a series of tasks that involve web crawling and the application of text mining algorithms, both important steps in the AnHALytics workflow.

The following tasks were implemented:

- Read an excel file containing URLs to thirty TEI documents from the HAL platform.
- Web crawling to obtain the content of these documents.
- Extraction of the English abstract.
- Tokenization and removal of stop words in these documents.
- Cosine similarity and TF-IDF metrics calculated for the English abstract of these documents.

For each of the documents obtained from the HAL platform, we extracted its English abstracts and calculated the cosine similarity and the TF-IDF measures when compared to the other documents.

The scenario that simulates the current state of AnHALytics was implemented using Python scripts, while the scientific workflow scenario was implemented in RapidMiner. In the scripting version, we needed to use several Python libraries to implement the algorithms we needed, such as libraries to exclude the stop words from the original text and to read and parse the XLS and XML files. With RapidMiner, all the functions we needed were either available off the shelf or implemented in the Text Processing and Web Mining extension, which are free and can be easily installed from the extension manager.

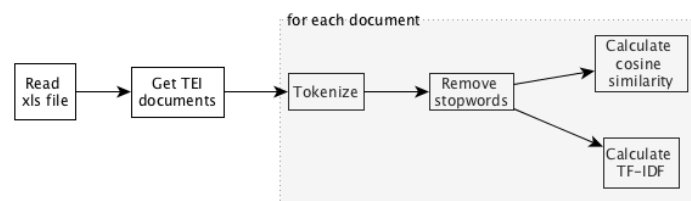
The simulation schemes are presented in the next subsections.

Script

The scripting scenario aims to simulate the behavior of the current implementation of the AnHALytics platform.

Figure 5.1 shows an scheme with the simulation scenario implemented with Python scripts.

Figure 5.1: Simulation scenario: scripting



Python is one of the most used programming languages in data mining applications, so it has external libraries that implement several data mining algorithms.

The following libraries were used in the Python script:

- NLTK (Natural Language Toolkit): used to tokenize and remove the stop words from the text.
- urllib: used to fetch the documents listed in the XLS file and extract their information.
- TextBlob: used to calculate the TF-IDF.
- xlrd: used to read the XLS file.
- NumPy: used to get more precise float numbers in the cosine similarity calculation.

Scientific workflow

The scientific workflow scenario was implemented in RapidMiner. As RapidMiner is focused on data science applications, it provides two extensions that implement text mining algorithms: the Text Processing and the Web Mining extensions. Consequently, in this scenario we only needed to use RapidMiner's operators, no external scripts were needed.

Figure 5.2: Simulation scenario: scientific workflow

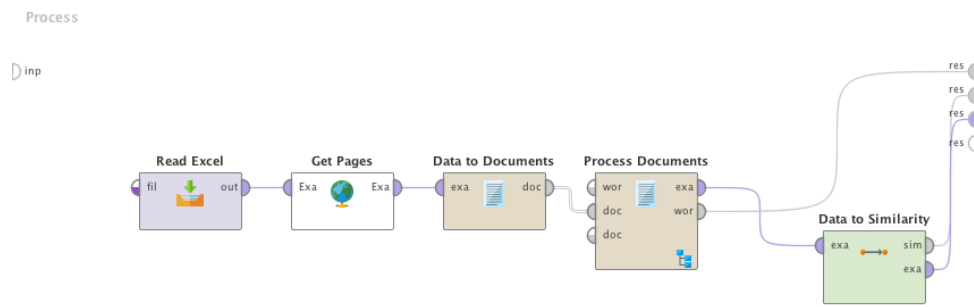
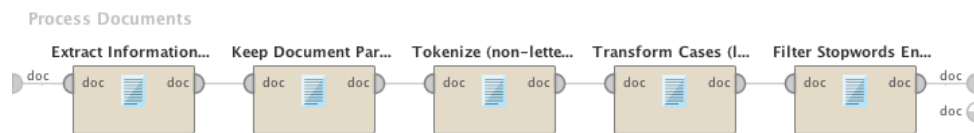


Figure 5.2 shows the scheme implemented in RapidMiner.

