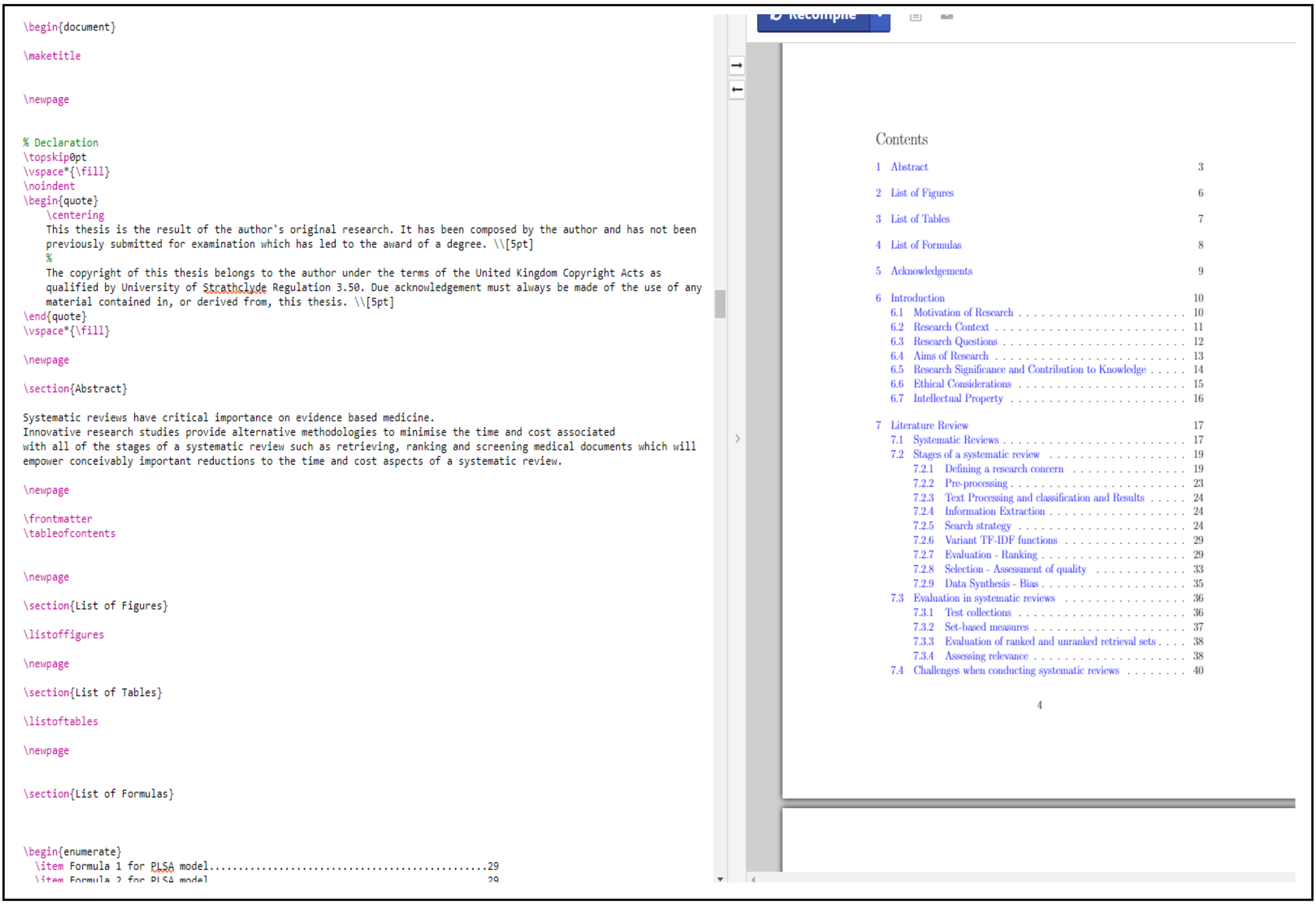
LaTeX

The self-paced learning classes in LaTeX provided by Strathclyde SharePoint have helped me significantly in the process of establishing fundamental LaTeX skills to my knowledgebase. During this process I had the opportunity to learn a variety of things including how to produce table of contents, list of figures, list of tables, sections, subsections, subsubsectins, various types of enumerations including customisation options for enumerations, declaring bibtex bibliographies to latex so that it can parse the references. Moreover, I learnt how to cite inside the begin and end sections of the document, I understood how some of the most important packages are imported, what are the attributes of some packages, as well as how to edit the parameters for certain packages, creating complex formulas, adding bookmarks and hyperlinks and many more .

Below there is a variety of indicative screenshots from some of my LaTeX documents.



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\begin{document}

\maketitle


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% Declaration
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\noindent
\begin{quote}
    \centering
    This thesis is the result of the author's original research. It has been composed by the author and has not been
    previously submitted for examination which has led to the award of a degree. \\[5pt]
    %
    The copyright of this thesis belongs to the author under the terms of the United Kingdom Copyright Acts as
    qualified by University of Strathclyde Regulation 3.50. Due acknowledgement must always be made of the use of any
    material contained in, or derived from, this thesis. \\[5pt]
\end{quote}
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\section{Abstract}

Systematic reviews have critical importance on evidence based medicine.
Innovative research studies provide alternative methodologies to minimise the time and cost associated
with all of the stages of a systematic review such as retrieving, ranking and screening medical documents which will
empower conceivably important reductions to the time and cost aspects of a systematic review.

