# ArxivDIGESTables: Synthesizing Scientific Literature into Tables using Language Models

Benjamin Newman<sup>\*</sup>, Yoonjoo Lee<sup>\*</sup>, Aakanksha Naik, Pao Siangliulue, Raymond Fok, Juho Kim, Daniel S. Weld, Joseph Chee Chang, Kyle Lo the second secon

University of Washington, KAIST, Allen Institute for Al

#### **Motivating Example**

Scientists use literature review tables to make sense of many research papers. Can we use LMs to generate these automatically?

		Large-scale Video Classification with Convolutional Neural Networks										
	Large-Scale Study of Perceptual Video Quality Zeina Sinno, Student Member, IEEE, and Alan Conrad Bovik, Fellow, IEEE Advaced—The great variation of properties and properties of properties and properties of a contrast and baselvidit environments, and digdays field to an contrast and baselvidit environments and the diversity of tables of the video that are uploaded daily exceeds 65 variation of the video content is without environments and environments and with a content in the video content is without environments and environments and with [2]. These numbers are continuing to rise	Andrej Karpathy <sup>1,2</sup> George Toderici <sup>1</sup> Sanketh Shetty <sup>1</sup> karpathyles stanford.edu         gtodericil@google.com         sanketh@google.com           Thomas Leung <sup>1</sup> Rahul Sukhankar <sup>1</sup> LiFei-Fei <sup>2</sup> leung1@google.com         sukthankar@google.com         feifeil@cs.stanford.edu <sup>1</sup> Google Research <sup>2</sup> Computer Science Department, Stanford University			Dataset	Size	Task	Annotations				
The Konstanz Natural Video Database (KoN Vlad How <sup>1</sup> , Franz Hahn <sup>1</sup> , Mohsen Jenadeleh <sup>1,2</sup> , Hashe Lin <sup>1</sup> , Hui Men <sup>1</sup> , Tamás Szirány <sup>2</sup> , Shuju <sup>12</sup> Poputnesi of Computer and Information Science, University of Konstanz, Cerma <sup>12</sup> Faulty of Computer Science and Engineering, Shahid Boheli University, G. C., Tohn <sup>13</sup> Initute for Computer Science and Escience, University of Science, Hung <sup>40</sup> Oputernet of Computer Science, University of Surrey, United Kingdom	The is true in part because available video quality assessment orgenized using a small number of counter devices by in the true of the tru	A Dataset for No-Reference Video sessment of Videos in-the-Wild r. We for Video Vide	do- s in have ti in obli- obli- tiety	Paper 1	KoNViD-1k	1200	VQA	114				
Anotaer-Schlertricht im genörn vonsensen (VX) i treifer in der Schlertrichten preisen in der Sch	and other parts of insome databases from the This and by the Integret 3000 series of the Integret 3000 series of the Integret 3000 series of the Integret 30000 series of the Integret 3000 series of the Integret 30	Vision method forms and utilities and utilit	introduction of the second sec	Paper 2	LIVE-VQC	585	VQA	240				
KywordsYako databar; anknetic vide; vide qudy ar- tessmit, far sampling: correlations: I. INTRODUCTION Most of the Internet traffic tody stems from user-generative videos on sharing web-sites and social networks. Yoki ya valibid database of video traffic tody stems from user-generative videos on sharing web-sites and social networks. Yoki ya valibid database of video traffic tody and the video traffic tody and the video traffic statistic tody and the video traffic tody and the video traffic statistic tody and the video traffic tody and the video traffic statistic tody and the video traffic tody and the video traffic statistic tody and the video traffic tody and the video traffic statistic tody and the video traffic tody and the video traffic statistic tody and the video traffic tody and the video traffic statistics. In Sec. IV we relide to uter statistics. In Sec. IV we relide to traffic tody and the video traffic tody database to video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody and the video traffic tody wideo traffic tody and the video traffic tody and the video traffic tody wideo traffic tody and the video traffic tody and the video traffic tody wideo traffic tody and the video traffic tody and the video traffic tody wideo traffic tody and the video traffic tody and the video traffic tody wideo traffic tody and the video traffic tody and the video traffic tody wideo traffic tody and the video traffic tody and the video traffic tody wideo traffic tody and the video traffic tody and the video traffic tody wideo traffic tody and the video traffic tody and the video traffic tody wideo traffic tody and the video traffic tody and the video traf	der KAVUD-11:, a bei funktionnung imm natwic carriegen unt wissen segenretes based on sin errorekel, auch auf der such dis Statisticht segenretes sin der die such dis Statisticht segenretes sin errorekel, auch ein Instagram. Erschler segenretes sin errorekel, auch ein Instagram. Erschler segenretes sin errorekel, auch ein Instagram. Erschler segen genretisticht ein Instagram. Erschler allen Genretisticht ein Instagram. Erschler sentiet ein Instatisticht ein Instagram. Erschler sentiet ein Instatisticht ein Instagram. Erschler sentiet ein Instatisticht ein Instatisticht ein Instagram. Erschler sentiet ein Instatisticht ein Instagram. Erschler sentiet ein Instatisticht ein In	ist method, MLSP-VQA: ist of control in the control in environmental psychology. The approximation of the series	Team Sports, Winter Joors with Animals, y the leaf level. For int types of boiling, and 23 types of bil- as and approximately nore than one class, iterally toy analyzong is investore data is the label of a video orithm fails or if the	Paper 3	KoNViD-150k	153,841	VQA	5				
basic operation for many video processing applications such as video quilly monitoring in trummission protocols, methods and the processing applications such as video quilly monitoring in trummission protocols, methods and the processing applications such and video methods. The processing applications such and video methods and the processing applications such and video methods. The processing applications such as video quality of a video sequence without any additional information above the original records with any additional sectors with little content diversity, than offening linesia support for discipant gala diversity and faily. Additionally, these disabases were mostly designed to lactate with discipant and without with were severe the original sectors were mostly designed to lactate with discipant and without with were severed and indiversity and faily. Comments were mostly designed to sequences and all discover the similarity.	ang conclusion of results and analysis results and analysis we required a 95% confidence interval for weraged over all stimuli, with a length not the 5-point ACR scale. This was achieved 50 judgments per video. This setup resulted wides in the first setup resulted the average US community generation in average used wide commission that average US community generation the average US community generation the average US community generation that average US community generation that average US community generation makes from 64 Commission that average US community generation that average US community that average US community that average US community that a billion hours of video: avecess of numerical avecess of average that the video R. It is to be noted that we as well as improvements in own as well as in	central medium for business in af the variant endown in the second of th	e video content, and annotated it may still me level. For exam- tain several shots of rs, the crowd, etc.	Paper 4	Sports-1M	1,133,158	Classification	<mark>- (auto)</mark>				
of workers did in 20% used a ratio at a zoom of up te	act view the videos unzoomed at 1:1, while generated content is produces f 0.9 to 0.75 and 14% displayed the videos 2 (including font scaling). F Goze Man. Y Lens, Usensy of the Compare Sizens, Usensys of the for the forth of the state of the sta	y auroaccurate. summary, news at an increasing inclusion of the dataset RoNVD-1k [20], the ecological validity and multiple defects. The off of KorVF-15K terms from its asis, content diversity, as well as naturally occurring, and thus representative degradations. 10 Source with the Portment of However, being two orders of magnitude Larger than existing magnitude larger to the state of th		L								

