MAIN PAPER TITLE:	MEMBERS:		
An Overview of Text Summarization Techniques.	Prasath k (61) Akhil Sanker(35)		
	Melvin		
	Abraham(29)		
	Doi Dropooth (FO)		
Reference Paper	Raj Praneeth (58) Concept and	Advantages	Drawbacks
TITLE and AUTHOR	Algorithms	Auvantages	Diawbacks
	7.186		
Text Summarization	-Text Summarization	-SVM is faster than	-Time consuming and
Techniques: SVM versus Neural	using two models and comparing their	Neural network	Computational
Networks	performances!	-Neural network is a	
	, personner	bit efficient compared	-Lack of Good
Shang Gaoa, Jawad	-SVM vs Neural	to SVM.	Corpuses.
Attari, Ken Barker	networks , because both are good at non-linear data and at large scale. -Find applicable corpus =>Extract features=>assign predictor class=>train	-When moved from normal MLP to Transformer models such as Bert , significant improvements were found -Helps to find the best	-Might not be the perfect one (real time) , Example as when taken into something more complex such as medicine , we might never know .
	and validate =>compare	approach	
Extractive Summarization using Continuous Vector Space Models Olof Mogren, Devdatt Dubhashi, Mikael Kageb °	-Focuses on notion of similarity of sentencesEmbeddings are created and mapped into latent space -tf-idf, vector distance	-Improve the existing models by applying better techniquesCompare DeepNN, RNN,Autoencoders.	-Highly Time consuming & Computationally costly -Word embedding Approach is comparatively slower
vagen	, cosine-similarity are used	Performance achieved	and high dimensional as embeddings itself will take a huge time.

Sequence GAN for	Triple RNN as	(seq2seq model	the generated
long Text	Discriminator and	achieves sota	summaries consist of
Summarization	Encoder Decoder as	it uses Most	repeating phrases.
Julilliarization	Generative.	Likekihood Estimation	repeating pinases.
	Generative.	(MLE) principle for	
Hao Xu, Yanan Cao,	Attention mechanism	training, which suffers	our model is still a
Yanbing Liu	Attention mechanism	from	supervised learning
randing Liu	RNN	exposure bias in	one relying on high-
	ININI	inference phase	quality training
	Encoder Decoder	therefore it performs	datasets which is
	Architecture.	worser than machine	scarce.
	7 Wernteetare.	learning algo LexRank	Scarce.
	Positional Encoding	learning algo Lexitanik	we will study an
	T ositional Encounts	GAN in machine	unsupervised or semi-
		translation using	supervised framework
		ANMT. Double	which can be applied
		Attention machanism.	to the text
			summarization task.
		Compare LexRank,abs-	
		baseline atttention-	
		based seq2seq	
		model,abs+INRNN by	
		introducing attention	
		in encoder,abs+	
		enahnced version of	
		abs,DeepRL,ANMT.	
		ATRNN - 41.565 IN	
		DAILY MAIL Corpus	
		and 31.40% in NLPCC	
		corpus	
PEGASUS: Pre-	Sparse Attention	evaluated PEGASUS	Need Large Corpus of
training with	mechanism.	model on 12	text data for pre-
Extracted Gap-		downstream./test	training objective.
sentences for		data summarization	
Abstractive	MLM (Masked	tasks spanning news,	Other than that no
Summarization	Language Model)	science, stories,	any drawbacks
	Transformer	instructions, emails,	because it latest paper
lingging 7hang * 1 Vac	Transformer	patents, and	released in july 2020 overcomes all the
Jingqing Zhang * 1 Yao Zhao * 2 Mohammad		legislative bills.	
Saleh 2 Peter J. Liu 2		Experiments	drawback of previous bird-pagasus.
Juicii Z i Clei J. Liu Z		demonstrate it	ona pagasus.
		achieves state-of-the-	Need indepth
		art performance on all	understanding of
		12 downstream	transformer and its
		datasets measured by	architecture to
		ROUGE scores	implemention
		model was able to	Of course really high
		adapt to unseen	computation speed .

		summarization	
		datasets very quickly	
Multi documents on	Graph	New approaches can	By using exiting
text summarization	LSA	be made and	techniques
techniques	Term frequency	developed with the	approaches there will
Author: Chintan Shah	Cluster	help of NLP and	be more time
and Anjali G Jivani	Cluster	Linguistic apperances	consuming and effort
,		which can help us to	towards will be more
		get better summary	
		,	
A.C	11 N. " 1	6	11.1.11.00
A Survey on Automatic Text	-Uses Naïve bayes	-Compares Performance and	-it is diffcult to
Summarization	-Decision Trees	decides which one is	replicate or extend the broader domains
Authors:-	-Hidden Markov	the best among these.	in abstractive
D.Das , AFT MArtins	Models	the best among these.	summarization
D.Das , 7 (1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	-Non Linear Models		34111114112411011
	Tron Emedi models		
Improving	- This model makes	- Can extract hidden semantic relations	
performance of Text Summarization	use of fuzzy logic extraction approach	between concepts in a	
Summanzation	for text	text unlike the	
Authors:	summarization.	traditional methods.	
S.A.Babara	Sammanzación.	traditional methods.	
Pallavi D.Patil	- Performs Latent	- Accurately captures	
	Semantic Analysis	semantic contents in	
	(LSA) as opposed to	sentences with the	
	performing direct	help of latent	
	word matching.	semantic analysis.	
	- Has high recall and		
	precision significance		
	test with manual		
A	evaluation results	Maria de la constanta de la co	A 1
Automatic	- content is extracted	- Works Instantly.	- Automatic
summarising: the	from the original data,	Reading the entire	summarization is a
state of the art	but the extracted content is not	article, dissecting it	complex task that consists of several
Author:	modified in any way.	and separating the important ideas from	sub-tasks.
Karen Spark Jones	mounica in any way.	the raw text takes	Sub tusks.
Karen Spark Jones	- Abstraction	time and effort	- Each of the sub-tasks
	transforms the		directly affects the
	extracted content by		ability to generate
	- Character content by	I	Some, to Bellerate

paraphrasing sections of the source document, to condense a text much more strongly.	- Can work with any languages without the need for manual intervention	high quality summaries.