ASSIGNMENT COVERSHEET

UTS: ENGINEERING & INFORMATION TECHNOLOGY							
SUBJECT NUMBER & NAME 32144 - Technology Research Preparation	NAME OF STUDENT(s) (PRINT CLEARLY) Jared Mayger				STUDENT ID(s) 13887967		
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ASSESSMENT ITEM NUMBER & TITLE Assessment Task 2 - Literature Review							
I confirm that I have read, understood and followed the guidelines for assignment submission and presentation on page 2 of this cover sheet. I confirm that I have read, understood and followed the advice in the Subject Outline about assessment requirements. I understand that if this assignment is submitted after the due date it may incur a penalty for lateness unless I have previously had an extension of time approved and have attached the written confirmation of this extension.							
Declaration of originality : The work contained in this assignment, other than that specifically attributed to another source, is that of the author(s) and has not been previously submitted for assessment. I understand that, should this declaration be found to be false, disciplinary action could be taken and penalties imposed in accordance with University policy and rules. In the statement below, I have indicated the extent to which I have collaborated with others, whom I have named.							
Statement of collaboration: Signature of student(s)	Statement of collaboration: Signature of student(s) Date01/09/2022						
ASSIGNMENT RECEIPT To be completed by the student if a receipt is required							
SUBJECT NUMBER & NAME			NAME OF TUTOR				

SIGNATURE OF TUTOR	RECEIVED DATE

Introduction:

Current fused multi-modal topic models don't accurately represent a customers potential shopping interests, current fashion trend analysis and customer personas to an outstanding degree. The paper aims to collate existing research papers and methods to answer the question of whether existing topic mining and fusion models in conjunction with data collection models, reflect the peak efficiency possible for the purpose of social networks and e-commerce. Pertaining specifically to the effectiveness of targeted advertisements found on social media platforms, this research when complete, will provide the grounds to increase the similarity between modelled customer personas and actual physical customer wants and needs. The consolidation of research in this paper provides a fountain of specific detail to be used for further improvement to the efficiency of said models as well as any improvements to e-commerce models in social media. This report will commence with a detailed critical evaulation of two reputable sources that will be further explored in the literature review. The review of existing papers and research will loosely follow the progression of knowledge, beginning with text summarisation and automatic text summarisation, moving through to data collection and non parametric image parsing and concluding with efficient multimodal topic modelling techniques and their applications in the context of social media.

Critical Evaluation of Two Sources:

Source 1: An Exploration of Post-Editing Effectiveness in Text Summarization -

1. Evaluating your Source/Article		Your Evaluation		
Relevance to Your Topic	Title	By assessing the effectiveness of post editing in text summarisation, coupled with the analysis of pre training models from other sources, an optimal method of NLP can be developed, nad used if necessary in my project.		
	Abstract	Introducing post-editing into text summarisation, including the collaboration between AI and Human summarisation. Relevant to my topic as machine learning techniques and their compatibility with human web crawling and data collection will be explored later on in the honours project.		

Reliability/ Authority	Authors: Names? Roles/Workplace? Credentials? Can contact?	Vivian Lai: University of Colorado Boulder - vivian.lai@colorado.edu Alison Smith-Renner: Dataminr Inc Ke Zhang: Dataminr Inc → @dataminr.com Ruijia Cheng: University of Washington - rcheng6@uw.edu Wenjuan Zhang: Dataminr Inc → @dataminr.com Joel Tetreault: Dataminr Inc → @dataminr.com Alejandro Jaimes: Dataminr Inc → @dataminr.com			
	Publication Type:	Peer-reviewed journal			
	Timeliness	June 2022 publication, extremely up to date and relevant to my research			
References contained within the paper	· Quantity? · Quality?	Not as many reference in comparison to other sources in this literature review, however the quality is paramount and accounts for more credibility than the quantity.			
Overall Evaluation	Why would you, at this stage, Include this article in your Literature Review? What level of significance would you place on this article? Why?	At this stage this source will undoubtedly be included in my literature report, or at least one section of it. Even though the review moves between text summarization, natural language processing, image parsing and topic modelling in e-commerce, the level of significance is still high as it will provide a solid base for project progression. Furthermore this article was found on multiple reputable databases, highlighting its relevancy and appropriateness for use in my report.			