The task "Process Documents" is a subworkflow. Its complete scheme is shown in figure 5.3. This subworkflow is responsible for the task of processing the documents: the English abstract is extracted, the stop words and punctuation signs are removed, and the result is tokenized. In the end, the TF-IDF metric is calculated.

Figure 5.3: Inside the "Process Documents" operator



Some of the operators used in the scenario were available by default in the RapidMiner application, others were implemented by the extensions Text Processing and Web Mining. The table 5.1 shows where each RapidMiner operator used in the scenario is implemented.

Table 5.1: Where RapidMiner operators are implemented

OPERATORS IMPLEMENTED	
EXTENSION	
RapidMiner	Read Excel, Data to Similarity
Text Processing	Data to Documents, Process Documents, Extract Information, Keep Document Parts, Tokenize, Transform Cases, Filter Stopwords
Web Mining	Get Pages

The evaluation for these two scenarios is described in the next section.

5.2 Evaluation

The goal of both scenarios is to simulate a simplified version of the behavior of the AnHALytics process.

The two simulation scenarios are evaluated under the same criteria, some of which was already discussed in section 4.7. We used the following criteria to evaluate the solutions:

- Reproducibility
- Execution time
- Execution management (resuming, pausing)
- Fault tolerance

All these criteria, with the exception of execution time, can be considered as qualitative. For this reason, we will discuss how they can be achieved in each scenario.

5.2.1 Reproducibility

Cacioppo et al. [7] argue that *reproducibility refers to the ability of a researcher to duplicate the results of a prior study using the same materials as were used by the original investigator.*

Marcus [27] links reproducibility with the credibility in scientific experiments, and states that *without credibility, others can't/won't build on our work, and as a result, the pace of scientific advance is slowed.* Reproducibility is one of the most important criteria we need to evaluate, as it is at the very basis of the scientific process.

In the scripting scenario, any means to achieve reproducibility have to be manually implemented, as they are not available by default. Most of modern programming languages have libraries that allow the user to create their own logs for an execution, but still it would be the user's choice to decide what to put into the log.

In the scientific workflow scenario, there are tools that can be used to achieve reproducibility, such as detailed logging and validation of a process workflow. The workflows generated are also portable, which makes it easier for a different observer to analyze the results obtained.

It is also important to note that RapidMiner provides a rich view of the results after the execution is finished, including statistics and charts to visualize the results. This is also a factor that is related to reproducibility, because it is much more simple to analyze and compare the results of the execution.

5.2.2 Execution Time

One of our goals with the automation of AnHALytics would be to reduce the execution time – mainly by optimizing the number of threads used to execute the application. As AnHALytics seem to be an application very prone to distribution, as each document is individually treated at each time, we expect the execution time to be reduced with the use of a scientific workflow controlling its execution.

The table 5.2 shows the results for execution time for the simulation scenarios. The scenarios were run on a MacBook Pro with the following configurations: processor Intel Core i7 3,1 GHz, 16GB RAM, OS version 10.12.6. The results show the mean execution time obtained in five executions for each scenario.

As shown by the table above, the RapidMiner scenario executes the text harvesting task in a time around 10% lower when compared to the scripting version. The computation of cosine similarity and TF-IDF take about the same amount of time in both scenarios.

Table 5.2: Execution time in the simulation scenarios

TASK	SCENARIO	
	Script	Scientific workflow
Text harvesting + tokenization	23.48s	21s
Cosine similarity /TF-IDF	0.34s	0.3s

5.2.3 Execution Management

The execution management, which comprises specially the resuming and pausing of the execution, is also an important criterion we need to evaluate.

The scripting solution does not provide any form of execution management, because programming languages do not provide such resource. The closest thing to an execution management that this solution can provide is adding breakpoints in some parts of the code. The execution stops at each breakpoint and the user can check the state of the variables, and then manually continue the execution until the next breakpoint.