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\subsection{Research Questions}


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  \begin{enumerate}
    \item sub numbering of 2nd question.
    \item sub numbering of 2nd question.
  \end{enumerate}
  \item[Q3] 3rd question.
\end{enumerate}


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\subsection{Aims of Research}

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  \item[A1] 1st aim.
  \item[A2] 2nd aim.
  \begin{enumerate}
    \item sub numbering of 2nd aim.
    \item sub numbering of 2nd aim.
  \end{enumerate}
  \item[A3] 3rd aim.
\end{enumerate}

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\subsection{Research Significance and Contribution to Knowledge}

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\subsection{Ethical Considerations}

No ethical considerations and implications apply to this study since the research will not involve human beings as participants. Emphasis will be given to avoid all sort of negative impacts and all data collected will be processed and presented in a fairly and lawfully way, while assuring quality and integrity in this research. Additionally, during the design and conduction of this research an effort has been made to ensure that this study is characterised by impartiality and independence.

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\subsection{Intellectual Property}

This thesis is the result of the author's original research.  It has
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6.3 Research Questions

Q1 1st question.

Q2 question.

(a) sub numbering of 2nd question.

(b) sub numbering of 2nd question.

Q3 3rd question.

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preliminary set of results so that the user can assess and categorise these documents as relevant or nonrelevant. Afterwards, the system calculates a improved representation of the query according to the user feedback see section \ref{Defining a research concern} and finally present a corrected sub collection of the acquired results.  \par

Furthermore, relevance feedback has it's own challenges, including the fact that it is not well accepted by users who are not so willing to spend time giving explicit and extensive feed backs (Manning et al., 2008) \cite{christopher2008introduction}.


Additionally, relevance feedback needs documents to be comparable in order to perform relevance assessments on them. There is also, the challenge of long queries created by standard relevance feedback methodologies, which require larger amount of resources\footnote{user time and cost}, which are not effective in a systematic review system. There are three types of relevance feedback. The first type of feedback is called explicit feedback or meta-linguistic feedback and it focuses on identifying errors and providing an explanation or alternatives. An example of explicit relevance feedback is Rochio's Algorithm\footnote{is a conventional method for conducting and combining relevance feedback into the vector space model (Manning et al., 2008) \cite{christopher2008introduction} which is examined in section \ref{Evaluation - Ranking}}.

Implicit feedback or indirect feedback is a more informal type of feedback. Furthermore, implicit feedback has it's own advantages and disadvantages, including the facts that it is less dependable than the explicit feedback and it is not so difficult to accumulate big numbers of relevance feedback (Manning et al., 2008) \cite{christopher2008introduction} with web search engines such as Google, Bing and Yahoo!. Also, in this instance the users are fulfilling their own wants and not for improving the IR system and the users are not aware all of the time that their selection of documents is used as relevance feedback (Kelly et al., 2003) \cite{kelly2003implicit}. An example of collecting indirect feedback is the methodology called DirectHit. The concept of DirectHit is to rank as better documents the ones that are clicked or visited the most. Finally, it is concluded that indirect feedback is more helpful than the methodology in the following paragraph, blind relevance feedback (Manning et al., 2008) \cite{christopher2008introduction}.

\par



Finally, the blind feedback or otherwise called pseudo relevance feedback gives a method for automatic local analysis (Manning et al., 2008) \cite{christopher2008introduction}. This methodology has it's advantages as it automates the manual process of relevance feedback, without the user having to spend significant amount of time. Moreover, this methodology has proved to increase the performance of the TREC ad hoc task (Manning et al., 2008) \cite{christopher2008introduction}.


mean average precision measurement. \par



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\subsubsection{Pre-processing}
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finally present a corrected sub collection of the acquired results.

Furthermore, relevance feedback has it's own challenges, including the fact that it is not well accepted by users who are not so willing to spend time giving explicit and extensive feed backs (Manning et al., 2008) [10].

Additionally, relevance feedback needs documents to be comparable in order to perform relevance assessments on them. There is also, the challenge of long queries created by standard relevance feedback methodologies, which require larger amount of resources[4], which are not effective in a systematic review system. There are three types of relevance feedback. The first type of feedback is called explicit feedback or meta-linguistic feedback and it focuses on identifying errors and providing an explanation or alternatives. An example of explicit relevance feedback is Rochio's Algorithm[5].

Implicit feedback or indirect feedback is a more informal type of feedback. Furthermore, implicit feedback has it's own advantages and disadvantages, including the facts that it is less dependable than the explicit feedback and it is not so difficult to accumulate big numbers of relevance feedback (Manning et al., 2008) [10] with web search engines such as Google, Bing and Yahoo!. Also, in this instance the users are fulfilling their own wants and not for improving the IR system and the users are not aware all of the time that their selection of documents is used as relevance feedback (Kelly et al., 2003) [28]. An example of collecting indirect feedback is the methodology called DirectHit. The concept of DirectHit is to rank as better documents the ones that are clicked or visited the most. Finally, it is concluded that indirect feedback is more helpful than the methodology in the following paragraph, blind relevance feedback (Manning et al., 2008) [10].

Finally, the blind feedback or otherwise called pseudo relevance feedback gives a method for automatic local analysis (Manning et al., 2008) [10]. This methodology has it's advantages as it automates the manual process of relevance feedback, without the user having to spend significant amount of time. Moreover, this methodology has proved to increase the performance of the TREC ad hoc task (Manning et al., 2008) [10].

mean average precision measurement.

[4]user time and cost

[5]is a conventional method for conducting and combining relevance feedback into the vector space model (Manning et al., 2008) [10] which is examined in section 7.2.7

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implementations in software libraries such as scipy and gensim. However, the LSA text mining model has some
disadvantages, some of which are that the latent semantic space form is dense, which makes it challenging to index
solely on distinctive dimensions. An additional disadvantage, is that because the method applied is the dimension
reducing linear projection, it is not the optimal solution when there are non linear dependencies (Amarappa, 2014)
\cite{amarappa2014data}. Lastly, the latent topic dimension can not be selected to a discretionary number, because it
is limited by the rank of the matrix (Hofmann, 1999) \cite{hofmann1999probabilistic}. \par

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Furthermore, the Probabilistic Latent Semantic Indexing (PLSI) model was suggested (Hofmann, 1999)
\cite{hofmann1999probabilistic} as a solution that overcomes the shortfalls presented by the representation that LSA
utilises. Some of the advantages of the PLSA model is the factor representation and that it's statistical
foundation\footnote{depends on the Law of Likelihood (Zhang et al., 2009) \cite{zhang2009law} an accepted framework
for defining published statistical evidence} is more solid than the corresponding of LSA (Hofmann, 1999), which
enables to systematically integrate a variety of models. The PLSA model, utilises factor analysis, which enables
effective handling of ambiguous words and allows to differentiate between a variety of meanings and kinds of word
usage (Hofmann, 1999) \cite{hofmann1999probabilistic}. \par

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The PLSA model, is statistical model named aspect model (Hofmann, 1999) \cite{hofmann1999probabilistic}. This model
connects an unobserved class variable (z), with each observation a word (w) from all the observations of a statistical
sample, such as a collection of words, with a class variable (d) from another sample like a collection of observed
documents. The formula\footnote{The formula has been taken from the 22nd SIGIR Conference paper "Probabilistic Latent
Semantic Indexing", (Hofmann, 1999) \cite{hofmann1999probabilistic}} that does this connection can be seen below
(Hofmann, 1999) \cite{hofmann1999probabilistic}: \newline
 \begin{equation} \label{eq:1}
     P(d,w) = P(d)P(w|d), where
 \end{equation}


 \begin{equation} \label{eq:2}
     P(w|d) = \sum_{z \epsilon Z}^{} P(w|z)P(z|d).
 \end{equation}

For the calculation of the $P(w \vline z)$ and $P(z \vline d)$ of the second formula Hofmann maximises the
log-likelihood of the objective function below:

\begin{equation} \label{eq:3}
    L = \sum_{d \epsilon D}^{} \sum_{w \epsilon W}^{} n(d,w)logP(d,w),
\end{equation}

Where n(d,w) stands for term frequency in documents. \par

Furthermore, in order to take advantage of the PLSA model for indexing two variations of the model have been proposed
the PLSI-U model and the PLSI-Q model (Hofmann, 1999) \cite{hofmann1999probabilistic}. The PLSI-U model is a
context-dependent uni gram model to equalise the experimental word distributions in documents. Moreover, the PLSI-U
model also breaks down to two further variations in order to be used in combination with the support vector machine
(SVM). The first variation is linearly combining the similarity measurements (standard cosine matching functions) for
LSI and the second variation is to additively combine the multinomials like in interpolation methods for language
modelling (Hofmann, 1999) \cite{hofmann1999probabilistic}. \par

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Lastly, the PLSI-Q is a latent space model which adds a low-dimensional document/query representation for the
evaluation of similarities (Hofmann, 1999) \cite{hofmann1999probabilistic}. This methodology also allows the
integration of several different models, but considering global term weights is partly answered by integrating the
cosine similarity scores of all models with a systematic weight. \par
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it is limited by the rank of the matrix (Hofmann, 1999) [23].

Furthermore, the Probabilistic Latent Semantic Indexing (PLSI) model was suggested (Hofmann, 1999) [23] as a solution that overcomes the shortfalls presented by the representation that LSA utilises. Some of the advantages of the PLSA model is the factor representation and that it's statistical foundation[20] is more solid than the corresponding of LSA (Hofmann, 1999), which enables to systematically integrate a variety of models. The PLSA model, utilises factor analysis, which enables effective handling of ambiguous words and allows to differentiate between a variety of meanings and kinds of word usage (Hofmann, 1999) [23].

The PLSA model, is statistical model named aspect model (Hofmann, 1999) [23]. This model connects an unobserved class variable (z), with each observation a word (w) from all the observations of a statistical sample, such as a collection of words, with a class variable (d) from another sample like a collection of observed documents. The formula[21] that does this connection can be seen below (Hofmann, 1999) [23]:

$$P(d,w) = P(d)P(w|d), where \tag{1}$$

$$P(w|d) = \sum_{z \epsilon Z} P(w|z)P(z|d). \tag{2}$$

For the calculation of the $P(w|z)$ and $P(z|d)$ of the second formula Hofmann maximises the log-likelihood of the objective function below:

$$L = \sum_{d \epsilon D} \sum_{w \epsilon W} n(d,w) log P(d,w), \tag{3}$$

Where n(d,w) stands for term frequency in documents.

Furthermore, in order to take advantage of the PLSA model for indexing two variations of the model have been proposed the PLSI-U model and the PLSI-Q model (Hofmann, 1999) [23]. The PLSI-U model is a context-dependent uni gram model to equalise the experimental word distributions in documents. Moreover, the PLSI-U model also breaks down to two further variations in order to be used in combination with the support vector machine

[20] depends on the Law of Likelihood (Zhang et al., 2009) [54] an accepted framework for defining published statistical evidence

[21] The formula has been taken from the 22nd SIGIR Conference paper "Probabilistic Latent Semantic Indexing", (Hofmann, 1999) [23]

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LSI and the second variation is to additively combine the multinomials like in interpolation methods for language
modelling (Hofmann, 1999) \cite{hofmann1999probabilistic}. \par

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Lastly, the PLSI-Q is a latent space model which adds a low-dimensional document/query representation for the
evaluation of similarities (Hofmann, 1999) \cite{hofmann1999probabilistic}. This methodology also allows the
integration of several different models, but considering global term weights is partly answered by integrating the
cosine similarity scores of all models with a systematic weight. \par


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The PageRank is a query-independent model which focuses on link-analysis by giving each node in the web
graph\footnote{this can also be thought as a collection of documents} a value between 0 and 1, which represents the
PageRank score. A web search engine then combines the PageRank and cosine similarity score, the term proximity and
more features to rank all the results against a specified research query. The concept of PageRank is that nodes that
are visited more frequently by surfers\footnote{one who starts on a web page and does a random or pre-determined walk
by visiting a number nodes to finally complete his walk on a different node/web page} who do random walks are more
significant than other nodes. PageRank has an operation called teleport\footnote{it allows the surfer to jump from one
node to another node in the web graph}, which is performed when a visited web page has no outgoing links to other
nodes, with a probability of teleporting to another or the current node 1/N, where N is the total number of web pages
in the web graph. The combination of random walk and teleport utilise Markov chains theory to compute the PageRank of
u, \pi (u). \par

The Markov chain model is a discrete-time stochastic process which develops in a succession of random decisions made
in time stages (Manning et al., 2008) \cite{christopher2008introduction}. The successful Markov chain model is usually
implemented on a stochastic matrix-table, which depicts the changeover probabilities from one condition to the next
(Pfeifer et al., 2000) \cite{pfeifer2000modeling}. The formula for the calculation of the PageRank score is given
below (Manning et al., 2008) \cite{christopher2008introduction}.



\begin{equation} \label{eq:4}
   \underset{\pi}{\rightarrow}  \underset{P}{} \hspace{0.1cm} \underset{=}{} \hspace{0.1cm} \underset{\lambda}{}
   \underset{\pi}{\rightarrow}
\end{equation}

Where $ \pi $ is the eigenvector\footnote{a non zero vector with non shifting direction after linear transformation is
applied} or the probability of the steady state distribution of the surfer across the nodes and $ \lambda = 1 $ is an
eigenvalue of P. Nonetheless, it has its negatives, due to its dimensionality, in complicated systems, where many
conditions are needed, it often leads to big solution times.\par




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(SVM). The first variation is linearly combining the similarity measurements (standard cosine matching functions) for LSI and the second variation is to additively combine the multinomials like in interpolation methods for language modelling (Hofmann, 1999) [23].

Lastly, the PLSI-Q is a latent space model which adds a low-dimensional document/query representation for the evaluation of similarities (Hofmann, 1999) [23]. This methodology also allows the integration of several different models, but considering global term weights is partly answered by integrating the cosine similarity scores of all models with a systematic weight.

The PageRank is a query-independent model which focuses on link-analysis by giving each node in the web graph[22] a value between 0 and 1, which represents the PageRank score. A web search engine then combines the PageRank and cosine similarity score, the term proximity and more features to rank all the results against a specified research query. The concept of PageRank is that nodes that are visited more frequently by surfers[23] who do random walks are more significant than other nodes. PageRank has an operation called teleport[24], which is performed when a visited web page has no outgoing links to other nodes, with a probability of teleporting to another or the current node 1/N, where N is the total number of web pages in the web graph. The combination of random walk and teleport utilise Markov chains theory to compute the PageRank of u, $\pi(u)$.

The Markov chain model is a discrete-time stochastic process which develops in a succession of random decisions made in time stages (Manning et al., 2008) [10]. The successful Markov chain model is usually implemented on a stochastic matrix-table, which depicts the changeover probabilities from one condition to the next (Pfeifer et al., 2000) [41]. The formula for the calculation of the PageRank score is given below (Manning et al., 2008) [10].

$$\underset{\pi}{\rightarrow} P = \lambda \underset{\pi}{\rightarrow} \tag{4}$$

Where π is the eigenvector[25] or the probability of the steady state distribution of the surfer across the nodes and $\lambda = 1$ is an eigenvalue of P. Nonetheless, it has its negatives, due to its dimensionality, in complicated

[22] this can also be thought as a collection of documents

[23] one who starts on a web page and does a random or pre-determined walk by visiting a number nodes to finally complete his walk on a different node/web page

[24] it allows the surfer to jump from one node to another node in the web graph

[25] a non zero vector with non shifting direction after linear transformation is applied

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Another highly recognised test collection is the TREC\footnote{Text Retrieval Conference, which is part of the IR test suite evaluation series of the U.S. National Institute of Standards and Technology (NIST) from 1992 (Manning et al., 2008) \cite{christopher2008introduction}} collection. From this test bed collection the evaluations from the first eight years are the most well recognised and consist of 1.89 million records of documents and relevance judgements for 450 queries. However, the most useful collection is probably a subset of TRECs 8 collections, because it is the most harmonised data set in terms of the similarity of topics (newswire and foreign broadcast information service articles) (Manning et al., 2008) \cite{christopher2008introduction}. \par

Lastly, the CLEF\footnote{Cross Language Evaluation Forum also known as Cross-Language Evaluation Forum, http://www.clef-campaign.org/, [Accessed: 2017-10-30]} Initiative collection is an IR test evaluation series which focuses on European languages, cross-language techniques, and interactive cross language information retrieval (Manning et al., 2008) \cite{christopher2008introduction}. All of the CLEF test collections, topics and experiments can be accessed through this link\footnote{http://direct.dei.unipd.it/ [Accessed: 2017-11-19]} \par

\subsubsection{Set-based measures}

The following three set-based measurements precision, recall, F-measure and balanced F-score are used commonly to evaluate unranked retrieval sets, (Manning et al., 2008) \cite{christopher2008introduction} (see section \ref{Evaluation of ranked and unranked retrieval sets}). Precision (P) is defined as the fraction of retrieved documents that are relevant to the query (Manning et al., 2008) \cite{christopher2008introduction}. \\
\begin{equation}
    P = \frac{number \hspace{0.1cm} of \hspace{0.1cm} relevant \hspace{0.1cm} items \hspace{0.1cm} retrieved}{number \hspace{0.1cm} of \hspace{0.1cm} retrieved \hspace{0.1cm} items}
\end{equation} \\

 Recall (R) on the other hand is defined as the fraction of relevant documents that are retrieved  (Manning et al., 2008) \cite{christopher2008introduction}. \\
\begin{equation}
    R = \frac{number \hspace{0.1cm} of \hspace{0.1cm} relevant \hspace{0.1cm} items \hspace{0.1cm} retrieved}{number \hspace{0.1cm} of \hspace{0.1cm} relevant \hspace{0.1cm} items}
\end{equation} \\

F measure is a technique that calculates the tradeoffs\footnote{weighted harmonic mean of precision and recall} between precision and recall (Manning et al., 2008) \cite{christopher2008introduction}. advantages and disadvantages \\
\begin{equation}
    F = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}
\end{equation} \\
\begin{equation}
   where, \beta^2 = \frac{1-\alpha}{\alpha}
\end{equation} \\
Where, a $\epsilon \big[0,1\big]$ and $\beta^2 \epsilon [0,\infty] $. The balanced F-score can be calculated with the same formula, if we assign to values a and $\beta$ to be equal with 1/2 and 1 respectively.

\subsubsection{Evaluation of ranked and unranked retrieval sets} \label{Evaluation of ranked and unranked retrieval sets}


\subsubsection{Assessing relevance} \label{Assessing relevance}

Some of the measurements often utilised to assess relevance are the following, pooling, kappa statistic and marginal relevance.  (Manning et al., 2008) \cite{christopher2008introduction}. To evaluate a system given the collection of documents, topics and queries, relevance assessments from people need to be gathered. For small test collections this process is easier but it still requires extensive assessments of relevance for all the combinations between documents and queries. For larger test collections relevance assessments are conducted for sub collections due to assessor time limitations. This is the most common methodology and is named pooling (Manning et al., 2008) \cite{christopher2008introduction}. This method involves calculations from information retrieval systems in the stage
```

Recall (R) on the other hand is defined as the fraction of relevant documents that are retrieved (Manning et al., 2008) [10].

$$R = \frac{number\ of\ relevant\ items\ retrieved}{number\ of\ relevant\ items} \tag{6}$$

F measure is a technique that calculates the tradeoffs[36] between precision and recall (Manning et al., 2008) [10]. advantages and disadvantages

$$F = \frac{(\beta^2 + 1)PR}{\beta^2 P + R} \tag{7}$$

$$where, \beta^2 = \frac{1-\alpha}{\alpha} \tag{8}$$

Where, a $\epsilon \big[0,1\big]$ and $\beta^2 \epsilon [0,\infty]$. The balanced F-score can be calculated with the same formula, if we assign to values a and β to be equal with 1/2 and 1 respectively.

7.3.3 Evaluation of ranked and unranked retrieval sets

7.3.4 Assessing relevance

Some of the measurements often utilised to assess relevance are the following, pooling, kappa statistic and marginal relevance. (Manning et al., 2008) [10]. To evaluate a system given the collection of documents, topics and queries, relevance assessments from people need to be gathered. For small test collections this process is easier but it still requires extensive assessments of relevance for all the combinations between documents and queries. For larger test collections relevance assessments are conducted for sub collections due to assessor time limitations. This is the most common methodology and is named pooling (Manning et al., 2008) [10]. This method involves calculations from information retrieval systems in the stage of screening for review, which focuses on sorting the documents so that only the K first documents can be forwarded for assessments by human participants. Even though, some

[36] weighted harmonic mean of precision and recall

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There are some studies focused on testing evaluation algorithms and comparing their performances across a variety of
different corpora. Part of this process is determining the stopping point in the collection. One study (Carterette et
al., 2007) \cite{carterette2007research} concentrated on the TREC collection, suggests picking random sub collections
and then run the chosen model to the fixed stopping point of each algorithm. However, some algorithm do not have a
pre-determined stopping point, in that instance the model needs to be executed in various distinctive stopping points
(Carterette et al., 2007) \cite{carterette2007research}. Afterwards, baseline algorithms are executed to the unchanged
stopping point on the same sub collections. It is also suggested that the decision for the stopping point relies upon
the measurement that is to be tested, which is determined most of the time by the initial hypothesis (Carterette et
al., 2007) \cite{carterette2007research}. Examples of such hypotheses, could be the testing for realising which model
produces the highest correlation or testing which model needs less judgments. These two hypotheses could be addressed
by executing both models for similar number of relevance judgments and by running both models to a certain stopping
point and examine the relevance judgments steps made up to that stopping point, respectively. \par


Kappa statistic is an appealing measurement to examine the agreement between judges there is on relevance judgments
(Manning et al., 2008) \cite{christopher2008introduction}. The model to calculate it, is given below (Manning et al.,
2008) \cite{christopher2008introduction}.

\begin{equation}
    Kappa = \frac{P(A) - P(E)}{1 - P(E)}
\end{equation}  \\

Where P(A) is the number of observed judgement agreements by the raters, and P(E) is the probability of the raters
coming to an agreement. P(E) can be calculated with the aid of the following formula.

\begin{equation}
    P(E) = P(nonrelevant)^2 + P(relevant)^2
\end{equation}

Maximal marginal relevance (MMR) is a measurement that calculates the relevance of each document by taking into
consideration the adding value of the information this document carries and the acquired information from previous
documents (Carbonell et al., 1998) \cite{carbonell1998use}.



\begin{equation}
    \underset{MMR}{} \underset{=}{def} \underset{Arg}{} \underset{\underset{Di\epsilon R \setminus S}{max}}{} \bigg[
    \underset{\lambda(Sim_{1}(Di,Q)-(1-\lambda) \underset{Dj\epsilon S}{max} Sim_{2}(Di,Dj))}{} \bigg]
\end{equation} \\

Where, $D_{i}$ stands for documents in the collection C, Q for query, R for relevant documents in C and S for current
result set (Carbonell et al., 1998) \cite{carbonell1998use}.


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\subsection{Challenges when conducting systematic reviews}


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\subsection{Efforts for reduction of systematic reviews workload}

As mentioned before there are studies for using cost-effectiveness analysis in the medical domain, one of which has
been conducted by Shemilt et al. . In this study, Shemilt et al. present the application of an economic evaluation
framework, in order to examine the impact of four different methodologies (Safety First, Single Screening, Single
Screening with text mining and Double Screening) which were described in the section \ref{Selection - Assessment of
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of the other documents are relevant, they are not assessed. One of the challenges of this task, is to determine where the stopping point should be set in the test collection of documents.

There are some studies focused on testing evaluation algorithms and comparing their performances across a variety of different corpora. Part of this process is determining the stopping point in the collection. One study (Carterette et al., 2007) [9] concentrated on the TREC collection, suggests picking random sub collections and then run the chosen model to the fixed stopping point of each algorithm. However, some algorithm do not have a pre-determined stopping point, in that instance the model needs to be executed in various distinctive stopping points (Carterette et al., 2007) [9]. Afterwards, baseline algorithms are executed to the unchanged stopping point on the same sub collections. It is also suggested that the decision for the stopping point relies upon the measurement that is to be tested, which is determined most of the time by the initial hypothesis (Carterette et al., 2007) [9]. Examples of such hypotheses, could be the testing for realising which model produces the highest correlation or testing which model needs less judgments. These two hypotheses could be addressed by executing both models for similar number of relevance judgments and by running both models to a certain stopping point and examine the relevance judgments steps made up to that stopping point, respectively.

Kappa statistic is an appealing measurement to examine the agreement between judges there is on relevance judgments (Manning et al., 2008) [10]. The model to calculate it, is given below (Manning et al., 2008) [10].

$$Kappa = \frac{P(A) - P(E)}{1 - P(E)} \tag{9}$$

Where P(A) is the number of observed judgement agreements by the raters, and P(E) is the probability of the raters coming to an agreement. P(E) can be calculated with the aid of the following formula.

$$P(E) = P(nonrelevant)^2 + P(relevant)^2 \tag{10}$$

Maximal marginal relevance (MMR) is a measurement that calculates the relevance of each document by taking into consideration the adding value of the information this document carries and the acquired information from

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\begin{equation}
    \underset{MMR}{} \underset{=}{def} \underset{Arg}{} \underset{\underset{Di\epsilon R \setminus S}{max}}{} \bigg[
    \underset{\lambda(Sim_{1}(Di,Q)-(1-\lambda) \underset{Dj\epsilon S}{max} Sim_{2}(Di,Dj))}{} \bigg]
\end{equation} \\

Where, $D_{i}$ stands for documents in the collection C, Q for query, R for relevant documents in C and S for current result set (Carbonell et al., 1998) \cite{carbonell1998use}.


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\subsection{Challenges when conducting systematic reviews}


%==================================================================================

\subsection{Efforts for reduction of systematic reviews workload}

As mentioned before there are studies for using cost-effectiveness analysis in the medical domain, one of which has been conducted by Shemilt et al. . In this study, Shemilt et al. present the application of an economic evaluation framework, in order to examine the impact of four different methodologies (Safety First, Single Screening, Single Screening with text mining and Double Screening) which were described in the section \ref{Selection - Assessment of quality} for determining suitable techniques for systematic reviews in the title-abstract and full text screening stage of a medical systematic review (Shemilt et al., 2016) \cite{shemilt2016use}. \par


\par
```

previous documents (Carbonell et al., 1998) [8].

$$MMR \overset{def}{=} Arg \underset{Di \in R \setminus S}{max} \bigg[\lambda(Sim_1(Di,Q)-(1-\lambda) \underset{Dj \in S}{max} Sim_2(Di,Dj)) \bigg] \quad (11)$$

Where, D_i stands for documents in the collection C, Q for query, R for relevant documents in C and S for current result set (Carbonell et al., 1998) [8].

7.4 Challenges when conducting systematic reviews

7.5 Efforts for reduction of systematic reviews workload

As mentioned before there are studies for using cost-effectiveness analysis in the medical domain, one of which has been conducted by Shemilt et al. . In this study, Shemilt et al. present the application of an economic evaluation framework, in order to examine the impact of four different methodologies (Safety First, Single Screening, Single Screening with text mining and Double

```latex
%==================================================================================

\section{References}

\Blinddocument
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\bibliographystyle{amsplain}
\bibliography{bibliography}

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\section{Acronyms}

\begin{enumerate}
  \item[ACR1] Acronym1:
  \item[ACR2] Acronym2:
  \item[ACR3] Acronym3:
  \item[ACR4] Acronym4:
  \item[ACR5] Acronym5:
  \item[ACR6] Acronym6:
  \item[ACR7] Acronym7:
  \item[ACR8] Acronym8:
  \item[ACR9] Acronym9:
  \item[ACR10] Acronym5:
  \item[ACR11] Acronym5:
  \item[ACR12] Acronym5:
  \item[ACR6] Acronym6:
  \item[ACR7] Acronym7:
  \item[ACR8] Acronym8:
  \item[ACR9] Acronym9:
  \item[ACR10] Acronym5:
  \item[ACR11] Acronym5:
  \item[ACR12] Acronym5:
  \item[ACR10] Acronym5:
  \item[ACR11] Acronym5:
  \item[ACR12] Acronym5:
  \item[ACR1] Acronym1:
  \item[ACR2] Acronym2:
  \item[ACR3] Acronym3:
  \item[ACR4] IR: Information Retrieval
  \item[ACR5] Acronym5:
  \item[ACR6] Acronym6:
  \item[ACR7] Acronym7:
  \item[ACR8] Acronym8:
  \item[ACR9] Acronym9:
  \item[ACR10] Acronym5:
  \item[ACR11] MMR: Maximal Marginal Relevance
  \item[ACR12] Acronym5:
  \item[ACR6] Acronym6:
  \item[ACR7] Acronym7:
  \item[ACR8] Acronym8:
  \item[ACR9] Acronym9:
  \item[ACR10] Acronym5:
  \item[ACR11] Acronym5:
  \item[ACR12] Acronym5:
  \item[ACR10] Acronym5:
  \item[ACR11] Acronym5:
  \item[ACR12] Acronym5:
```

12 References

References

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[8] Jaime Carbonell and Jade Goldstein, The use of mmr, diversity-bas reranking for reordering documents and producing summaries, Proce ings of the 21st annual international ACM SIGIR conference on Resea and development in information retrieval, ACM, 1998, pp. 335–336.

54

[9] Ben Carterette and James Allan, Research methodology in studies of

The following indicative section of LaTex is part of my resume (see page 10) which I did on my spare time.

```
\runsubsection{Newslines}
\descript{| Researcher - Data Analyst }
\location{Aug 2017 - Sep 2017 | Glasgow, UK}
\vspace{\topsep} % Hacky fix for awkward extra vertical space
\begin{tightemize}\item Text processing on media news stream using Python libraries such as nltk, beautiful soup, scikit-learn, pandas, num
\end{tightemize}
\sectionsep

\runsubsection{Central Bank of Greece}
\descript{| Technology Analyst Intern }
\location{Jul 2015 - Jul 2016 | Athens, Greece}
\begin{tightemize}
\item Participation in the implementation/migration to the Eurosystem Target II Security and database (production \& test) management.\item
\sectionsep

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%     Projects
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

\section{Projects}
\runsubsection{Strathclyde-iSchool Lab}
\descript{| Ph.D. Researcher}
\location{Sep 2017 - Present | Glasgow, UK}
Information Retrieval and Machine Learning on empirical systematic reviews.
\sectionsep

\runsubsection{University of Strathclyde}
\descript{| Post graduate Researcher}
\location{Feb 2017 - Jul 2017 | Glasgow, UK}
The purpose of the research was to assert the generality of the predictive RFMTC model as an improved more customisable alternative of the
\sectionsep

\runsubsection{Harokopion University Lab}
\descript{| Undergraduate Researcher}
\location{Jan 2016 - May 2016 | Athens, Greece}
Extended a system that encourages users of a website by proposing new films tailored to the needs of each user. More specifically, the algo
\sectionsep

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%     Workshops
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

\section{Workshops}
\begin{tabular}{rll}
May 2017 & J.P. Morgan Glasgow & \textsuperscript{}  Big Data Analytics Introduction \\
2016 & University of Piraeus, Athens \textsuperscript  & Fosscomm 2016\\
2014-2015 & ATHENA Research \& Innovation Center & Agriculture Development Systems\\
2014     & Technopolis Innovation Center Athens  & Presentation \& Communication \\
\end{tabular}
\sectionsep

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%     AWARDS
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

\section{AWARDS}
\begin{tabular}{rll}
2017-2020       & Univeristy of Strathclyde    & Ph.D. Scholarship Award (Stipend\&Bursary) \\
Dec 2016   & J.P. Morgan Glasgow  & 3rd place in Machine Learning Workshop \\
2016    &  TEDX Strathclyde  & 1st place Design Challenge \\
2016-Present  &  BCS   & Student Member\\
\end{tabular}
\sectionsep

\section{References}
\begin{tabular}{rll}
Univeristy of Strathclyde & Dr Martin Halvey and Dr Leif Azzopardi\\
Central Bank of Greece & Directors Dr Eythimios Gatzonas and Mr George Stubos
\end{tabular}
```

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		\sffamily
		\fontspec[Path = fonts/lato/]{Lato-Lig}\fontsize{14pt}{10cm}\selectfont #1
		\fontspec[Path = fonts/lato/]{Lato-Lig}\selectfont #2
	} \\
	\vspace{3pt}
	\centering{ \color{headings}\fontspec[Path = fonts/raleway/]{Raleway-Medium}\fontsize{10pt}{14pt}\selectfont
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	\vspace{-12pt}
}
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% Subeadings command
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\titlespacing{\subsubsection}{0pt}{\parskip}{-\parskip}
\newcommand{\runsubsection}[1]{\color{subheadings}
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% Descriptors command
\newcommand{\descript}[1]{\color{subheadings}\raggedright\scshape\fontspec[Path = fonts/raleway/]{Raleway-Medium}\fo

% Location command
\newcommand{\location}[1]{\color{headings}\raggedright\fontspec[Path = fonts/raleway/]{Raleway-Medium}\fontsize{10pt

% Section seperators command
\newcommand{\sectionsep}[0]{\vspace{8pt}}

% Bullet Lists with fewer gaps command
\newenvironment{tightemize}{\vspace{-\topsep}\begin{itemize}\itemsep1pt \parskip0pt \parsep0pt}{\end{itemize}\vspace

\usepackage{hyperref}




\hypersetup{
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        bookmarksopen=true,
        bookmarksnumbered=true,
    citebordercolor={0 0.61 0.50},
    filebordercolor=Red,
    linkbordercolor=Blue
}
```

October 14, 2017

Alexandros Ioannidis

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alexioanid@yahoo.gr | 7423350580

EDUCATION

UNIVERSITY OF STRATHCLYDE
PH.D. IN COMPUTER SCIENCE
EXP. END DATE: OCT/2020
CONC. MACHINE LEARNING, TEXT PROCESSING & INFORMATION RETRIEVAL
Glasgow, UK

UNIVERSITY OF STRATHCLYDE
PG RDP CERT | EXP. END DATE: OCT/2020
Glasgow, UK | ECTS 25 / 60

UNIVERSITY OF STRATHCLYDE
M.SC. IN ADVANCED COMPUTER SCIENCE
Glasgow, UK | Grade 69% (Merit)

HAROKOPION UNIVERSITY
B.SC. IN INFORMATICS AND TELEMATICS
Athens, Greece | Grade 7.42/10 (Merit)

2ND GENERAL LYCEUM OF VRILISSIA, TECHNOLOGICAL STREAM
Athens, Greece | Grade 17.8 / 20

LINKS

Github:// it21208
LinkedIn:// alexandrosioannidis
Twitter:// @it21208alex

COURSEWORK

GRADUATE
Advanced Machine Learning
Information Retrieval
(Research Asst. & Teaching Asst)

UNDERGRADUATE
Software Engineering
Operating Systems (Linux, Windows)
Artificial Intelligence
Unix Tools and Scripting
A bit of Functional Programming

SKILLS

PROGRAMMING
Over 20,000 lines:
R • Python • Java • JavaScript • HTML • Oracle SQL • LaTeX
Over 3,000 lines:
MySQL • MATLAB • SPIM MIPS • C
Familiar:
Apache Lucene • Apache Spark • SQL Plus

EXPERIENCE

NEWSLINES | RESEARCHER - DATA ANALYST
Aug 2017 – Sep 2017 | Glasgow, UK
- Text processing on media news stream using Python libraries such as nltk, beautiful soup, scikit-learn, pandas, numpy, re and many more.

CENTRAL BANK OF GREECE | TECHNOLOGY ANALYST INTERN
Jul 2015 – Jul 2016 | Athens, Greece
- Participation in the implementation/migration to the Eurosystem Target II Security and database (production & test) management.
- Operation of FT Console System for monitoring components of the Secondary Securities Market and contributed to the Bonds Report Server System in VS2012 & VB2012.

PROJECTS

STRATHCLYDE-ISCHOOL LAB | PH.D. RESEARCHER
Sep 2017 – Present | Glasgow, UK
Information Retrieval and Machine Learning on empirical systematic reviews.

UNIVERSITY OF STRATHCLYDE | POST GRADUATE RESEARCHER
Feb 2017 – Jul 2017 | Glasgow, UK
The purpose of the research was to assert the generality of the predictive RFMTC model as an improved more customisable alternative of the RFM model and other Machine Learning algorithms such as (SVM, Random Forest, K-Means, etc.) and justify the additional implementation complexity of some model parameters such as time since first purchase or donation of a customer in a certain period and churn rate as a productive one. Used extensively the R scripting language and CRAN repository for the minimisation of objective non linear functions and Excel.

HAROKOPION UNIVERSITY LAB | UNDERGRADUATE RESEARCHER
Jan 2016 – May 2016 | Athens, Greece
Extended a system that encourages users of a website by proposing new films tailored to the needs of each user. More specifically, the algorithm that was parallelized with Java and Apache Spark, is the third optimal algorithm in the Kaggle competition conducted by Netflix to find the best collaborative filtering algorithm for predicting user ratings for films based on previous reviews.

WORKSHOPS

May 2017	J.P. Morgan Glasgow	Big Data Analytics Introduction
2016	University of Piraeus, Athens	Fosscomm 2016
2014-2015	ATHENA Research & Innovation Center	Agriculture Development Systems
2014	Technopolis Innovation Center Athens	Presentation & Communication

AWARDS

2017-2020	Univeristy of Strathclyde	Ph.D. Scholarship Award (Stipend&Bursary)
Dec 2016	J.P. Morgan Glasgow	3rd place in Machine Learning Workshop
2016	TEDX Strathclyde	1st place Design Challenge
2016-Present	BCS	Student Member

REFERENCES

Univeristy of Strathclyde	Dr Martin Halvey and Dr Leif Azzopardi
Central Bank of Greece	Directors Dr Eythimios Gatzonas and Mr George Stubos

All in all, I believe this course LaTeX has helped me, helps me and will continue helping me significantly as a reference point in situations where I don't specific aspects regarding the editing of documents with several different document preparation system for high-quality typesetting such as Overleaf or ShareLaTeX. It will also help me in the future for editing any document of mine such as a resume or cover letter in order to make it look good but also for writing medium to large technical text reports and for various scientific documents for a variety of publishing purposes and it is not restricted to only this spectrum of options. This course has helped me enormously!!