4. Critical Evaluation & Analysis	Notes
Is the article well organized and written logically?	The article follows a fairly standard report format, and is coherent between paragraphs and sections.
Is the Literature Review complete?	Literature review contains summarisation of related work, snaking through automatic text summarisation, human text summarisation and post-editing Al-generated text. These topics are well researched, referenced and linked together cohesively, making for a complete literature review and a strong basis for the presented research.
Are the Research Methods appropriate?	For data collection a wide spread of human candidates were selected, to work alongside the text summarisation AI, so that the researchers could employ their post editing method. These results were then compared to a control of the same participants and same texts without any post-editing.
Are the results of the analysis validated? How? Is the analysis of the Results valid?	Comparison between AI summarisation and human summarisation and the effectiveness of post-editing was evaluated by a human source for summary

	quality. These participants were selected from a group of anotators from Amazon Mechanical Turk, scoring points for the validity of their analysis.
Is the Discussion logically derived from the Results?	Yes, the discussion is separated into 5 key sections, pertaining directly to the contents of the results, making statements regarding the usefulness of post-editing on text summarisation. Several references are used relating the discussion to the review literature.

Source 2: Efficient Few-Shot Fine-Tuning for Opinion Summarization -

1. Evaluating y	our Source/Article	Your Evaluation		
Relevance to Your Topic	Title	Opinion summarization, links to text summarization which can be linked to NLP which is relevant in crawling social media website text data .		
	Abstract	Abstractive summarization models and pre trained models, are a way to see how models are developed and trained, which my project requires later down the line		
Reliability/ Authority	Authors:	Arthur B: ILCC University of Edinburgh - Research scientist at Google - PhD Ramesh N: Amazon AWS - Contact via email Mohit B: UNC Chapel Hill NLP Group - PhD - Registered Email Markus D: Amazon - PhD John Hopkins University - Verified Email at cs.jhu.edu		
1	Publication Type:	Peer-reviewed journal		
	Timeliness	May 2022 Release, based on work from 2010's completed by all authors serarately		
References contained within the paper	· Quantity? · Quality?	Upwards of 30 sources for a 15 page report, consisting of journal articles and reputable conference papers		
Overall Evaluation	Why would you, at this stage, Include this article in your Literature Review? What level of significance would you place on this article? Why?	Similar to the first source, Efficient Few-Shot Fine-Tuning for Opinion Summarization will heighten the base knowledge to which my project can be carried out, rendering its significance fairly high. By combining the results from pre-training and post-editing summarization, an optimized approach can be devised. Furthermore this article was found on multiple reputable databases, highlighting its relevancy and appropriateness for use in my report.		

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Is the article well organized and written logically?	Article sports a well layed out format, with relevant headings and strong coherence between paragraphs and sections
Is the Literature Review complete?	A small literature review was completed outlining related work, other pre-trained models and their effectiveness, in order to compare their model in the conclusions.
Are the Research Methods appropriate?	Research methods were extremely appropriate, with the creation of synthetic databases in conjunction with the use of other pre-trained models as baselines for simple summarization and other summarization techniques
Are the results of the analysis validated? How? Is the analysis of the Results valid?	The proposed model was evaluated in terms of automatic metrics and against human efforts of summarization Evaluated: - Query-based Pre-training - Catastrophic Forgetting - Abstractiveness - Semantic Mistakes
Is the Discussion logically derived from the Results?	No define discussion section, however there is inherent discussion of results integrated into the analysis of results, hence it is logically derived.

Literature Review:

Text Summarization:

Text summarisation, specifically in its automatic form has been around since the 1950's (Luhn, 1958), however human summarisaiton undoubtedly dates back further as its usefulness in teaching and retaining information is paramount. An aspect of automatic summarisation is abstractive summarisation which plans to generate short summaries of essential information from long documents. Current models suffer from crucial problems like hallucinations (Maynez et al., 2020), low quality, factuality degradation and decreased efficiency, where summaries contain facts or entities not present in the original document. (Bansal et al, 2022). In an attempt to combat all these challenges, a combination of models from a number of sources has been explored, and analysed as to the affects of pre-training, finetuning and post editing in text summarisation. The FactPEGASUS model proposes a trident of components; a corrector to remove hallucinations, a contrastor to better

differentiate between fact and non-factual summaries and a connector to bridge the gap between finetuning and pre-training (Bansal et al, 2022). The method was tested on three abstractive summarisation datasets and was able to successfully improve factuality and conclude that the increase in extractivness is not solely responsible for overall factuality improvement.

In the case of customer reviews and other shorter, less connected writings like social media posts, most existing pre-trained models are not properly calibrated, leaving summaries full of semantic mistakes (Dreyer et al, 2022). As an alternative to fine-tuning the entirety of a model, adapters can be pre-trained task specifically and added onto a large dataset of unanotated reviews. Using human-annotations as a fine-tuning mechanism for adapters, becomes time consuming but is necessary for for the improvement of summary quality and can be utilized on smaller datasets. Pre-training adaters in a query based manner on customer reviews also results in better-organised summary content, improved coherence and fewer redundancies (Dreyer et al, 2022).

