## **Qualitative Analysis of Generated Summaries**

## Introduction

- 1. This document provides a qualitative analysis of the summaries written by 6 models tested in the W266 project, namely:
  - a) Baseline LED model ("allenai/led-base-16384"), with max input token length of 16384 & ~200M parameters
  - b) Off-the-shelf LED model ("allenai/led-large-16384-arxiv")<sup>1</sup>, with max input token length of 16384 & ~512M parameters
  - c) Off-the-shelf LED Centrum model ("ratishsp/Centrum"), with max input token length of 4096<sup>2</sup> & ~192M parameters
  - d) Finetuned LED model (our own model), with max input token length of 16384 but finetuned using inputs tokenized at 4096 max
  - e) Finetuned Centrum model (our own model), with max input token length of 4096
  - f) Two-step LED-to-Centrum model (our own model), with max input token length of 4096 at the second step<sup>3</sup>
- 2. A total of 25 randomly drawn samples<sup>4</sup> (from the 5093 samples in the X-Science test dataset) are analyzed. These 25 samples include:
  - a) 10 short samples, i.e. with total token lengths below the lower quartile
  - b) 10 medium samples, i.e. with total token lengths between the lower and upper quartiles
  - c) 5 long samples, i.e. with token lengths above the upper quartile
- 3. In analyzing the results, a few dimensions are looked at:
  - a) general fluency, i.e. whether the summary looks coherent and contains blatant errors or strange symbols
  - b) indication of multi-document summary ("MDS"), e.g. multiple sentences each attempting to summarize the work done in one or more of the journals being referenced
  - c) validity of MDS, e.g. whether sentences appearing to be summarizing different journals are in fact extracting key information from that journal's abstract
  - d) in addition, highest scores are highlighted in green, while lowest ones are in red, while key ideas from different articles are highlighted in different colors

# **High-level summary**

- 4. As set out in the main paper, this analysis provides us with further insights, and we note the following:
  - a) in general, the fine-tuned LED, fine-tuned Centrum and two-step model manages to summarize from multiple sources most of the time (see the different colors for excerpts for different parts of the source)
  - b) the writings from these three models are usually very fluent as well, though occasional strange formulations and factual inaccuracies are observed
  - c) furthermore, these models show clear signs of learning the desired writing style, especially in contrasting the main article with the other references
  - d) as a contrast, the baseline LED is prone to just copying from just the first part of the main article; while the off-the-shelf LED and Centrum either just copies or sometimes extracts from multiple sources

**Results** [only those referred to in the main paper included; full version of this document with all 25 samples available at Github.]

#### (a) Short samples

- 3157, 4820: Samples with used to illustrate the presence of long and compound nouns
- 4160: Short example where the off-the-shelf LED and off-the-shelf Centrum managed to extract information from multiple sources as well (i.e. in addition to the tuned and two-step models)

Abstracts	Label	Base LED	Off-the-shelf LED	Off-the-shelf Centrum	Tuned LED	Tuned Centrum	Two-step
):	The success of word embedding	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:
this paper, we study a novel approach for named entity recognition (NER) a	@cite encourages researchers to	- Rouge 2:	- Rouge 2:	- Rouge 2:	- Rouge 2:	- Rouge 2:	- Rouge 2:
d mention detection in natural language processing. Instead of treating NER	focus on machine-learned repre	0.0316 (prec)	0.0303 (prec)	0.035 (prec)	0.0685 (prec)	0.0 (prec)	0.049 (prec)
a sequence labelling problem, we propose a new local detection approach,	sentation instead of heavy featur	0.0463 (recall)	0.037 (recall)	0.0648 (recall)	0.0463 (recall)	0.0 (recall)	0.0463 (recall)
which rely on the recent fixed-size ordinally forgetting encoding (FOFE) meth	e engineering in NLP. Using word	0.0376 (f-1)	0.0333 (f-1)	0.0455 (f-1)	0.0552 (f-1)	0.0 (f-1)	0.0476 (f-1)
to fully encode each sentence fragment and its left right contexts into a fix	embedding as the typical featur	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:
d-size representation. Afterwards, a simple feedforward neural network is u	e representation for words, NNs	0.1132 (prec)	0.0977 (prec)	0.1045 (prec)	0.1757 (prec)	0.1957 (prec)	0.1942 (prec)
ed to reject or predict entity label for each individual fragment. The propose	become competitive to tradition	0.1651 (recall)	0.1193 (recall)	0.1927 (recall)	0.1193 (recall)	0.0826 (recall)	0.1835 (recall)
method has been evaluated in several popular NER and mention detection t	al approaches in NER. Many NLP	0.1343 (f-1)	0.1074 (f-1)	0.1355 (f-1)	0.1421 (f-1)	0.1161 (f-1)	0.1887 (f-1)
ks, including the CoNLL 2003 NER task and TAC-KBP2015 and TAC-KBP2016	tasks, such as NER, chunking and	Summary:	Summary:	Summary:	Summary:	Summary:	Summary:
i-lingual Entity Discovery and Linking (EDL) tasks. Our methods have yielded	part-of-speech (POS) tagging can	In this paper, we study a novel	in this paper, we study a novel	In this paper, we study a novel a	In @cite, the authors propose a	The Skip-gram model @cite @ci	In @cite, the authors proposed
retty strong performance in all of these examined tasks. This local detection	be formulated as sequence label	approach for named entity reco	approach for named entity reco	pproach for named entity recog	unified neural network architec	te is an efficient method for lea	a unified neural network archite
pproach has shown many advantages over the traditional sequence labellin	ing tasks. In @cite, deep convol	gnition (NER) and mention dete	gnition and mention detection i	nition (NER) and mention detec	ture and learning algorithm that	rning high-quality distributed ve	cture and learning algorithm th
methods.	utional neural networks (CNN) a	ction in natural language proces	n natural language processing. i	tion in natural language process	can be applied to various natur	ctor representations that captur	at can be applied to various nat
):	nd conditional random fields (CR	sing. Instead of treating NER as	nstead of treating named entity	ing. Instead of treating NER as a	al language processing tasks incl	e a large number of precise synt	ural language processing tasks i
d d d- d- i- i- p	mention detection in natural language processing. Instead of treating NER a sequence labelling problem, we propose a new local detection approach, nich rely on the recent fixed-size ordinally forgetting encoding (FOFE) meth to fully encode each sentence fragment and its left right contexts into a fix size representation. Afterwards, a simple feedforward neural network is unled to reject or predict entity label for each individual fragment. The propose nethod has been evaluated in several popular NER and mention detection the significant in the propose of the second process of the second	chis paper, we study a novel approach for named entity recognition (NER) a mention detection in natural language processing. Instead of treating NER as sequence labelling problem, we propose a new local detection approach, nich rely on the recent fixed-size ordinally forgetting encoding (FOFE) method to fully encode each sentence fragment and its left right contexts into a fix size representation. Afterwards, a simple feedforward neural network is under to reject or predict entity label for each individual fragment. The propose nethod has been evaluated in several popular NER and mention detection the significant of the sexual to reject or predict entity label for each individual fragment. The propose nethod has been evaluated in several popular NER and mention detection the significant of the sexual to reject or predict entity label for each individual fragment. The propose nethod has been evaluated in several popular NER and mention detection the significant of the sexual to reject or predict entity label for each individual fragment. 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Using word embedding as the typical feature representation for words, NNs become competitive to tradition all approaches in NER. Many NLP tasks, such as NER, chunking and part-of-speech (POS) tagging can be formulated as sequence label in grasks. In @cite encourages researchers to focus on machine-learned representation instead of heavy feature engineering in NLP. Using word embedding as the typical feature representation for words, NNs become competitive to tradition all approaches in NER. Many NLP tasks, such as NER, chunking and part-of-speech (POS) tagging can be formulated as sequence label in grasks. In @cite encourages researchers to focus on machine-learned representation instead of heavy feature engineering in NLP. Using word embedding as the typical feature representation for words, NNs become competitive to tradition all approaches in NER. Many NLP tasks, such as NER, chunking and part-of-speech (POS) tagging can be formulated as sequence label in grasks. In @cite encourages researchers to focus on machine-learned representation instead of heavy feature engineering in NLP. Using word embedding as the typical feature representation for words, NNs become competitive to tradition all approaches in NER. Many NLP tasks, such as NER, c	chis paper, we study a novel approach for named entity recognition (NER) a mention detection in natural language processing. Instead of treating NER as sequence labelling problem, we propose a new local detection approach, a sequence labelling problem, we propose a new local detection approach, a sequence labelling problem, we propose a new local detection approach, a sequence fixed-size ordinally forgetting encoding (FOFE) meth to fully encode each sentence fragment and its left right contexts into a fix engineering in NLP. Using word to reject or predict entity label for each individual fragment. The propose nethod has been evaluated in several popular NER and mention detection target size in the propose and Linking (EDL) tasks. Our methods have yielded entertools.  **Couge 2:  **O.0316 (prec)  **O.0463 (recall)  **O.0376 (f-1)  **O.0333 (f-1)  **O.0977 (prec)  **O.1132 (prec)  **O.1132 (prec)  **O.1132 (prec)  **O.1132 (prec)  **O.1132 (prec)  **O.1134 (f-1)  **Summary:  **In this paper, we study a novel approach for named entity recognition (NER) and mention detection in natural language processing. In natural language processing. In natural language processing. In natural language processing. Instead of treating NER focus on machine-learned representation instead of heavy feature engineering in NLP. Using word engineering in NLP. Using w	chis paper, we study a novel approach for named entity recognition (NER) a mention detection in natural language processing. Instead of treating NER as equence labelling problem, we propose a new local detection approach, inch rely on the recent fixed-size ordinally forgetting encoding (FOFE) meth to fully encode each sentence fragment and its left right contexts into a fix encepted or predict entity label for each individual fragment. The propose in the toroget or predict entity label for each individual fragment. The propose that shown many advantages over the traditional sequence labellin entity of the detection in natural language processing. Instead of treating NER as equence labelling problem, we propose a new local detection approach, focus on machine-learned representation instead of heavy feature engineering in NLP. Using word engineering in NLP.	chis paper, we study a novel approach for named entity recognition (NER) a mention detection in natural language processing. Instead of treating NER as equence labelling problem, we propose a new local detection approach, bich rely on the recent fixed-size ordinally forgetting encoding (FOFE) meth to fully encode each sentence fragment and its left right contexts into a fix erepresentation. Afterwards, a simple feedforward neural network is unto relieve to representation. Afterwards, a simple feedforward neural network is unto relieve to representation. Afterwards, a simple feedforward neural network is unto relieve to representation for words, NNs become competitive to tradition al approaches in NER. Many NLP tasks, such as NER, chunking and entity Discovery and Linking (EDL) tasks. Our methods have yielded proach for named entity recognition (NER) and mention detection in natural language processing. Instead of treating NER and sent to focus on machine-learned representation in stead of heavy featur e engineering in NLP. Using word on Words, NNs to fully encode each sentence fragment and its left right contexts into a fix erepresentation. Afterwards, a simple feedforward neural network is unto fully encode each sentence fragment and its left right contexts into a fix erepresentation. Afterwards, a simple feedforward neural network is unto fully erepresentation. Afterwards, a simple feedforward neural network is unto fully erepresentation. Afterwards, a simple feedforward neural network is unto fully erepresentation. Afterwards, a simple feedforward neural network is unto fully erepresentation for words, NNs become competitive to tradition al approaches in NER. Many NLP tasks, such as NER, Chunking and part-of-speech (POS) tagging can be tryling to fully erecent fixed-size ordinally forgetting encoding (FOFE) method has been evaluated in several popular NER and mention detection in all of these examined tasks. This local detection in part and part-of-speech (POS) tagging can be formulated as sequence labelling	chis paper, we study a novel approach for named entity recognition (NER) a mention detection in natural language processing. Instead of treating NER as sequence labeling problem, we propose a new local detection approach, on the recent fixed-size ordinally forgetting encoding (FOFE) method has been evaluated in several popular NER and mention detection all of these examined tasks. This local detection approach in this paper, we study a novel agroroach for named entity recognition (NER) a mention detection in natural language processing. Instead of treating NER focus on machine-learned representation instead of heavy feature engineering in NLP. Using word embedding as the typical feature engine

<sup>&</sup>lt;sup>1</sup> This model has been pre-trained by the authors for general summarization task using arXiv dataset.

<sup>&</sup>lt;sup>2</sup> The publicly available Centrum checkpoint was built upon the LED model architecture using the 4096 token version. This means Centrum is not able to take in 16384 tokens.

<sup>&</sup>lt;sup>3</sup> For the first step, none of the individual source articles in the X-science dataset contain more than 4096 tokens, so there is no issue of the first step model (i.e. the finetuned LED) receiving truncated inputs.

<sup>&</sup>lt;sup>4</sup> For details, please refer to the "Qualitative\_analysis.ipynb" notebook. We originally planned for 20 samples for each category but ended up doing 25 in total due to time limitations. The 10 are the first and last 5 of the randomly selected samples for the short and medium samples, and just the first 5 for the long samples.

No.	Abstracts	Label	Base LED	Off-the-shelf LED	Off-the-shelf Centrum	Tuned LED	Tuned Centrum	Two-step
7.007	We propose a unified neural network architecture and learning algorithm tha	F) are used to infer NER labels at	a sequence labelling problem,	recognition as a sequence label	sequence labelling problem, w	uding: part-of-speech tagging, c	actic and semantic word relatio	ncluding part-of-speech taggin
	t can be applied to various natural language processing tasks including: part-o	a sentence level, where they still	we propose a new local detecti	ling problem, we propose a new	e propose a new local detection	hunking, named entity recogniti	nships. By subsampling of the fr	g, chunking, named entity recog
	f-speech tagging, chunking, named entity recognition, and semantic role label	use many hand-crafted features	on approach, which rely on the	local detection approach, whic	approach, which rely on the rec	on, and semantic role labeling. I	equent words, it obtain significa	nition, and semantic role labelin
	ing. This versatility is achieved by trying to avoid task-specific engineering and	to improve performance, such as	recent fixed-size ordinally forge	h rely on the recent fixed-size o	ent fixed-size ordinally forgettin	n this work, we propose a new l	nt speedup and also learn more	g. However, unlike our work, th
	therefore disregarding a lot of prior knowledge. Instead of exploiting man-m ade input features carefully optimized for each task, our system learns intern	capitalization features explicitly defined based on first-letter capi	tting encoding (FOFE) method t o fully encode each sentence fr	rdinally forgetting encoding (FO FE ) method to fully encode eac	g encoding (FOFE) method to fu lly encoding each sentence frag	ocal detection approach, which rely on the recent fixed-size ord	regular word representations.  Comment:	ey do not use a deep neural net work to train their system. Inste
	al representations on the basis of vast amounts of mostly unlabeled training d	tal, non-initial capital and so on.	agment and its left right context	h sentence fragment and its left	ment and its left right contexts i	inally forgetting encoding (FOF	- Shows weak signs of MDS,	ad, they use a multi-task learnin
	ata. This work is then used as a basis for building a freely available tagging sys	tal, non malar capital and so om	s into a fixed-size representatio	right contexts into a fixed-size r	nto a fixed-size representation.	E) method to fully encode each	providing a summary of the 3 <sup>rd</sup>	g algorithm to train their netwo
	tem with good performance and minimal computational requirements.		n. Afterwards, a simple feedfor	epresentation.	Afterwards, a simple feedforwa	sentence fragment and its left ri	article only (blue) and	rk on a large amount of unlabel
	(3):		ward neural network is used to	afterwards, a simple feedforwa	rd neural network is used to rej	ght contexts into a fixed-size re	presenting it as different from	ed training data. <mark>In contrast</mark> , we
	The recently introduced continuous Skip-gram model is an efficient method f		reject or predict entity label for	rd neural network is used to rej	ect or predict entity label for ea	presentation.	the main one.	use a deep network to train our
	or learning high-quality distributed vector representations that capture a larg		each individual fragment. The p	ect or predict entity label for ea	ch individual fragment. The pro	Comment:		system on a much larger amou
	e number of precise syntactic and semantic word relationships. In this paper we present several extensions that improve both the quality of the vectors an		roposed method has been evalu ated in several popular NER and	ch individual fragment. the proposed method has been	posed method has been evaluat ed in several popular NER and	- Shows signs of MDS, which contrasts the 2 <sup>nd</sup> (green)		nt of training data, and we do not need to train our network on
	d the training speed. By subsampling of the frequent words we obtain signific		mention detection tasks, includ	evaluated in several popular na	mention detection tasks, includi	article with the 1st (yellow)		unlabeled data.
	ant speedup and also learn more regular word representations. We also descr		ing the CoNLL 2003 NER task an	med entity and mention detecti	ng the CoNLL 2003 NER task an	one.		Comment:
	ibe a simple alternative to the hierarchical softmax called negative sampling.		d TAC-KBP2016 Tri-lingual Entit	on tasks, including the coNLL 20	d TAC-KBP2015 and TAC -KBP20	- However, the 3 <sup>rd</sup> article is not		- Shows signs of MDS, providing
	An inherent limitation of word representations is their indifference to word o		y Discovery and Linking (EDL) ta	03 named entity recognition tas	16 Tri-lingual Entity Discovery a	covered at all		a summary of the 2 <sup>nd</sup> article
	rder and their inability to represent idiomatic phrases. For example, the mean		sks. Our methods have yielded	k and the tac-2015 and tac-201	nd Linking (EDL) tasks. Our met			(green) and contrasting it with
	ings of "Canada" and "Air" cannot be easily combined to obtain "Air Canada".		pretty strong performance in all	6 tri-lingual entity discovery and	hods have yielded pretty strong performance in all of these exa			the main one (red).
	Motivated by this example, we present a simple method for finding phrases in text, and show that learning good vector representations for millions of phr		of these examined tasks. This I ocal detection approach has sh	linking tasks.  our methods have yielded prett	mined tasks. This local detectio			<ul> <li>However, the red parts also contain hallucinations, not to</li> </ul>
	ases is possible.		own many advantages over the	y strong performance in all of th	n approach has shown many ad			mention the neglect of the 3 <sup>rd</sup>
	'		traditional sequence labelling m	ese examined tasks.	vantages over the traditional se			article
			ethods.     We propose a unifi	Comment:	quence labelling methods. We p			
			ed neural network architecture	- Copied the first tokens only,	ropose a unified neural network			
			and learning algorithm that can	except for the deletion of the	architecture and learning algori			
			be applied to various natural la nguage processing	acronym for NER (red) - No indication of MDS	thm that can be applied to vario us natural language processing t			
			Comment:	- No malcation of MD3	asks including: part-of-speech t			
			- Copied the first tokens only		agging, chunking, named entity			
			- No indication of MDS		recognition, and semantic role I			
					abeling. This versatility is achiev			
					ed by trying to avoid task-specif			
					ic engineering and therefore dis			
					regarding a lot of prior knowled ge. Instead of exploiting man-m			
					ade input			
					Comment:			
					- Copied the first tokens only			
					- No indication of MDS			
	(1)							_
4160	(1):  We present a method for extracting depth information from a rectified image	Recent work @cite @cite focuse	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:
	pair. We train a convolutional neural network to predict how well two image	d on estimating the confidence of the computed matching cost. u	- Rouge 2: 0.0523 (prec)	- Rouge 2: 0.0826 (prec)	- Rouge 2: 0.0468 (prec)	- Rouge 2: 0.1515 (prec)	- Rouge 2: 0.0517 (prec)	- Rouge 2: 0.1122 (prec)
	patches match and use it to compute the stereo matching cost. The cost is ref	sed a random forest classifier to	0.1579 (recall)	0.1579 (recall)	0.1404 (recall)	0.1754 (recall)	0.0526 (recall)	0.1122 (prec) 0.193 (recall)
	ined by cross-based cost aggregation and semiglobal matching, followed by a	combine several confidence mea	0.0786 (f-1)	0.1084 (f-1)	0.0702 (f-1)	0.1626 (f-1)	0.0522 (f-1)	0.1419 (f-1)
	left-right consistency check to eliminate errors in the occluded regions. Our st	sures. Similarly, trained a rando	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:
	ereo method achieves an error rate of 2.61 on the KITTI stereo dataset and is	m forest classifier to predict the	0.0983 (prec)	0.2 (prec)	0.1047 (prec)	0.2687 (prec)	0.2373 (prec)	0.2121 (prec)
	currently (August 2014) the top performing method on this dataset.	confidence of the matching cost	0.2931 (recall)	0.3793 (recall)	0.3103 (recall)	0.3103 (recall)	0.2414 (recall)	0.3621 (recall)
	(2): While machine learning has been instrumental to the ongoing progress in mo	and used the predictions as soft	0.1472 (f-1)	0.2619 (f-1)	0.1565 (f-1)	0.288 (f-1)	0.2393 (f-1)	0.2675 (f-1)
	st areas of computer vision, it has not been applied to the problem of stereo	constraints in a Markov random f ield to decrease the error of the	Summary: We present a method for extrac	Summary: we present a supervised learni	Summary: In this article, we're going to tak	Summary: Our work is closely related to @	Summary: Our work is also related to the s	Summary: In @cite @cite, the authors use
	matching with similar frequency or success. We present a supervised learning	stereo method.	ting depth information from a r	ng approach for predicting the c	e a look at a new method for pr	cite @cite in that they use a ran	emi-global matching stereo (SG	d a random forest to predict the
	approach for predicting the correctness of stereo matches based on a rando		ectified image pair. We train a c	orrectness of stereo matches ba	edicting the correctness of ster	dom forest to predict the correc	M) method @cite @cite, which	correctness of stereo matching
	m forest and a set of features that capture various forms of information abou		onvolutional neural network to	sed on a random forest and a se	eo matches based on a random	tness of stereo matches based o	is based on a random forest and	based on a random forest and a
	t each pixel. We show highly competitive results in predicting the correctness		predict how well two image pat	t of features that capture variou	forest and a set of features that	n a set of features that capture	a set of features that capture v	set of features that capture vari
	of matches and in confidence estimation, which allows us to rank pixels accor		ches match and use it to compu	s forms of information about ea	capture various forms of infor	various forms of information ab	arious forms of information abo	ous forms of information about
	ding to the reliability of their assigned disparities. Moreover, we show how the		te the stereo matching cost. Th	ch pixel.  we train a convolutional neural	mation about each pixel. We're using the random decision fores	out each pixel. However, our work is different in that we train	ut each pixel. SGM achieves an error rate of 2.61 on the KITTI st	each pixel. However, they do not consider sparsification. In addi
	ese confidence values can be used to improve the accuracy of disparity maps by integrating them with an MRF-based stereo algorithm. This is an important		e cost is refined by cross-based cost aggregation and semigloba	network to predict how well tw	t framework, which currently p	a convolutional neural network	error rate of 2.61 on the KITTI st ereo dataset and is currently th	tion, they did not use sparsificat
	distinction from current literature that has mainly focused on sparsification b		I matching, followed by a left-ri	o image patches match and use	oses higher challenges to stereo	to predict how well two image	e top performing method on thi	ion to improve the accuracy of t
	y removing potentially erroneous disparities to generate quasi-dense disparit		ght consistency check to elimin	it to compute the stereo matchi	solvers than other benchmarks	patches match and use it to co	s dataset.	he disparity maps, and they do
	y maps.		ate errors in the occluded regio	ng cost.	with ground truth for stereo ev	mpute the stereo matching cos	Comment:	not require sparsification in ord
	(3):		ns. Our stereo method achieves	the cost is refined by cross-bas	aluation. We experiment with s	t.	- Some signs of MDS, with the	er to improve the performance
	With the aim to improve accuracy of stereo confidence measures, we apply t		an error rate of 2.61 on the KIT	ed cost aggregation and semigl	emi global matching stereo (SG	Comment:	first green part showing an	of the matching. Moreover, thei
	he random decision forest framework to a large set of diverse stereo confiden		TI stereo dataset and is currentl	obal matching, followed by a lef	M) and a census data term, whi	- Clear sign of MDS, with the	attempt to make comparison	r work does not rely on the spar
	ce measures. Learning and testing sets were drawn from the recently introdu ced KITTI dataset, which currently poses higher challenges to stereo solvers the		y (August 2014) the top perfor ming method on this dataset.	t-right consistency check to eli minate errors in the occluded re	ch is the best performing real-ti me capable stereo method kno	sentence in red summarizing both the 2 <sup>nd</sup> and 3 <sup>rd</sup> articles	- The blue and 2 <sup>nd</sup> green part shows possible mix up	sification of sparsification, but r ather on sparsifying the disparit
	an other benchmarks with ground truth for stereo evaluation. We experiment			gions.	wn to date. On KITTI images, SG	(both uses random forests)	between the 2 <sup>nd</sup> and 3 <sup>rd</sup>	y maps in order to achieve spars
	with semi global matching stereo (SGM) and a census data term, which is the		been instrumental to the ongoi	our stereo method achieves an	M still produces a significant am	and contrasting that with a	models, caused probably by	ification without sparsification a
	best performing real-time capable stereo method known to date. On KITTI im		ng progress in most areas of co	error rate of 2.61 on the recentl	ount of error. We obtain consist	fact from the 1 <sup>st</sup> (yellow)	the repeated use of stereo and	nd without sparsifying.
	ages, SGM still produces a significant amount of error. We obtain consistently		mputer vision, it has not been a	y introduced kitti stereo dataset	ently improved area under curv		SGM	Comment:
	improved area under curve values of sparsification measures in comparison t		pplied to the problem of stereo	and is currently (August 2014 )	e values of sparsification measu		- In a similar vein, the red part is	- Clear sign of MDS, with the
	o best performing single stereo confidence measures where numbers of stere		matching with similar frequency	the top performing method on t	res in comparison to best perfor		from the 1st article (see	first sentence referring to the
	o errors are large. More specifically, our method performs best in all but one out of 194 frames of the KITTI dataset.		or success. We present a super vised learning approach for pre	his dataset.	ming single stereo confidence measures where numbers of ste		numbers in yellow) but the	2 <sup>nd</sup> and 3 <sup>rd</sup> examples, and
	Out of 134 Hairies of the KITH Udiaset.	<u>l</u>	vised learning approach for pre	Comment:	Incasures where multipers of ste	<u> </u>	sentence structure is unclear	

No.	Abstracts	Label	Base LED	Off-the-shelf LED	Off-the-shelf Centrum	Tuned LED	Tuned Centrum	Two-step
			dicting the correctness of stere o matches based on a random f orest and a set of features that capture various forms of inform ation about each pixel. We sho w highly competitive results in predicting the accuracy of matches and in confidence estimation, which allows us to rank  Comment:  - Copied the first tokens only - No indication of MDS	- Copied from the 1 <sup>st</sup> (yellow) and 2 <sup>nd</sup> (green) articles - No indication of MDS	reo errors are large. More specifically, our method performs be st in all but one out of 194 fram es of the KITTI dataset. This is a nimportant distinction from cur rent literature that has mainly focused on sparsification by removing potentially erroneous disparities to generate quasi-dense disparity maps.  Comment:  - Some sign of MDS by contrasting the 2nd (green) and 3rd (blue articles)  - However, the phrase in red is also copied from the 2nd article so it is uncertain if the model is actually doing MDS  - It also mixed up the facts in the 2nd and 3rd articles		as to whether the model is referring to the main article or not.	contrasting it with the main one.  - However, the red parts are hallucinations
4820	(1): This paper presents a new method and a constraint-based objective function to solve two problemsrelated to the design of optical telecommunication net works, namely the Synchronous Optical Net-work Ring Assignment Problem (SRAP) and the Intra-ring Synchronous Optical Network DesignProblem (IDP). These network topology problems can be represented as a graph partitioning withcapacity constraints as shown in previous works. W'e present here a new objective function and anew local search algorithm to solve these problems. Experiments conducted in C (2): This paper considers two problems that arise in the design of optical telecom munication networks when a ring-based topology is adopted, namely the SON ET Ring Assignment Problem and the Intraring Synchronous Optical Network Design Problem. We show that these two network topology problems corresp ond to graph partitioning problems with capacity constraints: the first is a vertex partitioning problem, while the latter is an edge partitioning problem. We consider solution methods for both problems, based on metaheuristic algorithms. We first describe variable objective functions that depend on the transition from one solution to a neighboring one, then we apply several diversification and intensification techniques including Path Relinking, exploring Tabu Search and Scatter Search. Finally, we propose a diversification method based on the use of multiple neighborhoods. A set of extensive computational results is used to compare the behaviour of the proposed methods and objective function in the compare the behaviour of the proposed methods and objective function in the proposed methods and objective functions in the proposed methods and objective functions in the proposed methods and objective functions in the proposed methods are p	The two other methods describe d in @cite are based on the idea that to save ADMs a good solution is should have very dense rings. They are both greedy and rely on a clique algorithm. In graph theo ry, a clique in an undirected graph @math is a subset of the vertex set @math, such that for every two vertices in @math, there exists an edge connecting the two. Finding a clique is not that easy, a way to do it is to use an "Union-Find" strategie, two clique @math and @math such that each node in @math is adjacent to each node in @math then merge the two cliques (). The associated heuristic starts by considering each node to be a clique of size one, and to merge two cliques into a lar ger clique until there are no more possible merges.	Rouge scores: - Rouge 2: 0.0132 (prec) 0.0144 (recall) 0.0138 (f-1) - Rouge L: 0.1316 (prec) 0.1429 (recall) 0.137 (f-1) Summary: This paper presents a new meth od and a constraint-based objective function to solve two problemsrelated to the design of optical telecommunication network s, namely the Synchronous Optical Net-work Ring Assignment Problem (SRAP) and the Intra-ring Synchronous optical Network DesignProblem (IDP). These net work topology problems can be represented as a graph partitioning withcapacity constraints as shown in previous works. We present here a new objective function and anew local search algorithm to solve these problems. Experiments conducted in CER N and the University of California, Berkeley.  This paper considers two problems that arise in the design of Optical telecommunication networks when a ring-based topology is adopted, namely the SONET Ring Assignment Problem and the Intraring Synchronous O Network Design Problem. We show that these two network topologies problems correspond to graph partitioning problems with capacity constraints: the first is a vertex partitioning problem, while the latter is an edge partitioning problem.  Comment: - Copied the first tokens only - No indication of MDS	Rouge scores: - Rouge 2: - Rouge 2: - Rouge 2: - Rouge (recall) - Rouge L: -	Rouge scores: - Rouge 2: 0.0205 (prec) 0.0288 (recall) 0.024 (f-1) - Rouge L: 0.1276 (prec) 0.1786 (recall) 0.1488 (f-1) Summary: This paper presents a new meth od and a constraint-based objective function to solve two problems related to the design of optical telecommunication networks, namely the Synchronous Optical Net-work Ring Assignment Problem (SRAP) and the Intraring Synchronous optical Network DesignProblem (IDP). These net work topology problems can be represented as a graph partitioning withcapacity constraints as shown in previous works. We present here a new objective function and anew local search algorithm to solve these problems. Experiments conducted in C This paper considers two problems that arise in the design of Optical telecommunication networks when a ring-based topology is a dopted, namely the SONET Ring Assignment Problem and the Intra-ring SynchronousOptical Network Design Problem. We show that these two network topology problem correspond to graph partitioning problems, while the latter is an edge partitioning problems with capacity constraints: the first is a partitioning problem, while the latter is an edge partitioning problem. We consider solution methods for both problems, based on metaheuristic algorithms. We first describe variable objective functions that depend on the transition from one solution to a neighboring one, then we apply several diversification and intensification techniques including Path Relinking, eXploring Tabu Search. Finally we propose a divers  Comment: - Copied the first tokens only	Rouge scores: - Rouge 2: 0.0189 (prec) 0.0072 (recall) 0.0104 (f-1) - Rouge L: 0.2407 (prec) 0.0929 (recall) 0.134 (f-1) Summary: In the context of optical teleco mmunication networks, the SO NET Ring Assignment Problem (SRAP) and the Intraring Synchr onous Optical Network Design P roblem (IDP) are two problems that arise when a ring-based to pology is adopted. The SRAP pr oblem can be represented as a graph partitioning problem, whi le the IDP problem is a edge par titioning problem. Comment: - Shows no sign of MDS, with the model just extracting the common theme of the 2 articles	Rouge scores: - Rouge 2: 0.0357 (prec) 0.0072 (recall) 0.012 (f-1) - Rouge L: 0.2414 (prec) 0.05 (recall) 0.0828 (f-1) Summary: In @cite, an objective function and a diversification method ar e proposed to solve the SONET Ring Assignment Problem (SRA P) and the Intra-ring Synchrono us Optical Network Design Problem (IDP). Comment: - Shows weak signs of MDS, which presents the 2 <sup>nd</sup> (green) article as different from the main one	Rouge scores: - Rouge 2: 0.1233 (prec) 0.0647 (recall) 0.0849 (f-1) - Rouge L: 0.2703 (prec) 0.1429 (recall) 0.1869 (f-1)  Summary: In @cite, the objective function s of the SONET ring assignment problem and the IDP problem a re discussed in terms of a meta heuristic algorithm. In particula r, the objective function for SO NET Ring Assignment Problem is described in @cite. The objective functions of SONet Ring Assignment Problem are defined as: where @math is the number of neighbors, @math the number of nodes in the network, @math and @math are the number of vertices in the network.  Comment: - Shows weak signs of MDS, which presents the 2 <sup>nd</sup> (green) article as different from the main one - Contains more relevant information that the other tuned models

No.	Abstracts	Label	Base LED	Off-the-shelf LED	Off-the-shelf Centrum	Tuned LED	Tuned Centrum	Two-step
					- No indication of MDS			
								!

# (b) Medium samples

- 831, 5068: examples where the tuned and two-step models show the ability to contrast and compare the main article with other references.
- 845: sample where the tuned models avoided quoting from the irrelevant input
- 4371: sample where even the off-the-shelf Centrum resorted to just copying from one of the articles

Abstracts	Label	Base LED	Off-the-shelf LED	Off-the-shelf Centrum	Tuned LED	Tuned Centrum	Two-st
(1):	Multi-task learning (MTL) resear	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:
Learning to drive faithfully in highly stochastic urban settings remains an open	ch shows the joint training of au	- Rouge 2:	- Rouge 2:	- Rouge 2:	- Rouge 2:	- Rouge 2:	- Rouge 2:
problem. To that end, we propose a Multi-task Learning from Demonstration	xiliary related side-tasks along wi	0.0721 (prec)	0.0276 (prec)	0.0192 (prec)	0.0492 (prec)	0.0494 (prec)	0.0541 (prec)
(MT-LfD) framework which uses supervised auxiliary task prediction to guide t	th the main task enhances the tr	0.0748 (recall)	0.0374 (recall)	0.0374 (recall)	0.028 (recall)	0.0374 (recall)	0.0561 (recall)
he main task of predicting the driving commands. Our framework involves an	aining performance . MTL in neu	0.0734 (f-1)	0.0317 (f-1)	0.0254 (f-1)	0.0357 (f-1)	0.0426 (f-1)	0.055 (f-1)
end-to-end trainable network for imitating the expert demonstrator's driving	ral networks has been successful	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:
commands. The network intermediately predicts visual affordances and actio	ly demonstrated in many tasks p	0.1786 (prec)	0.1301 (prec)	0.0861 (prec)	0.1774 (prec)	0.1585 (prec)	0.1786 (prec)
n primitives through direct supervision which provide the aforementioned au	reviously including text-to-speec	0.1852 (recall)	0.1759 (recall)	0.1667 (recall)	0.1019 (recall)	0.1204 (recall)	0.1852 (recall)
xiliary supervised guidance. We demonstrate that such joint learning and sup	h conversion , natural language	0.1818 (f-1)	0.1496 (f-1)	0.1136 (f-1)	0.1294 (f-1)	0.1368 (f-1)	0.1818 (f-1)
ervised guidance facilitates hierarchical task decomposition, assisting the age		, ,		Summary:	Summary:	Summary:	
-	processing , speech processing a	Summary:	Summary:	1	·	-	Summary:
nt to learn faster, achieve better driving performance and increases transpare	nd computer vision . In the field	Learning to drive faithfully in hi	learning to drive faithfully in hi	"Machine learning is the learnin	In @cite, an end-to-end deep n	Multi-task learning (MTL) @cite	In <u>@cite</u> , the auth
ncy of the otherwise black-box end-to-end network. We run our experiments	of sequential decision making, @	ghly stochastic urban settings re	ghly stochastic urban settings re	g of a mapping from situations t	eural network is used to learn t	@cite aims to learn a mapping f	a multi-modal MT
to validate the MT-LfD framework in CARLA, an open-source urban driving si	cite demonstrate MTL for 3D ga	mains an open problem. To that	mains an open problem. this pa	o actions so as to maximize a sc	o play Atari 2600 Atari games di	rom situations to actions so as t	ain a neural netwo
mulator. We introduce multiple non-player agents in CARLA and induce temp	me playing, @cite and @cite de	end, we propose a Multi-task L	per describes a technique for us	alar reward or reinforcement si	rectly from sensory experience.	o maximize a scalar reward or r	the steering angle
oral noise in them for realistic stochasticity.	monstrate MTL in 3D maze navig	earning from Demonstration (M	ing Multi-Modal Multi-Task lear	gnal. The learner is not told whi	The network is trained to imitat	einforcement signal. The learne	peed of a car. In @
(2):	ation task whereas @cite utilize	T-LfD) framework which uses su	ning that considers multiple beh	ch action to take, as in most for	e the steering angle and driving	r is not told which action to tak	ors proposed an e
An artificial agent is developed that learns to play a diverse range of classic At	the MTL framework for autonom	pervised auxiliary task predictio	avioral modalities as distinct mo	ms of machine learning, but inst	speed of human control of a ca	e, as in most forms of machine I	nable network for
ari 2600 computer games directly from sensory experience, achieving a perfor	ous driving. Instead of employin	n to guide the main task of pred	des of operation for an end-to-e	ead must discover which action	r. @cite proposed a multi-moda	earning, but instead must disco	expert demonstra
mance comparable to that of an expert human player; this work paves the wa	g future control outputs as auxili	icting the driving commands. O	nd autonomous deep neural ne	s yield the highest reward by try	I multi-task learning from demo	ver which actions yield the high	ommands. Howev
	ary tasks as shown by @cite , in t	ur framework involves an end-t	twork utilizing the insertion of	ing them. In the most interestin	nstration (MT-LfD) framework t	est reward by trying them. In th	t provide a direct
een perception and action.	his work we employ action and v	o-end trainable network for imi	modal information as secondary	g and challenging cases, actions	o train an agent to play Atari ga	e most interesting and challengi	echanism for the a
(3):	isual abstractions to guide the dr	tating the expert demonstrator	input data for tasks with relate	may affect not only the immedi	mos	ng cases, actions may affect not	the driving comma
	•			ate's reward, but also the next s	Comments	_ ·	
Reinforcement learning is the learning of a mapping from situations to action	iving behavior.	s driving commands. The netwo	d behaviors. using labeled data	1	Comment:	only the immediate's reward, b	not the case in ou
s so as to maximize a scalar reward or reinforcement signal. The learner is not		rk intermediately predicts visual	from hours of driving our fleet o	ituation, and through that all su	- Shows some sign of MDS,	ut also the next situation, and t	ver, the authors d
told which action to take, as in most forms of machine learning, but instead		affordances and action primitiv	f 1 10th scale model cars, we tr	bsequent rewards. These two c	summarizing the 2 <sup>nd</sup> (green)	hrough that all subsequent rew	a method to indu
must discover which actions yield the highest reward by trying them. In the m		es through direct supervision w	ained multiple neural networks	haracteristics—trial-and-error s	and 4 <sup>th</sup> (purple) articles.	ards @cite.	oise in the networ
ost interesting and challenging cases, actions may affect not only the immedi		hich provide the aforementione	to imitate the steering angle an	earch and delayed reward—are	- However, there is some mix up	Comment:	in our work, we p
ate's reward, but also the next situation, and through that all subsequent rew		d auxiliary supervised guidance.	d driving speed of human contr	the two most important disting	about the networks for the	- Summarized the 3 <sup>rd</sup> article only	hod that intermed
ards. These two characteristics—trial-and-error search and delayed reward—		We demonstrate that such join	ol of a car.	uishing features of reinforceme	two articles	- No indication of MDS	s the driving comn
are the two most important distinguishing features of reinforcement learning.		t learning and supervised guida	we show that in each case, our	nt learning." "In recent years dif	- The model then mentions the		e the agent to ach
(4):		nce facilitates hierarchical task	models trained with multi-mod	ferent lines of evidence have le	1 <sup>st</sup> article (yellow) but		ving performance
Several deep learning approaches have been applied to the autonomous drivi		decomposition, assisting the ag	al multi-task learning can match	d to the idea that motor actions	erroneously treated it as a		ransparency.
ng task, many employing end-to-end deep neural networks. Autonomous driv		ent to learn faster, achieve bett	or outperform multiple networ	and movements in both verteb	non-main article (red @cite)		Comment:
ing is complex, utilizing multiple behavioral modalities ranging from lane chan		er driving performance and incr	ks trained on individual tasks, w	rates and invertebrates are com	and that it is used to play Atari		- Shows some s
ging to turning and stopping. However, most existing approaches do not facto		eases transparency of the other	hile using a fraction of the para	posed of elementary building bl	games instead of driving (2 <sup>nd</sup>		contrasting the
r in the different behavioral modalities of the driving task into the training str		wise black-box end-to	meters and having more distinc	ocks. The entire motor repertoir			(yellow) with
		Comment:	t mode of operation than a net		red part)		
ategy. This paper describes a technique for using Multi-Modal Multi-Task Lear			•	e can be spanned by applying a			articles.
ning that considers multiple behavioral modalities as distinct modes of operat		- Copied the first tokens only	work trained without multi - mo	well-defined set of operations a			- However, the on
ion for an end-to-end autonomous deep neural network utilizing the insertion		- No indication of MDS	dal multi- task learning on the s	nd transformations to these pri			explicitly mention
of modal information as secondary input data. Using labeled data from hours			ame data.	mitives and by combining them			one (purple).
of driving our fleet of 1 10th scale model cars, we trained multiple neural net			Comment:	in many different ways accordin			
works to imitate the steering angle and driving speed of human control of a c			- Started from the 1st sentence	g to well-defined syntactic rule			
ar. We show that in each case, our models trained with MTL can match or out			of the 1st article (yellow), but	s. Motor and movement primiti			
perform multiple networks trained on individual tasks, while using a fraction			then moved to copy from the	ves and modules might exist at			
of the parameters and having more distinct modes of operation than a netwo			3 <sup>rd</sup> sentence of the 4 <sup>th</sup> article	the neural, dynamic and kinema			
rk trained without MTL on the same multi-modal data. These results should e			(purple)	tic levels with complicated map			
ncourage Multi-Modal MTL-style training with the insertion of Modal Informa			- Words in red also came from	ping among the elementary buil			
tion for tasks with related behaviors.			the 4 <sup>th</sup> article but from a later	ding blocks subserving these dif			
(5):				ferent levels of representation.			
In recent years different lines of evidence have led to the idea that motor acti			part - No indication of MDS	•			
			- NO INDICATION OF MIDS	Hence, while considerable prog			
ons and movements in both vertebrates and invertebrates are composed of e				ress has been made in recent ye			
lementary building blocks. The entire motor repertoire can be spanned by ap				ars in unravelling the nature of t			
plying a well-defined set of operations and transformations to these primitive				hese primitives, new experimen			
s and by combining them in many different ways according to well-defined sy				tal, computational			
ntactic rules. Motor and movement primitives and modules might exist at the				Comment:			
neural, dynamic and kinematic levels with complicated mapping among the e				- Copied from the 3 <sup>rd</sup> (purple)			
lementary building blocks subserving these different levels of representation.				and 5th (orange) articles only			
Hence, while considerable progress has been made in recent years in unravell				- No indication of MDS			
ing the nature of these primitives, new experimental, computational and conc							
eptual approaches are needed to further advance our understanding of moto				1			
epiudi approduies die needed to iditiel duvdike oul diideistdiidiig of 1110to		1	1	1	1	I .	1

No.	Abstracts	Label	Base LED	Off-the-shelf LED	Off-the-shelf Centrum	Tuned LED	Tuned Centrum	Two-step
845	(1):  We present a neural framework for opinion summarization from online product reviews which is knowledge-lean and only requires light supervision (e.g., i in the form of product domain labels and user-provided ratings). Our method combines two weakly supervised components to identify salient opinions and form extractive summaries from multiple reviews: an aspect extractor trained under a multi-task objective, and a sentiment predictor based on multiple insistance learning. We introduce an opinion summarization dataset that includes a training set of product reviews from six diverse domains and human-annotated development and test sets with gold standard aspect annotations, salience labels, and opinion summaries. Automatic evaluation shows significant improvements over baselines, and a large-scale study indicates that our opinion summaries are preferred by human judges according to multiple criteria.  (2):  The specification discloses a luggage carrier made up of a generally U-shaped frame. The frame has two spaced legs with a hook on the front which hooks o ver the bumper of an automobile. Two braces are attached to the cross mem ber of the U-shaped member and the front portion of the braces is received on fastening means welded to the under side of the car frame. The cross mem bers provide a supporting surface for carrying articles, boats and the like. A platform may be supported on the frame.  (3):  We develop a Ranking framework upon Recursive Neural Networks (R2N2) to rank sentences for multi-document summarization. It formulates the sentence ranking task as a hierarchical regression process, which simultaneously mea sures the salience of a sentence and its constituents (e.g., phrases) in the pars ing tree. This enables us to draw on word-level to sentence-level supervisions derived from reference summaries. In addition, recursive neural networks are used to automatically learn ranking features over the tree, with hand-crafted feature vectors of words as inputs. Hierarchical regressions are then conduct	A few extractive neural models have been recently applied to generic multi-document summarization. train a recursive neural network using a ranking objective to identify salient sentences, while follow-up work @cite employs a multi-task objective to improve sentence extraction, an idea we adapted to our task. propose a graph convolution network to represent sentence relations and estimate sentence salience. Our summarization method is tailored to the opinion extraction task, it identifies aspect-specific and salient units, while minimizing the redundancy of the final summary with a greedy selection algorith m@cite@cite. Redundancy is also addressed in who propose a graph-based framework for abstractive summarization. introduce an encoder-decoder neural method for extractive opinion summarization. Their approach requires direct supervision via gold-standard extractive summaries for training, in contrast to our weakly supervised formulation.	Rouge scores: - Rouge 2: 0.0732 (prec) 0.0889 (recall) 0.0803 (f-1) - Rouge L: 0.1394 (prec) 0.1691 (recall) 0.1528 (f-1) Summary: We present a neural framework for opinion summarization fro molline product reviews which is knowledge-lean and only requires light supervision (e.g., in the form of product domain labe Is and user-provided ratings). Our method combines two weakly supervised components to identify salient opinions and form extractive summaries from multiple reviews: an aspect extractor trained under a multi-task objective, and a sentiment predict or based on multiple instance learning. We introduce an opinion summarization dataset that in cludes a training set of product reviews from six diverse domains and human-annotated development and test sets with gold standard aspect annotations, salience labels, and opinion summaries. Automatic evaluation shows significant improvements over baselines, and a large-scale study indicates that our opinion summaries are preferred by human judges according to multiple criteria.           The specification discloses a luggage carrier madeu of a generally U-shaped frame. The frame has two spaced legs with a hook on the front which hooks over the bumper of a nautomobile Comment: - Copied the first tokens only - No indication of MDS	Rouge scores: - Rouge 2: - Rouge 2: - 0.0902 (prec) - 0.0815 (recall) - Rouge L: - 0.1707 (prec) - 0.1544 (recall) - 0.1622 (f-1)  Summary: - we present a neural framework for opinion summarization from online product reviews which is knowledge-lean and only requires light supervision (e.g., in the form of product domain labe Is and user-provided ratings) our method combines two weakly supervised components to identify salient opinions and form extractive summaries from multiple reviews: an aspect extract or trained under a multi-task objective, and a sentiment predict or based on multiple instance learning we introduce an opinion summarization dataset that includes a training set of product reviews from six diverse domains and human-annotated development and test sets with gold standard aspect annotations, salience labels, and opinion summaries large-scale study indicates that our opinion summaries are preferred by human judges according to multiple criteria.  Comment: - Copied the first tokens only, except that the phrase "Automatic evaluation shows significant improvements over baselines, and" is skipped before the red part - No indication of MDS	Rouge scores: - Rouge 2: 0.0651 (prec) 0.1037 (recall) 0.08 (f-1) - Rouge L: 0.1157 (prec) 0.1838 (recall) 0.142 (f-1) Summary: We present a neural framework for opinion summarization fro monline product reviews which is knowledge-lean and only requires light supervision (e.g., in the form of product domain labe ls and user-provided ratings). Our method combines two weakly supervised components to identify salient opinions and form extractive summaries from multiple reviews: an aspect extractor trained under a multi-task objective, and a sentiment predict or based on multiple instance learning. We introduce an opinion summarization dataset that in cludes a training set of product reviews from six diverse domains and human-annotated development and test sets with gold standard aspect annotations, salience labels, and opinion summaries. Automatic evaluation shows significant improvements over baselines, and a large-scale study indicates that our opinion summaries are preferred by human judges according to multiple criteria. The specification discloses a luggage carrier made up of a generally U-shaped frame. The frame has two spaced legs with a hook on the front which hook so over the bumper of an automobile. Two braces are attached to the cross member of the U-shaped member and the front portion of the braces is received on fastening means welded to the under side of the car frame. The cross members provide a supporting surface for carrying articles, boats and the like. A platform may  Comment: - Copied the first tokens only - No indication of MDS	Rouge scores: - Rouge 2: 0.1695 (prec) 0.0741 (recall) 0.1031 (f-1) - Rouge L: 0.3333 (prec) 0.1471 (recall) 0.2041 (f-1)  Summary: In the context of multi-docume nt summarization, R2N2 @cite is a recurrent neural network (RNN) for extracting salience labels. The RNN is trained on sentence relation graphs, and the salience labels are extracted using a greedy heuristic to extract salient sentences while avoiding redundancy @cite @cite. In this work, we use the RNN to extract salience labels from product reviews.  Comment: - Shows clear sign of MDS, summarizing the 3rd (blue) and 4th (purple) articles, while clearly contrasting the main article (yellow) The RNN notation proved slightly confusing for the model though, the 2nd article used "Recursive Neural Network", not "Recurrent Neural Network" - The 2nd article appears completely unrelated to the task, and the model probably correctly omits it.	Rouge scores: - Rouge 2: 0.1186 (prec) 0.0519 (recall) 0.0722 (f-1) - Rouge L: 0.2167 (prec) 0.0956 (recall) 0.1327 (f-1) Summary: There is a large body of work on multi-document summarization, including @cite @cite, @cite and @cite. However, most of these works focus on extracting features from a single review. In this work, we focus on extractive summaries from multiple reviews: an aspect extractor trained under a multi-task objective, and a sentiment predictor trained based on multiple instance learning.  Comment: - Shows some sign of MDS, with the model summarizing what the main article does (yellow), and trying to contrast that with other literature (red) - However, the red part is actually not factually based, and the phrase "a large body of work" is probably picked up from the summarization training.	Rouge scores: - Rouge 2: 0.1594 (prec) 0.0815 (recall) 0.1078 (f-1) - Rouge L: 0.2429 (prec) 0.125 (recall) 0.165 (f-1) Summary: In the context of summarizatio n, @cite employ a Graph Convolutional Network (GCN) on the relation graphs, with sentence embeddings obtained from Recurrent Neural Networks as input node features for salience estimation. However, they do not consider sentence relation graphs and do not consider the representation power of deep neural networks. In contrast, we use salience labels and salience labels to identify salient opinions and form extractive summaries from multiple reviews.  Comment: - Shows some sign of MDS, the model summarizing what the main article does (yellow), and trying to contrast that with other literature (purple) - However, the red-and-purple part contains erroneous facts. The model wrongly assumes that the 4th article did not look at sentence relation graphs when the authors explicitly say they did.
4371	(1): In contrast to XML query languages as e.g. XPath which require knowledge on the query language as well as on the document structure, keyword search is open to anybody. As the size of XML sources grows rapidly, the need for effici ent search indices on XML data that support keyword search increases. In this paper, we present an approach of XML keyword search which is based on the DAG of the XML data, where repeated substructures are considered only once, and therefore, have to be searched only once. As our performance evaluati on shows, this DAG-based extension of the set intersection search algorithm [1], [2], can lead to search times that are on large documents more than twice as fast as the search times of the XML-based approach. Additionally, we utiliz e a smaller index, i.e., we consume less main memory to compute the results. (2):  Recent works have shown the benefits of keyword proximity search in querying XML documents in addition to text documents. For example, given query k	Similar to XRANK @cite is the stack-based approach presented in @cite. In contrast to the previous stack-based appraoches, the authors do not used the DeweylD to identify a node and to calculate the ancestor-descendant or even parent-child relationships, but they propose to use a combination of preorder position, postorder position, and depth of the node.	Rouge scores: - Rouge 2: 0.0244 (prec) 0.069 (recall) 0.036 (f-1) - Rouge L: 0.0788 (prec) 0.2203 (recall) 0.1161 (f-1) Summary: In contrast to XML query langua ges as e.g. XPath which require knowledge on the query langua ge as well as on the document s tructure, keyword search is ope	Rouge scores: - Rouge 2: 0.0 (prec) 0.0 (recall) 0.0 (f-1) - Rouge L: 0.1282 (prec) 0.1695 (recall) 0.146 (f-1) Summary: in this paper, we consider the p roblem of efficiently producing ranked results for keyword sear ch queries over hyperlinked XM L documents.	Rouge scores: - Rouge 2: 0.0061 (prec) 0.0172 (recall) 0.009 (f-1) - Rouge L: 0.0793 (prec) 0.2203 (recall) 0.1166 (f-1) Summary: "We consider the problem of ef ficiently producing ranked resul ts for keyword search queries o ver hyperlinked Xie documents, as opposed to (conceptually) fla	Rouge scores: - Rouge 2: 0.0429 (prec) 0.0517 (recall) 0.0469 (f-1) - Rouge L: 0.1831 (prec) 0.2203 (recall) 0.2 (f-1) Summary: XRANK @cite is an extension of the set intersection search algor ithm @cite, which is based on the DAG of the XML data. XRANK is a hyperlink based HTML sear	Rouge scores: - Rouge 2: 0.125 (prec) 0.0517 (recall) 0.0732 (f-1) - Rouge L: 0.4 (prec) 0.1695 (recall) 0.2381 (f-1) Summary: XRANK @cite is an extension of the set intersection search algor ithm @cite. XRANK can be used to query a mix of HTML and XM L documents.	Rouge scores: - Rouge 2: 0.04 (prec) 0.0862 (recall) 0.0546 (f-1) - Rouge L: 0.1349 (prec) 0.2881 (recall) 0.1838 (f-1) Summary: XRANK @cite is a hyperlink base d HTML search engine. It is desi gned to perform keyword search over hyperlinked XML documents. However, it does not consi

No.	Abstracts	Label	Base LED	Off-the-shelf LED	Off-the-shelf Centrum	Tuned LED	Tuned Centrum	Two-step
	eywords over Shakespeare's plays in XML, the user might be interested in kno		n to anybody. As the size of XM	we present an approach of XM	t HTML documents, introduces	ch engine that can be used to q	Comment:	der the nested structure of the
	wing how the keywords cooccur. In this paper, we focus on XML trees and def		L sources grows rapidly, the nee	L keyword search which is base	many new challenges," the auth	uery a mix of hyperlink based X	- Shows very weak signs of MDS,	XML documents. XRANK can be
	ine XML keyword, proximity queries to return the (possibly heterogeneous) s		d for efficient search indices on	d on the set intersection search	ors write. "First, Xie XRANK doe	ML documents. X-RANK is desig	with an attempt to reference	used to query a mix of HTML an
	et of minimum connecting trees (MCTs) of the matches to the individual keyw		XML data that support keyword	algorithm, where repeated subs	s not always return entire docu	ned to handle the problem of ef	multiple @cite.	d XML documents, but it does n
	ords in the query. We consider efficiently executing keyword proximity querie		search increases. In this paper,	tructures are considered only o	ments, but can return deeply ne	ficiently producing ranked resul	- Even worse than tuned LED	ot require a hyperlink search en
	s on labeled trees (XML) in various settings: 1) when the XML database has be		we present an approach of XML	nce, and therefore, have to be s	sting markup that contains the	ts for keyword search queries o	- However, none of the	gine, and it does not need a hyp
	en preprocessed and 2) when no indices are available on the XML database.		keyword search which is based	earched only once.	desired keywords. Second, the	ver hyperlinked XML document	sentences generated are	erlink, and it is not required to s
	We perform a detailed experimental evaluation to study the benefits of our a		on the DAG of the XML data, w	we perform a detailed experim	nesting structure of markup im	s, as opposed to (conceptually) f	coherent, showing difficulties	earch for hyperlinks in a hyperli
	pproach and show that our algorithms considerably outperform prior algorithms and other applicable approaches.		here repeated substructures ar e considered only once, and the	ental evaluation to study the be nefits of our approach and sho	plies that the notion of ranking i s no longer at the granularity of	lat HTML documents. Comment:	of the model when dealing with articles filled with	nk document. Moreover, XRAN K is designed to handle the nest
	(3):		refore, have to be searched onl	w that our algorithms considera	a document, but at the granular	- Shows very weak signs of MDS,	acronyms (XML, HTML) which	ed structures of the XML docum
	We consider the problem of efficiently producing ranked results for keyword		y once. As our performance eva	bly outperform prior algorithms	of an markup. Finally, the notio	with an attempt to reference	it does not understand	ent. In contrast, our approach is
	search queries over hyperlinked XML documents. Evaluating keyword search		luation shows, this DAG-based	and other applicable approach	n of keyword proximity is more	multiple @cite.	it abes not unacrotana	based on a DAG-based extensio
	queries over hierarchical XML documents, as opposed to (conceptually) flat H		extension of the set intersectio	es.	complex in the hierarchical mar	- However, none of the		n of the set intersection search
	TML documents, introduces many new challenges. First, XML keyword search		n search algorithm[1], [2], can I	Comment:	kup data model. In this paper,	sentences generated are		algorithm, which can lead to sea
	queries do not always return entire documents, but can return deeply nested		ead to search times that are on	- Very weak signs of MDS, with	we present the XRANK system t	coherent, showing difficulties		rch times that are more than tw
	XML elements that contain the desired keywords. Second, the nested structur		large documents more than twi	all 3 articles covered.	hat is designed to handle these	of the model when dealing		ice as fast as the search time of
	e of XML implies that the notion of ranking is no longer at the granularity of a		ce as fast as the search times of	- However, they are all	novel features of Xie keyword s	with articles filled with		the XML-based approach.
	document, but at the granularity of an XML element. Finally, the notion of ke		the XML-based approach. Addit	presented as a single	earch. Our experimental results	acronyms (XML, HTML) which		Comment:
	yword proximity is more complex in the hierarchical XML data model. In this p		ionally, we utilize a smaller inde	document.	show that XRANK offers both sp	it does not understand		- Shows signs of MDS, with the
	aper, we present the XRANK system that is designed to handle these novel fe atures of XML keyword search. Our experimental results show that XRANK off		x, i.e., we consume less main m emory to compute the results.	<ul> <li>The model also performs like an extractive model</li> </ul>	ace and performance benefits when compared with existing a			yellow part contrasting the approach of the main article
	ers both space and performance benefits when compared with existing appro			all extractive model	pproaches. An interesting featu			with that of the 3 <sup>rd</sup> (blue)
	aches. An interesting feature of XRANK is that it naturally generalizes a hyperl		he benefits of keyword proximit		re of XRANK is that it naturally g			- However, the red parts still
	ink based HTML search engine such as Google. XRANK can thus be used to qu		y search in querying XML docu		eneralizes a hyperlink based HT			show hallucination
	ery a mix of HTML and XML documents.		ments in addition to text docu		ML search engine such as Googl			- The first step LED model in the
			ments.		e. XRANK can thus be used to q			two-step model probably
			Comment:		uery a mix of HTML and markup			helped simplify the meaning of
			- Copied the first tokens only		markup."			the individual passages?
			- No indication of MDS		Comment:			
					- Copied the 3 <sup>rd</sup> article in full			
					- No indication of MDS			
4858	(1):	Concerning set packings the situ	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:
4030	It is shown that one can count @math -edge paths in an @math -vertex graph	ation is analogous, albeit the res	- Rouge 2:	- Rouge 2:	- Rouge 2:	- Rouge 2:	- Rouge 2:	- Rouge 2:
	and @math -set @math -packings on an @math -element universe, respective	earch has been somewhat less e	0.1079 (prec)	0.0612 (prec)	0.0791 (prec)	0.125 (prec)	0.082 (prec)	0.0745 (prec)
	ely, in time @math and @math , up to a factor polynomial in @math , @math	xtensive. Deciding whether a giv	0.1442 (recall)	0.0577 (recall)	0.1346 (recall)	0.0769 (recall)	0.0962 (recall)	0.0673 (recall)
	, and @math ; in polynomial space, the bounds hold if multiplied by @math o	en family of @math subsets of a	0.1235 (f-1)	0.0594 (f-1)	0.0996 (f-1)	0.0952 (f-1)	0.0885 (f-1)	0.0707 (f-1)
	r @math , respectively. These are implications of a more general result: given	n @math -element universe cont	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:
	two set families on an @math -element universe, one can count the disjoint p	ains a @math -packing is known	0.1714 (prec)	0.2222 (prec)	0.1348 (prec)	0.2923 (prec)	0.1951 (prec)	0.1895 (prec)
	airs of sets in the Cartesian product of the two families with @math basic ope	to be W[1]-hard @cite , and thus	0.2286 (recall)	0.2095 (recall)	0.2286 (recall)	0.181 (recall)	0.2286 (recall)	0.1714 (recall)
	rations, where @math is the number of members in the two families and thei	it is unlikely that the problem is	0.1959 (f-1)	0.2157 (f-1)	0.1696 (f-1)	0.2235 (f-1)	0.2105 (f-1)	0.18 (f-1)
	<mark>r subsets</mark> .	fixed parameter tractable, that i	Summary:	Summary:	Summary:	Summary:	Summary:	Summary:
	(2):	s, solvable in time @math for so	It is shown that one can count	given a set @math with @math	It is shown that one can count	For the Steiner tree problem @	In @cite, Bjorklund and Husfeld	In @cite, Dreyfus-Wagner algori
	We present a fast algorithm for the subset convolution problem:given function	me function @math and constan	@math -edge paths in a @math	elements and a family @math	@math -edge paths in an @mat	cite, one can count the disjoint	t showed that one can partition	thm @cite was presented, whic
	ns f and g defined on the lattice of subsets of ann-element set n, compute the ir subset convolution f*g, defined for $S \subseteq N$ by $[(f * g)(S) = [T \subseteq S] f(T) g(S T)_{,r}]$	t @math . If @math is fairly larg e, say exponential in @math , th	-vertex graph and @math -set	of subsets, we show how to par	h -vertex graph and @math -set	pairs of sets in the Cartesian pro duct of the two families with @	a set @math into @math subse	h is based on an @math time bound of the classical DREW algo
	where addition and multiplication is carried out in an arbitrary ring. Via Mobi	e fastest known algorithms actua	@math -packings on an @math -element universe, respectively,	tition @math into @math such subsets in @math time.	@math -packings on an @math -element universe, respectively,	math basic operations, where	ts in @math time, where @mat h is the number of members in t	rithm. The algorithm was exten
	us transform and inversion, our algorithm evaluates the subset convolution in	lly count the packings by employ	in time @math and @math, up	we also consider variations of t	in time @math and @math, up	@math is the number of memb	he two families and their subset	ded to the Steiner Tree problem
	O(n2 2n) additions and multiplications, substanti y improving upon the straig	ing the inclusionexclusion mac	to a factor polynomial in @mat	his problem where the subsets	to a factor polyn Chocobo in @	ers in the two families and their	s. They also showed how to part	by @cite and presented an O(3
	htforward O(3n) algorithm. Specifically, if the input functions have aninteger r	hinery @cite @cite and run in ti	h, @math, and @math; in poly	may overlap or are weighted, a	math, @math, and @math; in	subsets @math. For the subset	ition the set into @math such s	n - @math ) time bound for the
	ange [-M,-M+1,,M], their subset convolution over the ordinary sumproduc	me @math . This bound holds al	nomial space, the bounds hold i	nd we solve the decision, counti	polyn Chocobo space, the boun	convolution problem, one can c	ubsets in time @math, where	subgraphs with bounded intege
	t ring can be computed in O(2n log M) time; the notation O suppresses polylo	so for the presented algorithm (c	f multiplied by @math or @mat	ng, summation, and optimizatio	ds hold if multiplied by @math	ount @math -edge paths in an	@math and @math are the sub	r weights. In the case where @
	garithmic factors.Furthermore, using a standard embedding technique we ca	f. Theorem ).	h, respectively. These are implic	n versions of these problems.	or @math, respectively. These a	@math -vertex graph and @ma	sets of @math. They also gave a	math is not available, @cite sho
	n compute the subset convolution over the maxsum or minsum semiring i		ations of a more general result:	our algorithms are based on th	re implications of a more gener	th -set @math -packings in time	family of polynomial space app	wed how to partition @math in
	n O(2n M) time. To demonstrate the applicability of fast subset convolution,		given two set families on an @x	e principle of inclusion-exclusio	al result: given two set families	@math.	roximation algorithms that find	to @math such subsets in polyn
	wepresent the first O(2k n2 + n m) algorithm for the Steiner tree problem in g		-element universe, one can cou	n and the zeta transform.	on an @ math -element univers	Comment:	a number between @math and	omial time and @math in time
	raphs with n vertices, k terminals, and m edges with bounded integer weight s, improving upon the O(3kn + 2k n2 + n m) time bound of the classical Dreyfu		nt the disjoint pairs of sets in th	in effect we get exact algorithm	e, one can count the disjoint pai	- No indication of MDS	the @math in @math. @cite gave a fast algorithm for the subse	@cite. In this case, @math and
			e Cartesian product of the two f	s in time @math for several wel	rs of sets in the Cartesian produ	behavior, basically just mixing		@math are polynomial in time,
	s-Wagner algorithm. We also discuss extensions to recent O(2n)-time algorith ms for covering and partitioning problems (Bjorklund and Husfeldt, FOCS 200		amilies with @math basic opera tions, where @math is the num	I - studied partition problems in cluding domatic number, chrom	ct of the two families with @ma th basic operations, where @m	in some words of the 2 <sup>nd</sup> article (green) with the 1 <sup>st</sup> (yellow)	t convolution problem in graphs with @math vertices, @math t	and @cite gives an approximati on algorithm for chromatic num
	6; Koivisto, FOCS 2006).		ber of members in the two fami	atic number, maximum @math	ath is the number of members i	- Shows once again how the	erminals, and @math edges wit	ber and domatic number.
	1 12 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2	•		-cut, bin packing, list coloring, a	n the two families and their sub	model fails to understand	h bounded integer weights, imp	Comment:
	(3):		I lies aliu tileli subsets. I i i i vve		1		roving upon the classical Dreyfu	- Best performing of all 3 tuned
	(3): Given a set @math with @math elements and a family @math of subsets, we		lies and their subsets.    We present a fast algorithm for the	nd the chromatic polynomial.	sets. We present a fast algorith	words used in unusual settings		
	1 7 7				sets. We present a fast algorith m for the subset convolution pr	(e.g. mathematics)	s-Wagner algorithm. They also d	models, showing strong signs
	Given a set @math with @math elements and a family @math of subsets, we		present a fast algorithm for the subset convolution problem:giv en functions f and g defined on	nd the chromatic polynomial.				•
	Given a set @math with @math elements and a family @math of subsets, we show how to partition @math into @math such subsets in @math time. We also consider variations of this problem where the subsets may overlap or are weighted, and we solve the decision, counting, summation, and optimization		present a fast algorithm for the subset convolution problem:giv	nd the chromatic polynomial.  Comment:  - Copied all of the 3 <sup>rd</sup> article except for last 2 sentences	m for the subset convolution pr		s-Wagner algorithm. They also d	models, showing strong signs
	Given a set @math with @math elements and a family @math of subsets, we show how to partition @math into @math such subsets in @math time. We also consider variations of this problem where the subsets may overlap or are weighted, and we solve the decision, counting, summation, and optimization versions of these problems. Our algorithms are based on the principle of inclu		present a fast algorithm for the subset convolution problem:giv en functions f and g defined on the lattice of subsets of ann-ele ment set n, compute their subs	nd the chromatic polynomial.  Comment: - Copied all of the 3 <sup>rd</sup> article	m for the subset convolution pr oblem:given functions f and g d efined on the lattice of subsets of ann-element set n, compute		s-Wagner algorithm. They also d iscussed extensions to recent @ math -time algorithms for covering and partitioning problems.	models, showing strong signs of MDS with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue) articles reflected.
	Given a set @math with @math elements and a family @math of subsets, we show how to partition @math into @math such subsets in @math time. We also consider variations of this problem where the subsets may overlap or are weighted, and we solve the decision, counting, summation, and optimization versions of these problems. Our algorithms are based on the principle of inclu sion-exclusion and the zeta transform. In effect we get exact algorithms in @		present a fast algorithm for the subset convolution problem:giv en functions f and g defined on the lattice of subsets of ann-ele	nd the chromatic polynomial.  Comment:  - Copied all of the 3 <sup>rd</sup> article except for last 2 sentences	m for the subset convolution pr oblem:given functions f and g d efined on the lattice of subsets of ann-element set n, compute their subset convolution f*g, de		s-Wagner algorithm. They also d iscussed extensions to recent @ math -time algorithms for covering and partitioning problems.  Comment:	models, showing strong signs of MDS with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue) articles reflected.  The red part appears to
	Given a set @math with @math elements and a family @math of subsets, we show how to partition @math into @math such subsets in @math time. We also consider variations of this problem where the subsets may overlap or are weighted, and we solve the decision, counting, summation, and optimization versions of these problems. Our algorithms are based on the principle of inclu sion-exclusion and the zeta transform. In effect we get exact algorithms in @ math time for several well-studied partition problems including domatic num		present a fast algorithm for the subset convolution problem:giv en functions f and g defined on the lattice of subsets of ann-ele ment set n, compute their subs et convolution f*g, defined for S ⊆	nd the chromatic polynomial.  Comment:  - Copied all of the 3 <sup>rd</sup> article except for last 2 sentences	m for the subset convolution pr oblem:given functions f and g d efined on the lattice of subsets of ann-element set n, compute their subset convolution f*g, de fined for S⊆ N by [ (f * g)(S) = [T		s-Wagner algorithm. They also d iscussed extensions to recent @ math -time algorithms for covering and partitioning problems.  Comment: - Some weak signs of MDS, with	models, showing strong signs of MDS with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue) articles reflected.  The red part appears to contain some factual errors,
	Given a set @math with @math elements and a family @math of subsets, we show how to partition @math into @math such subsets in @math time. We also consider variations of this problem where the subsets may overlap or are weighted, and we solve the decision, counting, summation, and optimization versions of these problems. Our algorithms are based on the principle of inclu sion-exclusion and the zeta transform. In effect we get exact algorithms in @math time for several well-studied partition problems including domatic number, chromatic number, maximum @math -cut, bin packing, list coloring, and		present a fast algorithm for the subset convolution problem:giv en functions f and g defined on the lattice of subsets of ann-ele ment set n, compute their subs et convolution f*g, defined for S ⊆ Comment:	nd the chromatic polynomial.  Comment:  - Copied all of the 3 <sup>rd</sup> article except for last 2 sentences	m for the subset convolution pr oblem:given functions f and g d efined on the lattice of subsets of ann-element set n, compute their subset convolution f*g, de fined for S⊆ N by [ (f * g)(S) = [T ⊆ S] f(T) g(S T),]where addition		s-Wagner algorithm. They also d iscussed extensions to recent @ math -time algorithms for covering and partitioning problems.  Comment:  - Some weak signs of MDS, with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue)	models, showing strong signs of MDS with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue) articles reflected.  The red part appears to contain some factual errors, with the original "O(3kn + 2k
	Given a set @math with @math elements and a family @math of subsets, we show how to partition @math into @math such subsets in @math time. We also consider variations of this problem where the subsets may overlap or are weighted, and we solve the decision, counting, summation, and optimization versions of these problems. Our algorithms are based on the principle of inclu sion-exclusion and the zeta transform. In effect we get exact algorithms in @math time for several well-studied partition problems including domatic number, chromatic number, maximum @math -cut, bin packing, list coloring, and the chromatic polynomial. We also have applications to Bayesian learning wit		present a fast algorithm for the subset convolution problem:giv en functions f and g defined on the lattice of subsets of ann-ele ment set n, compute their subs et convolution f*g, defined for S ⊆  Comment: - Copied the first tokens only	nd the chromatic polynomial.  Comment:  - Copied all of the 3 <sup>rd</sup> article except for last 2 sentences	m for the subset convolution pr oblem:given functions f and g d efined on the lattice of subsets of ann-element set n, compute their subset convolution f*g, de fined for S⊆ N by [ (f * g)(S) = [T ⊆ S] f(T) g(S T),]where addition and multiplication is carried out		s-Wagner algorithm. They also d iscussed extensions to recent @ math -time algorithms for covering and partitioning problems.  Comment:  - Some weak signs of MDS, with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue) articles referenced and mixed	models, showing strong signs of MDS with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue) articles reflected.  The red part appears to contain some factual errors, with the original "O(3kn + 2k n2 + n m)" changed to "O(3n -
	Given a set @math with @math elements and a family @math of subsets, we show how to partition @math into @math such subsets in @math time. We also consider variations of this problem where the subsets may overlap or are weighted, and we solve the decision, counting, summation, and optimization versions of these problems. Our algorithms are based on the principle of inclu sion-exclusion and the zeta transform. In effect we get exact algorithms in @math time for several well-studied partition problems including domatic number, chromatic number, maximum @math -cut, bin packing, list coloring, and the chromatic polynomial. We also have applications to Bayesian learning with decision graphs and to model-based data clustering. If only polynomial space		present a fast algorithm for the subset convolution problem:giv en functions f and g defined on the lattice of subsets of ann-ele ment set n, compute their subs et convolution f*g, defined for S ⊆  Comment:  - Copied the first tokens only - No indication of MDS	nd the chromatic polynomial.  Comment:  - Copied all of the 3 <sup>rd</sup> article except for last 2 sentences	m for the subset convolution pr oblem:given functions f and g d efined on the lattice of subsets of ann-element set n, compute their subset convolution f*g, de fined for S⊆ N by [ (f * g)(S) = [T ⊆ S] f(T) g(S T),]where addition and multiplication is carried out in an arbitrary ring. Via Mobius		s-Wagner algorithm. They also d iscussed extensions to recent @ math -time algorithms for covering and partitioning problems.  Comment:  - Some weak signs of MDS, with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue) articles referenced and mixed with the 1 <sup>st</sup> (yellow)	models, showing strong signs of MDS with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue) articles reflected.  The red part appears to contain some factual errors, with the original "O(3kn + 2k n2 + n m)" changed to "O(3n - @math)"
	Given a set @math with @math elements and a family @math of subsets, we show how to partition @math into @math such subsets in @math time. We also consider variations of this problem where the subsets may overlap or are weighted, and we solve the decision, counting, summation, and optimization versions of these problems. Our algorithms are based on the principle of inclu sion-exclusion and the zeta transform. In effect we get exact algorithms in @math time for several well-studied partition problems including domatic number, chromatic number, maximum @math -cut, bin packing, list coloring, and the chromatic polynomial. We also have applications to Bayesian learning with decision graphs and to model-based data clustering. If only polynomial space is available, our algorithms run in time @math if membership in @math can		present a fast algorithm for the subset convolution problem:giv en functions f and g defined on the lattice of subsets of ann-ele ment set n, compute their subs et convolution f*g, defined for S ⊆  Comment:  - Copied the first tokens only - No indication of MDS - Random word change noted	nd the chromatic polynomial.  Comment:  - Copied all of the 3 <sup>rd</sup> article except for last 2 sentences	m for the subset convolution pr oblem:given functions f and g d efined on the lattice of subsets of ann-element set n, compute their subset convolution f*g, de fined for S⊆ N by [ (f * g)(S) = [T ⊆ S] f(T) g(S T),]where addition and multiplication is carried out in an arbitrary ring. Via Mobius transform and inversion, our alg		s-Wagner algorithm. They also d iscussed extensions to recent @ math -time algorithms for covering and partitioning problems.  Comment:  - Some weak signs of MDS, with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue) articles referenced and mixed with the 1 <sup>st</sup> (yellow)  - Shows once again how the	models, showing strong signs of MDS with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue) articles reflected.  The red part appears to contain some factual errors, with the original "O(3kn + 2k n2 + n m)" changed to "O(3n - @math)"  The first step LED model in the
	Given a set @math with @math elements and a family @math of subsets, we show how to partition @math into @math such subsets in @math time. We also consider variations of this problem where the subsets may overlap or are weighted, and we solve the decision, counting, summation, and optimization versions of these problems. Our algorithms are based on the principle of inclu sion-exclusion and the zeta transform. In effect we get exact algorithms in @math time for several well-studied partition problems including domatic number, chromatic number, maximum @math -cut, bin packing, list coloring, and the chromatic polynomial. We also have applications to Bayesian learning with decision graphs and to model-based data clustering. If only polynomial space		present a fast algorithm for the subset convolution problem:giv en functions f and g defined on the lattice of subsets of ann-ele ment set n, compute their subs et convolution f*g, defined for S ⊆  Comment:  - Copied the first tokens only - No indication of MDS	nd the chromatic polynomial.  Comment:  - Copied all of the 3 <sup>rd</sup> article except for last 2 sentences	m for the subset convolution pr oblem:given functions f and g d efined on the lattice of subsets of ann-element set n, compute their subset convolution f*g, de fined for S⊆ N by [ (f * g)(S) = [T ⊆ S] f(T) g(S T),]where addition and multiplication is carried out in an arbitrary ring. Via Mobius		s-Wagner algorithm. They also d iscussed extensions to recent @ math -time algorithms for covering and partitioning problems.  Comment:  - Some weak signs of MDS, with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue) articles referenced and mixed with the 1 <sup>st</sup> (yellow)	models, showing strong signs of MDS with the 2 <sup>nd</sup> (green) and 3 <sup>rd</sup> (blue) articles reflected.  The red part appears to contain some factual errors, with the original "O(3kn + 2k n2 + n m)" changed to "O(3n - @math)"

No.	Abstracts	Label	Base LED	Off-the-shelf LED	Off-the-shelf Centrum	Tuned LED	Tuned Centrum	Two-step
	I space approximation algorithms that find a number between @math and @				Comment:		words used in unusual settings	helped simplify the meaning of
	math in time @math .				- Copied the first tokens only		(e.g. mathematics)	the individual passages?
					<ul><li>No indication of MDS</li><li>Random word change noted</li></ul>			
					(red)			
					(**************************************			
5068	(1):	Another bunch of related works i	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:
	Convolutional neural networks have gained a remarkable success in computer vision. However, most usable network architectures are hand-crafted and us	nclude hyper-parameter optimiz ation @cite , meta-learning @cit	- Rouge 2: 0.0596 (prec)	- Rouge 2: 0.0723 (prec)	- Rouge 2: 0.0513 (prec)	- Rouge 2: 0.0811 (prec)	- Rouge 2: 0.0952 (prec)	- Rouge 2: 0.0899 (prec)
	ually require expertise and elaborate design. In this paper, we provide a block	e and learning to learn methods	0.1169 (recall)	0.0723 (prec) 0.0779 (recall)	0.1299 (recall)	0.031 (prec) 0.039 (recall)	0.1299 (recall)	0.1039 (prec)
	-wise network generation pipeline called BlockQNN which automatically build	@cite @cite . However, the goal	0.0789 (f-1)	0.075 (f-1)	0.0735 (f-1)	0.0526 (f-1)	0.1099 (f-1)	0.0964 (f-1)
	s high-performance networks using the Q-Learning paradigm with epsilon-gre	of these works is to use meta-da	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:
	edy exploration strategy. The optimal network block is constructed by the lea	ta to improve the performance o	0.1053 (prec)	0.1548 (prec)	0.0969 (prec)	0.1842 (prec)	0.1698 (prec)	0.2111 (prec)
	rning agent which is trained sequentially to choose component layers. We stack the block to construct the whole auto-generated network. To accelerate the	f the existing algorithms, such as finding the optimal learning rate	0.2051 (recall) 0.1391 (f-1)	0.1667 (recall) 0.1605 (f-1)	0.2436 (recall) 0.1387 (f-1)	0.0897 (recall) 0.1207 (f-1)	0.2308 (recall) 0.1957 (f-1)	0.2436 (recall) 0.2262 (f-1)
	e generation process, we also propose a distributed asynchronous framework	of optimization methods or the o	Summary:	Summary:	Summary:	Summary:	Summary:	Summary:
	and an early stop strategy. The block-wise generation brings unique advantag	ptimal number of hidden layers t	Convolutional neural networks	in this paper we show how the	Convolutional neural networks	In this paper, we propose a bloc	Recently, meta-learning @cite	@cite proposed a gradien
	es: (1) it performs competitive results in comparison to the hand-crafted state	o construct the network. In this	have gained a remarkable succe	design of an optimization algori	have gained a remarkable succe	k-wise network generation pipel	@cite has gained a lot of attenti	t descent method for meta-lear
	-of-the-art networks on image classification, additionally, the best network ge	paper, we focus on learning the	ss in computer vision. However,	thm can be cast as a learning pr	ss in computer vision. However,	ine using the Q-learning paradig	on in the machine learning liter	ning. The gradient descent met
	nerated by BlockQNN achieves 3.54 top-1 error rate on CIFAR-10 which beats all existing auto-generate networks. (2) in the meanwhile, it offers tremendou	entire topological architecture of network blocks to improve the p	most usable network architect ures are hand-crafted and usual	oblem, allowing the algorithm to learn to exploit structure in the	most usable network architect ures are hand-crafted and usual	m with epsilon-greedy exploration on strategy. We also propose a	ature. In this paper, we propose a block-wise network generatio	hod is similar to our method, but differs from our method in tw
	s reduction of the search space in designing networks which only spends 3 da	erformance.	ly require expertise and elabora	e problems of interest in an aut	ly require expertise and elabora	distributed asynchronous frame	n pipeline called BlockQNN which	o important aspects. First, the g
	ys with 32 GPUs, and (3) moreover, it has strong generalizability that the net		te design. In this paper, we prov	omatic way.	te design. In this paper, we prov	work and an early stop strategy	h automatically builds high-perf	radient descent method does n
	work built on CIFAR also performs well on a larger-scale ImageNet dataset.		ide a block-wise network gener	we make meta-learning in large	ide a block-wise network gener	to accelerate the generation pr	ormance networks using the Q-	ot rely on the gradient of the gr
	(2):		ation pipeline called BlockQNN	systems feasible by using recur	ation pipeline called BlockQNN	ocess.	Learning paradigm with epsilon-	adient. Second, it does not requ
	This paper introduces the application of gradient descent methods to meta-le arning. The concept of "meta-learning", i.e. of a system that improves or disc		which automatically builds high performance networks using th	rent neural networks withth eir attendant learning routines as	which automatically builds high- performance networks using th	Comment: - Only extracted 2 sentences	greedy exploration strategy. The optimal network block is cons	ire the gradient of a gradient to be learned. In this paper, we sh
	overs a learning algorithm, has been of interest in machine learning for decad		e Q-Learning paradigm with eps	meta-learning systems.	e Q-learning paradigm with epsi	from the 1 <sup>st</sup> article (yellow)	tructed sequentially by the lear	ow that the gradient of our met
	es because of its appealing applications. Previous meta-learning approaches h		ilon-greedy exploration strateg	our learned algorithms outperf	lon-greedy exploration strategy.	- No indication of MDS	ning agent which is trained sequ	hod can be used as a meta-lear
	ave been based on evolutionary methods and, therefore, have been restricte		y. The optimal network block is	orm generic, hand-designed co	The optimal network block is c		entially to choose component la	ning method. We also show tha
	d to small models with few free parameters. We make meta-learning in large		constructed by the learning age	mpetitors on the tasks for whic	onstructed by the learning agen		yers. In addition, it offers treme	t our approach can be applied t
	systems feasible by using recurrent neural networks withth eir attendant lear ning routines as meta-learning systems. Our system derived complex well per		nt which is trained sequentially to choose component layers. W	h they are trained, and also gen eralize well to new tasks with si	t which is trained sequentially t o choose component layers. We		ndous reduction of the search space in designing networks whi	o large systems with few free parameters.
	forming learning algorithms from scratch. In this paper we also show that our		e stack the block to construct th	milar structure.	stack the block to construct the		ch only spend 3 days with 32 GP	Comment:
	approachp erforms non-stationary time series prediction.		e whole auto-generated networ	Comment:	whole auto-generated networ		Us, and it has strong generaliza	- Shows some sign of MDS, with
	(3):		k. To accelerate the generation	- Copied most of the 4 <sup>th</sup> article	k. To accelerate the generation		bility that the network built on	the 2 <sup>nd</sup> article (green) being
	Different researchers hold different views of what the term meta-learning exa ctly means. The first part of this paper provides our own perspective view in		process, we also propose a distributed asynchronous framewor	(purple) and just inserted a sentence from the 2 <sup>nd</sup> (green)	process, we also propose a distributed asynchronous framewor		CIFAR-10 also performs well on a larger-scale ImageNet datase	mentioned However, the other parts are
	which the goal is to build self-adaptive learners (i.e. learning algorithms that i		k and an early stop strategy. Th	- No indication of MDS	k and an early stop strategy. Th		t.	mostly hallucinations
	mprove their bias dynamically through experience by accumulating meta-kno		e block-wise generation brings		e block-wise generation brings		Comment:	, , , , , , , , , , , , , , , , , , , ,
	wledge). The second part provides a survey of meta-learning as reported by t		unique advantages: (1) it perfor		unique advantages: (1) it perfor		- No indication of MDS, except	
	he machine-learning literature. We find that, despite different views and rese		ms competitive results in comp		ms competitive results in comp		for the red part where the	
	arch lines, a question remains constant: how can we exploit knowledge about learning (i.e. meta-knowledge) to improve the performance of learning algori		arison to the hand-crafted state -of-the-art networks on image c		arison to the hand-crafted state -of-the-art networks on image c		model noted "meta-learning" is a recurring theme	
	thms? Clearly the answer to this question is key to the advancement of the fie		lassification, additionally, the b		lassification, additionally, the be		is a recurring theme	
	ld and continues being the subject of intensive research.		est network generated by Block		st network generated by BlockQ			
	(4):		QNN achieves 3.54 top-1 error r		NN achieves 3.54 top-1 error ra			
	The move from hand-designed features to learned features in machine learni		ate on CIFAR-10 which beats all		te on CIFAR-10 which beats all e			
	ng has been wildly successful. In spite of this, optimization algorithms are still designed by hand. In this paper we show how the design of an optimization al		existing auto-generate network s. (2)		xisting auto-generate networks. (2) in the meanwhile, it offers t			
	gorithm can be cast as a learning problem, allowing the algorithm to learn to		Comment:		remendous reduction of the sea			
	exploit structure in the problems of interest in an automatic way. Our learned		- Copied the first tokens only		rch space in designing networks			
	algorithms, implemented by LSTMs, outperform generic, hand-designed com		- No indication of MDS		which only spends 3 days with			
	petitors on the tasks for which they are trained, and also generalize well to ne w tasks with similar structure. We demonstrate this on a number of tasks, incl				32 GPUs, and (3) moreover, it h as strong generalizability that th			
	uding simple convex problems, training neural networks, and styling images w				e network built on CIFar also pe			
1	ith neural art.				rforms well on a larger-scale Im			
1					ageNet dataset.			
					Comment:			
					<ul> <li>Copied the first tokens only</li> <li>No indication of MDS</li> </ul>			

# (c) Long samples

- 485: sample where the strong performance of the tuned and two-step models can be seen

No.	Abstracts	Label	Base LED	Off-the-shelf LED	Off-the-shelf Centrum	Tuned LED	Tuned Centrum	Two-step
485	(1):	In learning classifier with web da	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:	Rouge scores:
	Learning from web data has attracted lots of research interest in recent years.	ta, previous works focus on hand	- Rouge 2:	- Rouge 2:	- Rouge 2:	- Rouge 2:	- Rouge 2:	- Rouge 2:
	However, crawled web images usually have two types of noises, label noise a	ling the label noise in three direc	0.0175 (prec)	0.0258 (prec)	0.0048 (prec)	0.0485 (prec)	0.0266 (prec)	0.0287 (prec)
	nd background noise, which induce extra difficulties in utilizing them effective	tions, removing label noise @cit	0.0732 (recall)	0.0976 (recall)	0.0244 (recall)	0.122 (recall)	0.122 (recall)	0.1463 (recall)
	ly. Most existing methods either rely on human supervision or ignore the back	e @cite @cite @cite @cit	0.0283 (f-1)	0.0408 (f-1)	0.0081 (f-1)	0.0694 (f-1)	0.0437 (f-1)	0.048 (f-1)
	ground noise. In this paper, we propose a novel method, which is capable of h	e @cite , building noise-robust m	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:	- Rouge L:

No.	Abstracts	Label	Base LED	Off-the-shelf LED	Off-the-shelf Centrum	Tuned LED	Tuned Centrum	Two-step
140.	andling these two types of noises together, without the supervision of clean i	odel @cite @cite @cite @	0.064 (prec)	0.0705 (prec)	0.0433 (prec)	0.1058 (prec)	0.0688 (prec)	0.0667 (prec)
	mages in the training stage. Particularly, we formulate our method under the	cite @cite @cite @cite @cite @	0.2619 (recall)	0.2619 (recall)	0.2143 (recall)	0.2619 (recall)	0.3095 (recall)	0.3333 (recall)
	framework of multi-instance learning by grouping ROIs (i.e., images and their	ng @cite @cite .	0.1028 (f-1)	0.1111 (f-1)	0.072 (f-1)	0.1507 (f-1)	0.1126 (f-1)	0.1111 (f-1)
	region proposals) from the same category into bags. ROIs in each bag are assi	ng wate wate.	Summary:	Summary:	Summary:	Summary:	Summary:	Summary:
	gned with different weights based on the representative discriminative scores		Learning from web data has attr	learning from web data is incre	We present a simple yet efficie	Label noise is an important issu	The label noise problem has be	Recently, there has been a lot o
	of their nearest clusters, in which the clusters and their scores are obtained v		acted lots of research interest i	asingly popular due to abundan	nt approach capable of training	e in image classification, with m	en widely studied in the literatu	f research on label noise cleanin
	ia our designed memory module. Our memory module could be naturally inte		n recent years. However, it is sti	t free web resources.	deep neural networks on large-	any potential negative consequ	re @cite @cite. In @cite, the la	g. In @cite @cite, the label nois
	grated with the classification module, leading to an end-to-end trainable syst		Il very difficult to learn from we	however, the performance gap	scale weakly-supervised web im	ences @cite @cite. For exampl	bel noise is treated as a label no	e is treated as a set of instances
	em. Extensive experiments on four benchmark datasets demonstrate the effe		b data without the supervision	between webly supervised lear	ages, which are crawled raw fro	e, the label noise can be class-c	ise, and the label noise can be cl	that are mislabeled, and the la
	ctiveness of our method.		of a human. In this paper, we st	ning and traditional supervised I	m the Internet by using text qu	onditional @cite, which is not s	ass-conditional. @cite and @cit	bel cleansing algorithm is propo
	(2):		udy the problem of learning fro	earning is still very large, due to	eries, without any human super	calable for large-scale weakly-s	e address the label noise by usi	sed to deal with the label noise.
	We study the problem of automatically removing outliers from noisy data, wit		m web data. The problem is tha	the label noise of web data as	vision. We develop a principled	upervised learning. To address t	ng the abundant surrogate loss	In addition, @cite proposed an
	h application for removing outlier images from an image collection. We addre		t web images usually have two t	well as the domain shift betwee	learning strategy by leveraging	his problem, several methods h	functions designed for the tradi	active learning approach for re
	ss this problem by utilizing the reconstruction errors of an autoencoder. We o		ypes of noises, label noise and b	n web data and test data. to fill	curriculum learning, with the go	ave been proposed. @cite prop	tional classification problem wh	moving outliers from an image c
	bserve that when data are reconstructed from low-dimensional representatio		ackground noise, which induce	this gap, most existing methods	al of handling a massive amoun	osed a method for learning fro	en there is label noise. Recently,	ollection @cite, which does not
	ns, the inliers and the outliers can be well separated according to their recons		extra difficulties in utilizing the	propose to purify or augment	t of noisy labels and data imbal	m unlabeled web data, which is	@cite proposed a method to re	require a large amount of traini
	truction errors. Based on this basic observation, we gradually inject discrimina		m effectively. Most existing met	web data using instance-level s	ance effectively. We design a ne	based on the assumption that t	move outlier images from an im	ng data to train the model, and
	tive information in the learning process of an autoencoder to make the inliers		hods either rely on human supe	upervision, which generally req	w learning curriculum by measu	he unlabeled data can be used t	age collection by utilizing the re	they do not need any annotated
	and the outliers more separable. Experiments on a variety of image datasets		rvision or ignore the backgroun	uires heavy annotation.	ring the complexity of data usin	o improve the classification perf	construction errors of an autoe	labels for training. Moreover, t
	validate our approach.		d noise. In this article, we propo	instead, we propose to address	g its distribution density in a fea	ormance. However, these meth	ncoder. In this paper, we propo	he label noise cleansing algorith
	(3):		se a novel method, which is cap	the label noise and domain shif	ture space, and rank the compl	ods do not consider the label no	se a novel method, which is cap	ms are defined as follows: first,
	We present a theoretically grounded approach to train deep neural networks,		able of handling these two type	t by using more accessible categ	exity in an unsupervised manne	ise of web data. In contrast, our	able of handling both label nois	the labels of the instances are la
	including recurrent networks, subject to class-dependent label noise. We pro		s of noise together, without the	ory-level supervision.	r. This allows for an efficient im	method is able to deal with the	e and background noise togethe	beled, and second, the labels on
	pose two procedures for loss correction that are agnostic to both application		supervision or supervision of cle	in particular, we build our deep	plementation of curriculum lear	label noise without the supervi	r, without the supervision of cle	the labels are labeled, respectiv
	domain and network architecture. They simply amount to at most a matrix in		an images in the training stage.	probabilistic framework upon v	ning on large- scale web image	sion of the classification modul	an images in the training stage.	ely. The labels are labeled by th
	version and multiplication, provided that we know the probability of each clas		Particularly, we formulate our	ariational autoencoder (VAE ), i	s, resulting in a high-performan	e.	In addition, we formulate our m	e label noise correction algorith
	s being corrupted into another. We further show how one can estimate these		method under the framework o	n which classification network a	ce CNN the model, where the n	Comment:	ethod under the framework of	m and the labels of mislabeled i
	probabilities, adapting a recent technique for noise estimation to the multi-cl		f multi-instance learning by gro	nd VAE can jointly leverage cate	egative impact of noisy labels is	- Some sign of MDS, using the	multi-instance learning by grou	nstances are labeled by label no
	ass setting, and thus providing an end-to-end framework. Extensive experime		uping ROIs (i.e., images and thei	gory-level hybrid information. o	reduced substantially. Importan	context information from the	ping ROIs (i.e., images and their	ise cleansing. @cite used curric
	nts on MNIST, IMDB, CIFAR-10, CIFAR-100 and a large scale dataset of clothin		r region proposals) from the sa	ur memory module could be na	tly, we show by experiments th	1 <sup>st</sup> article (yellow) as	region proposals) from the sam	ulum learning to train a deep ne
	g images employing a diversity of architectures — stacking dense, con		me category into bags. ROIs in e	turally integrated with the classi	at those images with highly nois	background, and also	e category into bags. ROIs in ea	ural network on large-scale web
	volutional, pooling, dropout, batch normalization, word embedding, LSTM an d residual layers — demonstrate the noise robustness of our proposal		ach bag are assigned with differ ent weights based on the repres	fication module, leading to an e nd-to-end trainable system.	y labels can surprisingly improv e the generalization capability o	mentioned correctly some	ch bag are assigned with differe	images, which are crawled raw from the Internet by using text
	s. Incidentally, we also prove that, when ReLU is the only non-linearity, the los		entative discriminative scores o	we design a new learning curric	f model, by serving as a manner	elements of the current study - Elements of 4 <sup>th</sup> article (purple)	nt weights based on the represe ntative discriminative scores of	queries, without any human an
	s curvature is immune to class-dependent label noise.		f their nearest clusters, in which	ulum by measuring the complex	of regularization. Our approach	is clear while the 1 <sup>st</sup> red part is	their nearest clusters, in which t	notation. However, curriculum I
	(4):		the clusters and their scores ar	ity of data using its distribution	es obtain state-of-the-art perfor	true for many samples.	he clusters and their scores are	earning can significantly improv
	In this paper, we study the problem of learning image classification models wi		e obtained via our designed me	density, in an unsupervised ma	mance on four benchmarks: We	true for many sumpless	obtained via our designed mem	e the generalization capability o
	th label noise. Existing approaches depending on human supervision are gene		mory module.	nner in an	bVision, ImageNet, Clothing-1M		ory module. Our memory modu	f the model, by reducing the nu
	rally not scalable as manually identifying correct or incorrect labels is time-co		Comment:	Comment:	and Food-101. With an ensemb		le could be naturally integrated	mber of noisy labels, and by usi
	nsuming, whereas approaches not relying on human supervision are scalable		- Copied the first tokens only	- Copied the 6th article, except	le of multiple models, we achie		with the classification module, I	ng curriculum learning to reduc
	but less effective. To reduce the amount of human supervision for label noise		- No indication of MDS	replacing the last 2 sentences	ved a top-5 error rate of 5.2 on		eading to an end-to-end trainab	e the amount of data imbalance
	cleaning, we introduce CleanNet, a joint neural embedding network, which on			with another sentence from	the WebVision challenge [18] fo		<mark>le system.</mark>	in the training process. Moreov
	ly requires a fraction of the classes being manually verified to provide the kno			the 5 <sup>th</sup> article (orange)	r 1000-category classification. T		Comment:	er, curriculum learning is effecti
	wledge of label noise that can be transferred to other classes. We further inte			- No indication of MDS	his result was the top performa		- Clear signs of MDS, with the $1^{\text{st}}$	ve in handling noisy labels and t
	grate CleanNet and conventional convolutional neural network classifier into				nce by a wide margin, outperfor		article (yellow) used for both	he data imbalance effectively.
	one framework for image classification learning. We demonstrate the effectiv				ming second place by a nearly 5		context (at the beginning) and	Comment:
	eness of the proposed algorithm on both of the label noise detection task and				0 relative		contrast with other studies in	- Some sign of MDS, with the 1st
	the image classification on noisy data task on several large-scale datasets. Ex				Comment:		the latter half	article (yellow) used for
	perimental results show that CleanNet can reduce label noise detection error				- Copied the 5 <sup>th</sup> article only		- 3 other articles are cited,	context, and the 2 <sup>nd</sup> (green),
	rate on held-out classes where no human supervision available by 41.5 compa				- No indication of MDS		though the red parts shows a	7 <sup>th</sup> (pink) and 8 <sup>th</sup> (deep blue)
	red to current weakly supervised methods. It also achieves 47 of the perform						poorly written sentence.	articles referenced.
	ance gain of verifying all images with only 3.2 images verified on an image cla ssification task. Source code and dataset will be available at kuanghuei.githu							<ul> <li>Contains much hallucinations though as noted in the red</li> </ul>
	b.io CleanNetProject.							•
	(5):							parts.
	We present a simple yet efficient approach capable of training deep neural ne							
	tworks on large-scale weakly-supervised web images, which are crawled raw f							
	rom the Internet by using text queries, without any human annotation. We de							
	velop a principled learning strategy by leveraging curriculum learning, with th							
	e goal of handling a massive amount of noisy labels and data imbalance effect							
	ively. We design a new learning curriculum by measuring the complexity of da							
	ta using its distribution density in a feature space, and rank the complexity in							
	an unsupervised manner. This allows for an efficient implementation of curric							
	ulum learning on large-scale web images, resulting in a high-performance CN							
	N the model, where the negative impact of noisy labels is reduced substantiall							
	y. Importantly, we show by experiments that those images with highly noisy l							
	abels can surprisingly improve the generalization capability of model, by servi							
	ng as a manner of regularization. Our approaches obtain state-of-the-art perf							
	ormance on four benchmarks: WebVision, ImageNet, Clothing-1M and Food-1							
	01. With an ensemble of multiple models, we achieved a top-5 error rate of 5.							
	2 on the WebVision challenge [18] for 1000-category classification. This result was the top performance by a wide margin, outperforming second place by a							
	nearly 50 relative error rate. Code and models are available at: https://github.							
	com MalongTech CurriculumNet.							
	(6):							
	Learning from web data is increasingly popular due to abundant free web res							
	ources. However, the performance gap between webly supervised learning a							

No.	Abstracts	Label	Base LED	Off-the-shelf LED	Off-the-shelf Centrum	Tuned LED	Tuned Centrum	Two-step
	nd traditional supervised learning is still very large, due to the label noise of w							
	eb data as well as the domain shift between web data and test data. To fill thi							
	s gap, most existing methods propose to purify or augment web data using in							
	stance-level supervision, which generally requires heavy annotation. Instead,							
	we propose to address the label noise and domain shift by using more accessi							
	ble category-level supervision. In particular, we build our deep probabilistic fr							
	amework upon variational autoencoder (VAE), in which classification network							
	and VAE can jointly leverage category-level hybrid information. Then, we ext							
	end our method for domain adaptation followed by our low-rank refinement							
	strategy. Extensive experiments on three benchmark datasets demonstrate th							
	e effectiveness of our proposed method.							
	(7):							
	Label noise is an important issue in classification, with many potential negative							
	e consequences. For example, the accuracy of predictions may decrease, whe							
	reas the complexity of inferred models and the number of necessary training samples may increase. Many works in the literature have been devoted to the							
	study of label noise and the development of techniques to deal with label noi							
	se. However, the field lacks a comprehensive survey on the different types of							
	label noise, their consequences and the algorithms that consider label noise.							
	This paper proposes to fill this gap. First, the definitions and sources of label n							
	oise are considered and a taxonomy of the types of label noise is proposed. S							
	econd, the potential consequences of label noise are discussed. Third, label n							
	oise-robust, label noise cleansing, and label noise-tolerant algorithms are revi							
	ewed. For each category of approaches, a short discussion is proposed to help							
	the practitioner to choose the most suitable technique in its own particular fi							
	eld of application. Eventually, the design of experiments is also discussed, wh							
	at may interest the researchers who would like to test their own algorithms.							
	n this paper, label noise consists of mislabeled instances: no additional inform							
	ation is assumed to be available like e.g., confidences on labels.							
	(8):							
	In this paper, we study a classification problem in which sample labels are ran							
	domly corrupted. In this scenario, there is an unobservable sample with noise							
	-free labels. However, before being observed, the true labels are independent							
	ly flipped with a probability @math, and the random label noise can be class-							
	conditional. Here, we address two fundamental problems raised by this scena							
	rio. The first is how to best use the abundant surrogate loss functions designe							
	d for the traditional classification problem when there is label noise. We prov							
	e that any surrogate loss function can be used for classification with noisy lab							
	els by using importance reweighting, with consistency assurance that the labe							
	I noise does not ultimately hinder the search for the optimal classifier of the n							
	oise-free sample. The other is the open problem of how to obtain the noise ra							
	te @math . We show that the rate is upper bounded by the conditional proba							
	bility @math of the noisy sample. Consequently, the rate can be estimated, b							
	ecause the upper bound can be easily reached in classification problems. Exp							
	erimental results on synthetic and real datasets confirm the efficiency of our							
	methods.							
	(9):							
	Current approaches for fine-grained recognition do the following: First, recrui							
	t experts to annotate a dataset of images, optionally also collecting more stru							
	ctured data in the form of part annotations and bounding boxes. Second, trai							
	n a model utilizing this data. Toward the goal of solving fine-grained recogniti							
	on, we introduce an alternative approach, leveraging free, noisy data from the							
	e web and simple, generic methods of recognition. This approach has benefits							
	in both performance and scalability. We demonstrate its efficacy on four fine							
	-grained datasets, greatly exceeding existing state of the art without the man ual collection of even a single label, and furthermore show first results at scali							
	ng to more than 10,000 fine-grained categories. Quantitatively, we achieve to							
	p-1 accuracies of (92.3, ) on CUB-200-2011, (85.4, ) on Birdsnap, (93.4, ) on F							
	GVC-Aircraft, and (80.8, ) on Stanford Dogs without using their annotated training sets. We compare our approach to an active learning approach for expan							
	ding fine-grained datasets.							
	uma me-grameu uarasers.							
				l .	1	l	l	<u> </u>