In the scientific workflow scenario we also have the option of using breakpoints for debugging, but the platform allows a user to pause/resume the execution of the workflow by pressing a button.

5.2.4 Fault Tolerance

Fault tolerance is another important criterion to be evaluated, as it ensures that the work previously executed will not be lost if a technical problem happens in the middle of the execution process.

The scripting solution does not provide fault tolerance in itself, but could be executed in an environment that guarantees fault tolerance.

It is on the basis of scientific workflows to provide fault tolerance. In the case of RapidMiner it is provided by its Radoop extension. Radoop is a Hadoop implementation for RapidMiner, so it provides fault tolerance. In the implemented scenario we do not use Radoop, so the resources for fault tolerance were not being used.

5.2.5 Discussion

According to the evaluation results shown in table 5.3, it can be seen that the RapidMiner solution provides some significant advantages when compared to the scripting solution.

By using RapidMiner it is easier to achieve workflow reproducibility and the execution time was about 10% lower when compared to the scripting solution. improved. RapidMiner also provides tools that allow a better execution management and deployment, with the possibility of pausing and resuming the execution at any time, as well as easily adding breakpoints in any part of the workflow process.

We believe that the results found in the simulation will also be found in an actual implementation.

Table 5.3: Overview of criteria in the simulation scenarios

CRITERION	SCENARIO	
	Script	Scientific workflow
Reproducibility	It has to be manually implemented	Easier to achieve with the automatic logs and portability of solution
Fault Tolerance	It has to be manually implemented	Execution can be restarted from last point
Execution time	Slower computation (of harvesting + tokenization)	Faster computation (of harvesting + tokenization)
Execution management	Does not provide it	Provides breakpoints and pausing/resuming of the workflow

Conclusion

We presented an overview of the field of workflows to automate processes, as well as discussed the differences between the two most important types of workflows – business and scientific.

We presented the AnHALytics platform and explained the issues with the current solution. We discussed how we could use automated workflows to improve AnHALytics, and performed a thorough study on which type of workflow and which workflow system would be more appropriate to automate AnHALytics, taking into consideration the inherent characteristics of AnHALytics and our priorities in terms of quantitative and qualitative results of this implementation.

Then we presented a simulation scenario which aims to represent the AnHALytics process workflow, and we implemented it in two ways: one was integrated into the scientific workflow, and the other was manually executed (scripting) – a solution similar to the current implementation of AnHALytics.

An evaluation of the two simulation scenarios was presented, taking into account the most important criteria concerning the execution of the AnHALytics workflow. We discussed the results obtained with the evaluation, which have shown a considerable advantage in the scenario that uses the scientific workflow approach.

The simulation results have shown that the scenario implemented on RapidMiner performed better than the scripting scenario in terms of execution time, and that it provides tools for achieving reproducibility and better execution management and deployment.

For our purposes one of the most important criterion is the reproducibility, which is hard to guarantee in the current AnHALytics version, but with the use of scientific workflows it can be achieved much more easily.

Taking these results in consideration and extrapolating it to the real life implementation, we strongly believe that the automation of AnHALytics would also show improvements in the criteria under which it was evaluated, specially reproducibility and easier execution management.

The natural next step within the context of this research project is the implementation of the studied concepts directly on the AnHALytics platform – that is, to integrate AnHALytics with the chosen scientific workflow workbench, Kepler. Although the implementation was proven to be more difficult than we expected, we believe that the results show that the additional effort pays off, in delivering an application that will be more reliable and efficient in the long run.

Concerning scientific workflows and the remarkable growth in data science research in the last few years, we believe that new platforms aimed at these types of applications are to be expected in the near future. RapidMiner, which is the only workbench among those we studied that provides tools off-the-shelf for implementing machine learning algorithms, seems to indi-

cate that this could be a trend in the next years, which will strongly facilitate the development and deployment of data science applications.

The results obtained with this study are not limited to the AnHALytics platform or even to text mining applications. Our results demonstrate that using scientific workflows to organize complex process flows can improve the execution in several aspects and it is well worth the additional work.

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