Furthermore, significant exploration is needed into the collaboration between humans and artificial intelligence in order to determine whether post-editing summaries offers advantages in efficiency and the reduction of human workload. Conducted experiments with a fairly small group of participants found there were both benefits and drawbacks as participants needed assistance which became time consuming and almost all of them employed differing editing strategies (Jaimes et al, 2022). While, Al's attention for detail is lack luster, its efficiency and the standardised nature in which it summarises a text is unprecedented. In longer resources, where computational potential is decreased the quadratic memory complexity prevents long document summarisation. Additionally, models apply input truncation, resulting in a performance drop as potential summary-relevant content is left out, causing destruction for semantic text analysis (Ragazzi et al, 2022).'

Big Data and Natural Language Processing:

Throughout the project, large sets of data will be collected and processed as a preliminary step of model training and leter down the line customer persona analysis. Working on large datasets is a completely different challenge to small ones and hence significant research needs to be undertaken for existing methods and future directions. Big data is considered 'unstructured' when it includes both textual (posts and captions) and non-textual (images, videos and stories) formants (Erevelles et al., 2016), similar that seen on social media sites like Twitter and Instagram. In order to deal with this unstructured data in the same way that other structured data can be processed in three stages of transformation (Burns et al, 2021). In addition, to preprocess the big data, cutting-edge natural language processing techniques can be implemented for semantic categorization of large amounts of textual data (Manning & Schütze, 1999). JSON file format is extremely useful for downloading raw social media post information via the applications API as it stores data in key/value pairs and field information can easily be extracted. Following this, a series of natural language processing techniques can be utilised, allowing the unstructured text data to be used alongside other quantitative variables. Processes such as tokenizaiton (spliting a sentence or paragraph into words and punctuation) and tagging (finding the part of speech of a word) heavily affect the accuracy

and usefulness of structured text data (Burns et al, 2021). Finally the two types of data (quantitative and the transformed qualitative) can easily be loaded into a relational database for further processing or analysis. Databases liek MySQL can provide functions to aggregate the immense amount of collected social media 'big data' into a monthly panel data set to integrate them into econometric models, which can be used in e-commerce and in building customer personas and targeting ads (Netzer, Feldman, Goldenberg, & Fresko, 2012).

Summarization using topic modeling:

As an extension of the text summarisation that was discussed earlier, topic modeling can provide an interesting unsupervised approach to assimilate text data from larger documents, relatively quickly. An unsupervised extractive summarisation approach was able to successfully reduce topic bais by combining Latent Dirichlet Allocaiton for topic modelling and K-Medoids clustering (Kumar et al, 2022). One particular experiment made use of the Recall Oriented-Understudy for Gisting Evaluation (ROUGE) metrics for comparative analysis against recently reported techniques, specifically ROUGE-1 (R-1), ROUGE-2 (R-2), and ROUGE-L (R-L). The suggested framework offered scores of 34.80%, 9.13%, and 32.30% on the Wikihow Dataset, 43.90%, 19.01%, and 41.50% on the CNN/DailyMail Dataset, and 49.35%, 31.53%, and 41.72% on the DUC2002 Corpus (R-1, R-2, R-L respectively) (Kumar et al, 2022). Additionally other experiments suggested that topic modelling algorithms such as NonNegative Matrix Factorization and LSA could undoubtedly be beneficial in extractive text summarisation. (Salama et al, 2021).

Integrated natural language processing (NLP), text mining, and machine learning approach for intelligent Request for Quotation summarization can also be applied as it helps engineers shorten the time to identify all specifications and reduces the risk of missing important requirements during manual RFQ reading (Chien et al, 2022). Whilst this isn't directly applicable, the knowledge can be used to further improve the efficiency of extensive text summarisation and multimodal topic modeling of social networks for e-commerce. Notwithstanding its applicability to any domain within RFG documentation, the automatic collective intelligence summarisation system can be transferred to other domains, as its proven to reduce the risk of missing important summary information in manual reading.

NonParametric Image Parsing:

Image parsing, alongside text summarisation and natural language processing are extremely applicable to topic modelling in social networks because of the nature of a social media post. Unfortunately, image parsing holds implicit challenges as it combines tasks such as object detection, segmentation, and multilabel recognition to which algorithmic solutions can be divided into two categories, paramentric and nonparametric. Specifically for this research focus will be placed on the nonparametric methods based on lazy learning, that can easily scale to datasets with tens of thousands of images and hundreds of labels (Lazebnik et al, 2012). Many approaches to this problem have been proposed recently, includingpixel by pixel estimation(He et al. 2004; Ladicky et al. 2010; Shotton et al. 2006, 2008), ones that aggregate features over segmentation regions (Galleguillos et al. 2010; Gould et al. 2009; Hoiem et al. 2007; Malisiewicz and Efros 2008; Rabinovich et al. 2007; Socher et al. 2011), and others that successfully predict object bounding boxes (Divvala et al. 2009; Felzenszwalb et al. 2008; Heitz and Koller 2008; Russell et al. 2007).