## **Curating ArxivDIGESTables**

We release a high-quality dataset of 2.2k literature review tables curated from arXiv papers. Every table includes:

🔽 table schema (columns), 🔽 table values (rows), 🔽 table captions, 🔽 in-text references, 🔽 full texts for cited papers

Filter out misformatted tables	Convert table to JSON	Semantic Scholar data match	Filtering and reformatting	-							
				High quality			Min	Max	Median	Mean	Total
u tables	L taples 8.45%	98.78%	83.56%	(1.27%, 2.23k) Medium quality (12.73%, 22.28k)		Papers Aspects	$\frac{1}{2}$	$\begin{array}{c} 35\\ 13 \end{array}$	$\begin{array}{c} 3.0\\ 3.0\end{array}$	$4.944 \\ 3.426$	$\begin{array}{c} 11016\\7634\end{array}$
2.5 millio	211k XN	ALC NUCL	Itt	86.00%		Aspect Type Category Entity Numeric	$\begin{array}{r} \% \text{ of Cols} \\ 35.5\% \\ 27.3\% \\ 21.7\% \end{array}$		Example Value "Open" vs "Proprieta "CNN/Daily Mail", "Re "10,000"		lue rietary" "Reddit"
≈ 91.55% 1.22% 16.44% Data Filtering Pipeline						Text Boolean	9. 5.	9.7% " collected via vari 5.8% " $\checkmark$ " vs " $\checkmark$ "		rious"	
						Summary					

#### **Generating Literature Review Tables**

• We introduce two-stage decomposed generation -(1) schema generation, (2) value generation - that outperforms naive single LM prompts.

• We also explore different ways of providing additional context to ground the generation (e.g., table caption, in-text references, in-context examples)

### Step 2: Value Generation -

Step 1: Schema Generation

#### **Metric Development**

#### **Evaluation Intended Application** Annotation method **Dataset size Metric** Objective VQA method 1,200 video sequences Paper 1 Subjectively annotated Subjective Mean Opinion Score development Subjective video quality scores NR video quality prediction Subjective video quality scores Paper 2 585 videos via crowdsourcing advancement Spearman rank-order Coarsely annotated set with Deep-learning VQA model Paper 3 153,841 videos five quality ratings each correlation coefficient training Large-scale video classification Performance improvements over 1 million YouTube videos N/A Paper 4 and action recognition baselines

#### **!** Automatic evaluation is hard!

Tables use **short texts** & generations have **low lexical overlap** with reference tables.

Can we use **decontextualization** to expand short table texts?

Can we use LMs to match predictions to (gold) references?

#### Findings

- > Decontextualization + SBERT better evaluator than Llama 3, which hallucinates alignments.
- > 🕜 More provided context, 🕥 higher recall for schema generation, but doesn't help value generation.