One method which combines global scene-level matching against a training set followed by superpixel-level matching and efficient Markov random field (MRF) optimization for incorporating neighborhood context, is able to compute the labelling of image regions into geometric and semantic classes. Even though it suffers from an inability of low-level global features, like indoor and outdoor class labels miing together, said method outperformed a state-of-the-art nonparametric method based on SIFT Flow on a dataset of 2,688 images and 33 labels (Lazebnik et al, 2012). In order to boost the superpixel matching process,

locality-sensitive hashing (LSH) can be embedded to encode the features representative in few bits (instead of bytes) for large-scale matching (Yan et al, 2015). The prevailing consensus in the community is that image parsing requires context (Divvala et al. 2009; Galleguillos and Belongie 2010; Heitz and Koller 2008; Hoiem et al. 2007; Rabinovich et al. 2007), and its usefulness can ultimately applied to the research conducted in topic modeling and e-commerce in social media.

Multimodal Topic Modeling:

To reiterate, earlier points in the review topic modeling allows improvement in searching and browsing through the extraction of semantic themes from web sources and social media sites. Regularized topic models are proved to be able to increase the coherence of learned topics when compared to the baseline LDA method, as assessed by human workers in Amazon Mechanical Turk (Wray et al, 2011). Social media posts are more multifaceted than simply text summarisation or image processing and it can be deduced that the text of a post is usually linked to one topic whilst the image is mapped to the same topic among others. As a result of the rich informaiton expressed in images (Zhang et al, 2022) a small number of cases see the topics of text and image to be different, hence past topic models fail to model these characteristics amd produce low-quality topics. An experiment conducted by (Zhang et al. 2022) propose an unsupervised multimodal topic model SMMTM to model the social media posts. In the SMMTM model, only one topic is sampled for the text while an image can belong to different topics, as because of of the lack of co-ocurrence patterns, the assumption of multiple topics for short texts leads to data sparsity and an incoherance between topics. Other topic models like multimodal-LDA assume that there is only one topic for both the textual words and the visuals which are the same(Zhang et al, 2022), meaning that the new comprehensive SMMTM model was able to out-preform existing models on the three datasets below [figure 1.1].

TABLE V AVERAGE C_v Topic Coherence of All the Models on the Three Datasets. Higher is Better.

Dataset	Model	K = 20	K = 40	K = 60	K = 80	K = 100
	mmLDA	0.283	0.284	0.290	0.291	0.291
	Corr-LDA	0.281	0.281	0.278	0.282	0.281
	multimodal-LDA	0.277	0.280	0.283	0.288	0.296
Twitter100k	VELDA	0.277	0.279	0.283	0.285	0.285
	mmETM	0.299	0.299	0.301	0.299	0.300
	KBMMWTM	0.278	0.277	0.277	0.277	0.277
	SMMTM	0.326	0.332	0.335	0.338	0.340
	mmLDA	0.382	0.386	0.382	0.388	0.392
	Corr-LDA	0.390	0.387	0.385	0.383	0.385
	multimodal-LDA	0.386	0.395	0.402	0.398	0.400
mmdata	VELDA	0.397	0.391	0.387	0.386	0.388
	mmETM	0.404	0.391	0.398	0.392	0.391
	KBMMWTM	0.380	0.388	0.395	0.399	0.399
	SMMTM	0.411	0.403	0.403	0.407	0.407
	mmLDA	0.465	0.508	0.506	0.508	0.512
Weibo	Corr-LDA	0.471	0.478	0.483	0.491	0.496
	multimodal-LDA	0.462	0.521	0.552	0.525	0.534
	VELDA	0.453	0.450	0.464	0.467	0.480
	mmETM	0.411	0.441	0.449	0.458	0.457
	KBMMWTM	0.399	0.425	0.460	0.463	0.471
	SMMTM-Multi-Topics	0.433	0.482	0.516	0.562	0.556
	SMMTM	0.545	0.566	0.567	0.582	0.573

Conclusion:

Finally, to synthesise all points of this review significant research has already been undertaken in numerous subtopics, that will prove extremely useful when concatenated under the big topic of social network based multimodal topic modelling in e-commerce. All in order to anser the question of the of whether existing topic mining and fusion models in conjunction with data collection models, reflect the peak efficiency possible for the purpose of social networks and e-commerce. Ideally, improving specifically to the effectiveness of targeted advertisements found on social media platforms, this research when complete, will provide the grounds to increase the similarity between modelled customer personas and actual physical customer wants and needs. The main type of research methods that will be used as part of my research will be a mixture of qualitative and quantitative. As a result of a conjunction between post positivism and social constructivism epistimologies, existing research can be used to guage social consensus, in addition to select numerical results. Validation of results will mostly occur after data collection, unless it is concluded that further experiments aren't needed and efficient models can be drawn from existing works.

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Appendix:





