Attention is All They Need: Exploring the Media Archaeology of the Computer Vision Research Paper

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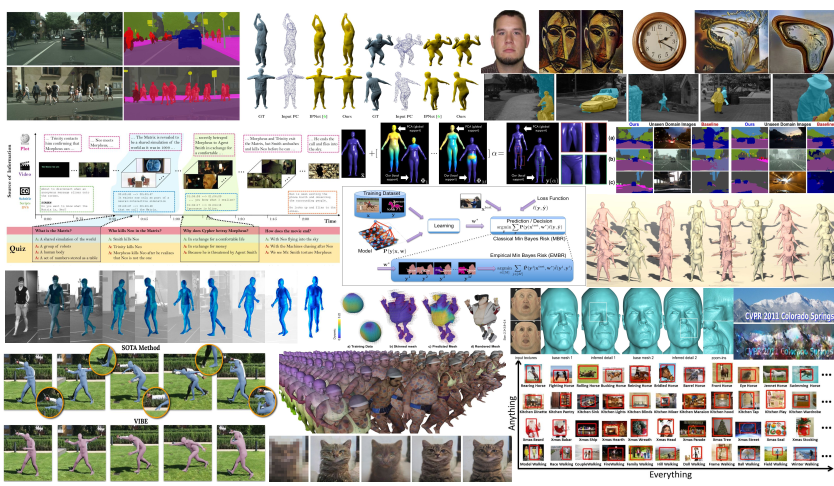

Fig. 1. Teasers from computer vision papers [5, 7, 12, 19, 24, 30, 55, 59, 63, 70, 84, 97, 98, 106, 107, 113, 114]. Best viewed in color.

Research papers, in addition to textual documents, are a designed interface through which researchers communicate. Recently, rapid growth has transformed that interface in many fields of computing. In this work, we examine the effects of this growth from a media archaeology perspective, through the changes to figures and tables in research papers. Specifically, we study these changes in computer vision over the past decade, as the deep learning revolution has driven unprecedented growth in the discipline. We ground our investigation through interviews with veteran researchers spanning computer vision, graphics, and visualization. Our analysis focuses on the research attention economy: how research paper elements contribute towards advertising, measuring, and disseminating an increasingly commodified "contribution." Through this work, we seek to motivate future discussion surrounding the design of both the research paper itself as well as

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the larger sociotechnical research publishing system, including tools for finding, reading, and writing research papers.

CCS Concepts: • **Human-centered computing** → *Visualization*; • **Applied computing** → *Digital libraries and archives*; *Arts and humanities*; • **Computing methodologies** → *Computer vision*.

Additional Key Words and Phrases: Media archaeology, Design history, Attention economy, Culture of computing

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1 Introduction

The research paper has many meanings. It is a contribution to knowledge, often responding—according to formal and informal rules of scientific discourse—to a decades-long conversation. It signals to peers, funding agencies, future employers, and future students that the authors are knowledgeable about a topic and actively studying it. It is a unit of productivity which indicates progress towards a PhD, tenure, or promotion. But beneath all of those layers of interaction, it is a digital media artifact, an element of the sociotechnical research publishing system, with a visual form that both influences, and is influenced by, its discipline.

We propose thinking about the research paper not as a neutral medium for disseminating textual scientific content, but as a designed media artifact with which researchers—its "users"—interact with digitally. For example, we might **glance** at its title in a list of papers, **click** on it, get **hooked** by its first page figure, **scroll** through its pages in a PDF viewer, **scanning** a table of results. We may also **print** the paper and **carry** it with us, **write** in its margin and leave it on a desk, and then **find** it months or years later. In all of these interactions, the design of both the visual and textual content, as well as the design of the larger technical system, which produced the PDF, delivered it to us, rendered its image to a screen and transferred it to paper, affects and shapes our interactive attentive experience. Moreover, research papers are cultural objects shaped by disciplinary culture. Bruno Latour, for example, writes extensively about the social nature of the research paper and the important rhetorical role its figures and tables play in creating scientific truth [64]. Taking this further, we view the research paper as a media object [72], an assemblage of designed technologies—like rendered data visualizations, LaTeX, and the PDF file format—viewed on a screen or printed on paper, which have technological affordances and, as we will discuss, accessibility concerns.

In this paper, we study the changes to computing papers in one area—*computer vision*—over the past decade. While changes occur over time in the research papers of every discipline, computer vision is a particularly information-rich site [80, p. 242] for understanding the paper as a media artifact both because of its inherently visual nature and its unprecedented recent growth. Over the past decade, the "deep learning revolution" has transformed several fields of computer science altering both the fields themselves and the way researchers and practitioners feel about them [96]. In computer vision specifically, Su and Crandall find "a general mood of malaise" [96] which permeates the field. We argue that this malaise is a symptom of increased commodification of scholarly attention, which is materially documented in the changing design of research papers.

By attention, we evoke the attention economy, first proposed by Herbert Simon [92] and applied to the internet by authors such as Goldhaber [42] and Davenport and Beck [26]. An attention economy in the workplace has been discussed in CSCW, for example in the work of Yardi et al. on the attention economy of internal corporate blogs [112] or Kraut et al. on the attention economy of email marketing [61]. To understand its commodification, we turn to the post-Marxist analysis of Claudio Celis Bueno [15]. Bueno frames online attention not just as a scarce resource, but as a form of labor—human activity which has the potential to generate surplus value. We claim that this theory of attention as labor applies to the attention paid to academic research as well, and helps to explain recent changes to computer vision.

Research papers in computing have had a rich history of debate (e.g., conferences vs. journals [102]). In the field of HCI and its subfields, including CSCW, debates continue to arise regarding the form and content of the research paper [40, 105]. Canonical works like Dourish's "Implications for Design" comment on the relationship between scholarly publishing and larger issues of power in disciplinary culture [32]. Sometimes, new formats arise in response; for instance, the pictorial format addresses the need to foreground visual imagery as a significant contribution to HCI [10, 11]. In HCI, these debates exist both as meta-scholarship, shaping the practices of a discipline, and as subject matter, studying the research publishing system as a technological platform.

Perhaps the biggest hint that the design of computer vision papers has changed with the rapid changes in its disciplinary culture is scholarly humor. In the 2010 computer vision satire paper "Paper Gestalt" [103], the pseudonymous authors "take the simple intuition that the quality of a paper can be estimated by merely glancing through the general layout, and use this intuition to build a system that employs basic computer vision techniques to predict if the paper should be accepted or rejected" [103], and suggest that this system might replace the peer review process. The visual design of the paper parodies the qualities it observes, including unnecessary complex equations and long algorithms.

But in 2018, Jia Bin Huang published a sequel, "Deep Paper Gestalt" [53], which updates both the methods and the jokes. Juxtaposing these two papers gives a glimpse of how the style of computer vision research papers has changed in just eight years. Instead of using overly complex algorithms and equations, Huang proposes a benchmark dataset, CVPG (the "Computer Vision Paper Gestalt" benchmark), and uses deep learning to significantly outperform the "hand-crafted features" of "Paper Gestalt" [103]. Then, it presents an unnecessarily dense table and gratuitously large figure of class activation heatmaps to show the page regions which predict good papers. Though satire, these papers raise real questions about the research paper as a media artifact.

In the following sections, we examine historical computer vision research papers from a media archaeology perspective, focused on the way their visual style has developed over time. To better understand these developments in context, we also report results of interviews with twelve veteran researchers whose work spans computer vision, graphics, and visualization. Our approach focuses on elements of the research paper and larger publication system based on their roles in advertising, measuring, and disseminating an increasingly commodified "contribution." We find that as academic discourse has moved online, the limiting factor on publishing has shifted from printing costs to the attention of other researchers, which has changed both the culture of computer vision as well as the design of its research papers. While this finding echoes existing discourse surrounding "publish or perish" [39, 65], the "marketization" of academic discourse [34], use of "hype" in science communication [93], or promotional qualities in titles and abstracts [56], we emphasize the novelty of our approach. To the best of our knowledge ours is the first connection between these discussions of scholarly discourse and the designed visual artifact of the research paper.

2 Related Work

Our inquiry sits at the intersection of several scholarly conversations in and around HCI and CSCW, including data mining of research paper figures, studies of digital media objects, designing for readers and writers of research papers, and studies of the culture of computer vision.

2.1 Research Papers as Media Objects

The fascinating satire paper "Paper Gestalt" [103] is both a related work and a primary source in our inquiry. It claims, facetiously, that "the quality of a paper can be estimated by merely glancing through the general layout" and uses machine learning to predict whether papers will be accepted or rejected from their page images. The (unknown) authors identify that certain features, like sophisticated math and large figures, are predictive of acceptance while large, dense tables are predictive of rejection. A sequel, Jia-Bin Huang's "Deep Paper Gestalt" [53], updates this methodology using deep learning. These papers are a commentary on the the reality of the modern computer vision community: a reliance on visual performance to ensure successful dissemination and influence of papers.

There is also work surrounding the analysis of research papers in document image analysis [27] and data visualization [22, 111]. These methods, however, treat the figure as a neutral data source, where there is an objective correspondence between the original data and the figure for each chart type. More recent work has started to, for example, see data visualization as not merely objective reporting of facts but as a communicative medium that has affective impact [66, 101]. We respond to this literature by pointing out the cultural layers which may interfere with the neutrality and machine-readability of visualization across disciplines.

2.2 Studies of Digital Media Objects

There has been growing interest in analyzing code and its visual results as media objects: artifacts which trace the development of a media culture over time, like wax cylinders or old television sets. Jacob Gaboury's *Image Objects: An Archaeology of Computer Graphics* [37] takes a media archaeology approach to five such objects in the history of computer graphics: the hidden surface problem, the frame buffer, the virtual teapot, object orientation, and the GPU. In *10 PRINT CHR* [75], Montfort et al. study a line of BASIC code used to generate a random maze and use it as an entry-point to explore the cultural history of the Commodore 64 as well as topics including mazes, grids and randomness. These works live within the space charted by Lev Manovich's now-canonical *The Language of New Media* [72], which frames "new media" as visual artifacts produced by textual code, and argues that new media demands new theoretical perspectives.

2.3 The Research Paper as a Site for Interaction Design Research

Closer to CSCW, there are several studies of the research paper as a site for social computing research and designs for digital literature reviewing: Chang et al. introduce CiteSee, a tool for visually augmenting citations in PDF documents based on the reader's prior research activity [20]. Qian et al. describe commercial tools for PDF management as "iTunes for papers," as they treat the research paper as a fundamental unit of scholarship, and propose a literature review tool to break down papers further into collections of specific grounded claims [85].

This research community is also interested in designing for the writing process: Head et al. study ways of augmenting digital documents with definitions of terms and symbols to improve readability [50], and how authors improve readability by augmenting the visual design of their equations [51]. Manzoor et al. develop a LaTeX editor extension to improve the accessibility of LaTeX for authors with visual impairments [73], and Hara et al. develop a system for generating Braille documents from mathematical expressions written in LaTeX [47]. Gobert and Beaudouin-Lafon conduct a study of LaTeX users and design an extension for VSCode that uses transitional representations of document objects like tables to improve the editing experience [41]. Haber et al. study how groups of coworkers interact differently when using physical vs. virtual documents [46].

While we do not design or develop any technical tools, our work provides additional evidence for the importance of further design studies of research paper reading and writing.

2.4 The Culture of Computer Vision

Motivated by the dangers of algorithmic discrimination and safety concerns in systems relying on computer vision algorithms, several recent papers have studied the culture of the computer vision research community and its understanding of data and truth, often using research papers as texts for analysis. Su and Crandall study the emotional state of the computer vision community, finding that the deep learning revolution and subsequent growth have had a profound effect on its culture, leading both to excitement as well as isolation and malaise [96]. Denton et al. use a discourse analysis approach to study the history of the ImageNet dataset through the research papers and presentation slides of Fei-Fei Li [29]. Scheuerman, Denton, and Hanna study a corpus of 500 papers describing computer vision datasets and analyze the values implicit in their writing: efficiency, universality, impartiality, and model development over dataset development [90]. While our work also analyzes computer vision though its research papers, our interest is in studying these papers as primarily visual media.

A wide variety of authors have written critically about the culture of data collection and dataset use in machine learning. For example, Sculley et al. and Ethayarajh and Jurafsky critique the concept of benchmarks and leaderboards in machine learning, arguing in different ways that steadily increasing scores do not always correspond to progress [33, 91]. For a more comprehensive survey, please see Paullada et al. [81]. Our work here, which does not investigate data collection or dataset usage directly, nevertheless echoes these themes.

3 Methods

Our inquiry began through visual analysis of historical computer vision research papers. We were surprised by visual design changes across these papers, particularly the increasing prevalence of highly complex figures, and decided to investigate further by conducting semi-structured interviews with researchers who had been active in computer vision, graphics, and visualization for several decades, as well as computational analysis of a corpus of research papers published between 2013 and 2021 in the IEEE/CVF Conference on Computer Vision and Pattern Recognition—the highest-ranked publication venue in computer science and second highest in all of science, according to Google Scholar as of August 2024 [2]. We study this conference, rather than similar conferences in machine learning or natural language processing, because of the importance of visual presentation in computer vision. Along the way, our visual analysis, interviews, and computational findings coalesced into a media archaeology approach.

3.1 Media Archaeology

Inspired by recent work on the history of computer graphics [37], we examine historical research papers through the lens of media archaeology. “Archaeology” here refers to Foucault’s concept of archaeology as the “uncovering of the archive” [36, p. 131], rather than physical excavation. Media archaeology, as defined by Huhtamo and Parikka, “rummages textual, visual and auditory archives as well as collections of artifacts, emphasizing both the discursive and material manifestations of culture” [54, p. 3]. In other words, we study digital media objects as components of a media culture: a system of practices and meanings which structure our interpretation [89]. We also consider their digital materiality as physical patterns of bits on hard drives, produced through the labor of researchers. By drawing attention to material culture, media archaeology is in dialogue with theories of historical materialism, which consider economic factors—production and consumption of goods and services—as the driving force of history, rather than revolutionary ideas or progress narratives [37, p. 5].

To illustrate these concepts, consider Figure 2(d), a teaser image from a paper in the proceedings of the IEEE Winter Conference on Applications of Computer Vision (WACV) [60]. This figure is split into 5 similar subfigures, with different combinations of black lines and teal dots. With the requisite disciplinary knowledge, a viewer can interpret the meaning of the figure: the five subfigures represent an occluded image and four attempts to reconstruct the wireframe of the original using different automated methods. Using our understanding of the task, we clearly see that the fifth subfigure labeled "ours" is the best, because its dots and lines align with the geometry of the depicted room. These inferential steps require a degree of initiation in computer vision, an understanding of both the goal of a research paper and the system of meaning that these papers use. The goal of media archaeology is to dissect these inferences and identify how their layers of meaning developed over time.

In addition to our computational analysis and detailed study of the CVPR proceedings, we "rummaged" research papers from the IEEE, Computer Vision Foundation, and ACM digital archives, including the IEEE International Conference on Computer Vision (ICCV), European Conference on Computer Vision (ECCV), IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), and the ACM Special Interest Group on Graphics and Interactive Techniques conference (SIGGRAPH). We examined ICCV, ECCV, and PAMI in addition to CVPR because they are the four most influential computer vision venues according to Google Scholar,[1] and SIGGRAPH due to its historical significance and prevalence in our interviews. We turned to these venues to build context for the results we were seeing in CVPR. While we did not systematically code the enormous number of papers published in these venues, we collected dozens of screenshots of interesting figures and tables and discussed their visual style in weekly meetings, integrating interview and computational results which eventually coalesced into historical narratives.

3.2 Interviews

To augment our visual analysis, we conducted interviews with veteran computer vision researchers. As there are a relatively small number of eligible participants, we recruited individuals via email and in-person at the CVPR 2022 conference. Participants are listed by years of industry and academic experience in Table 1. This sample is highly non-representative, showing both survival bias based on who remains in the field over a long period of time and selection bias based on who agreed to an interview, so it does not serve as the sole source of our claims. Instead, it provides important social context to our visual analysis.

We conducted interviews in person and over the Zoom videoconferencing platform between March and August 2022. To avoid participants historicizing or theorizing themselves, we asked each participant to discuss a specific research paper from their early career, and asked them to explain the different elements and tell us stories about the writing process for that paper. Additionally, we asked each participant how they read research papers at that time of that paper, and how those reading and writing processes differ from those of the present. This method of interviewing mirrors that of previous studies examining media artifacts such as websites [23, 44].

After transcribing the interviews, we engaged in a process of iterative memoing, integrated into our weekly meetings where we compared examples from historical research papers and interview excerpts which shared common themes. We focused our analysis on identifying patterns from the context that participants provided while telling stories about their writing, as well how

[1] https://web.archive.org/web/20220709182958/https://scholar.google.com/citations?view_op=top_venues&hl=en&vq=eng_computervisionpatternrecognition

Participant	Discipline	Years Industry	Years Academia
P1	CV,G	9	33
P2	G,V	3	17
P3	CV	0	**42**
P4	CV	**21**	3
P5	CV	15	11
P6	CV	0	10
P7	CV	0	36
P8	CV	0	16
P9	CV	0	19
P10	CV,V	0	22
P11	V	11	0
P12	CV,G	0	23

Table 1. List of participants. Discipline is some combination of computer vision (CV), graphics (G), and visualization (V). Years in industry and academia are defined as years since PhD spent employed by a university or an industry research lab. Joint appointments are counted as academia for simplicity. 10 identify as men and 2 identify as women, and 7 identify as white and 5 identify as Asian.

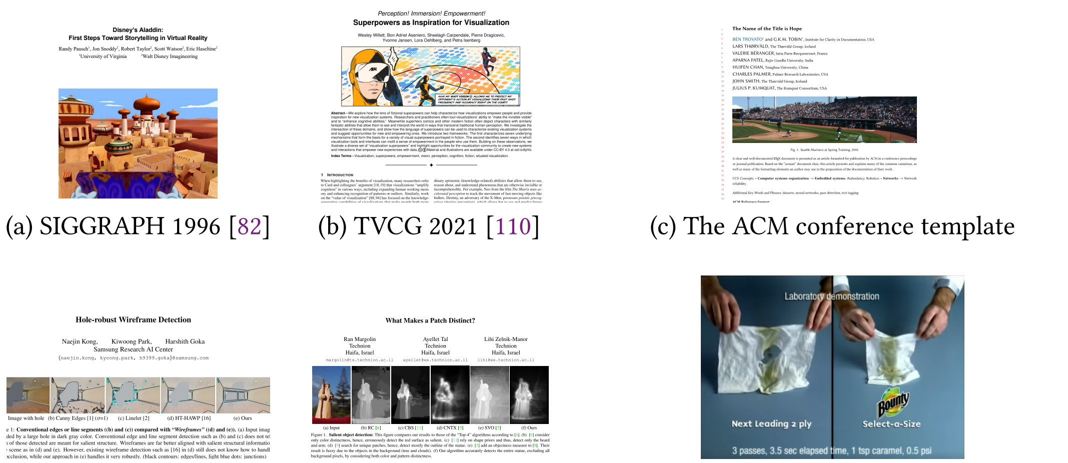
participants thought about their papers in relation to changing disciplinary practices, rather than simply analyzing the papers participants discussed or discussing our participants' analysis of their own work.

3.3 Computational Analysis

As both qualitative approaches rely on the analysis of specific examples, we used supplementary quantitative analysis to verify that phenomena we observed in the interviews and media archaeology were actually as pervasive as participants seemed to think. Specifically, we were interested in whether teaser images, figures and tables were becoming more prevalent in CVPR papers over time, and whether more titles were following a particular format containing an acronym followed by a colon. To answer these questions, we collected PDFs of papers from the Computer Vision Foundation's Open Access Repository (thecvf.com) published in CVPR 2013 to 2021 and article metadata from IEEE Xplore (ieeexplore.ieee.org) for CVPR 1992 to 2020. We manually inspected PDFs from thecvf.com to count teaser images, then used the Linux `pdftotext` tool combined with regular expressions to count figures and tables. From the Xplore metadata, we used regular expressions to parse paper titles, treating a word with more than two capital letters as an acronym, and an acronym as unique if it only appears once in a given year of data.

4 Findings

Through our analysis, we found that several elements of the contemporary computer vision research paper serve as material traces of the disciplinary change which took place during the 2010s. We find that papers are written to promote a specific contribution which is increasingly commodified. By "contribution," we mean the model, algorithm, method, dataset, or other system that the paper offers to readers. By commodified, we mean reduced to its exchange value in terms of the attention it generates. As Simon theorized [92], and authors including Goldhaber [42] and Davenport and Beck [26] have applied to the web, when "capital, labor, information and knowledge are all in plentiful supply" the limiting factor is the attention of consumers, which begins to be treated like a commodity [26].



(a) SIGGRAPH 1996 [82] (b) TVCG 2021 [110] (c) The ACM conference template

(d) WACV 2022 [60] (e) CVPR 2013 (f) A paper towel ad from the early 2000s [1].

Fig. 2. Five teaser images from papers in different venues, and a still image from a television advertisement for paper towels. Figures look best zoomed in.

However, this concept of the attention economy presupposes that attention is valuable, which is unhelpful for understanding why academics seek the attention of their peers instead of the larger research community or general public. To better understand why academic attention is uniquely valuable, we employ Bueno's explanation, that online attention, in addition to a commodity, is a form of labor [15]. This claim relies on Romano Alquati's concept of "valorization information" via Pasquinelli [79]. Alquati, in his study of an Olivetti computer factory, found that workers contribute to mostly-automated production processes through their micro-decisions, which served as a feedback-control signal for the production process. Bueno argues that attention can provide a similar signal. Specifically, by monitoring attention, companies can forecast consumer behavior and more efficiently follow market trends. By doing so, these companies extract surplus value from online behavior data [15, Ch. 2]. We believe a similar process may be at play in academic publishing, where authors can leverage highly specialized early attention to increase the prestige value of their research. This process can take the form of feedback, where authors improve their work based on an early online response, or simply where early viewers find a paper interesting and share it, judging it as valuable, putting it in front of more eyes and increasing the chance that it will reach the right audience. Eventually, that attention translates into citations, jobs, students, grants, and other benefits of academic prestige.

We study three aspects of contemporary research papers: the teaser image, the results table, and the high resolution figure. We have grouped our results into thematic sections surrounding these three elements in relation to the concept of a paper's contribution.

4.1 Advertising the Contribution

4.1.1 Teaser images. The "teaser image" is a large first-page figure which summarizes the paper. Several examples of teaser images are shown in Figures 1 and 2. These figures are functionally similar to the trend of "visual abstracts" [86] and "table of contents images" [17] in the biomedical sciences; however unlike these forms which are graphical summaries of the text, teaser images are part of the main paper and are usually a visualized system output that the authors want to show.

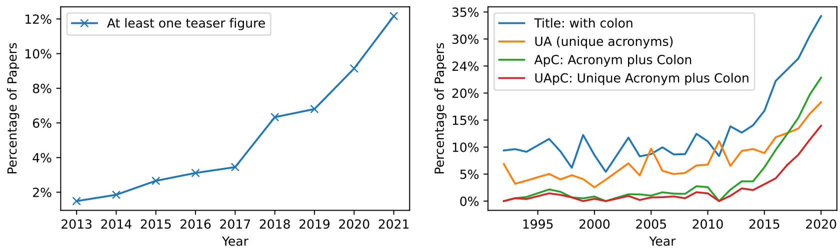


Fig. 3. Left: fraction of CVPR papers with a teaser image. Right: fraction of CVPR paper titles with colons, unique acronyms, acronyms followed by a colon, and unique acronyms followed by colons. Differing timescales are due to differing availability of full PDFs vs. title data.

Teaser images have been steadily gaining popularity at CVPR, as shown in Figure 3 (left). For this analysis, we define the teaser image as a first-page figure which covers the entire width of the page, not just a column.

P12 ascribes the teaser image to the famous graphics researcher Randy Pausch: *"Randy Pausch...takes credit for putting the teaser image in SIGGRAPH papers...he claimed that he did a paper where half the first page was a teaser image and after that that became the norm where people started always putting these images."* The paper in question is pictured in Figure 2 (a). While Pausch did not invent the large first-page figure (Tim Berners-Lee famously used one in his 1989 proposal for the world wide web [8]), he did publish the first paper in SIGGRAPH with this layout, and it quickly became popular. P2 and P10 point to the quick adoption of teaser images, which even became institutionalized in the SIGGRAPH template and later the template for all ACM conferences (Figure 2 (c)).

P12 defines the teaser as a visualization of either a result or a system and explains that it has spread to many other conferences because of the way it attracts attention: *"It's a trailer. It's to get people in...I think it's a very compelling way to convey what the paper does."* For her, the teaser is a highly effective innovation which improves research papers. P2 echoes that sentiment: *"They just made the papers look good! I mean, it's much more memorable and there are some papers still today that I don't remember the title, but you see the picture and you're like, 'Oh yeah, that's the Randy Pausch paper on the VR for whatever, right?' So yeah there's a few of those that are just like, really iconic first pagers."* P2 is referencing the same Pausch paper as P12 [82], highlighting its memorability.

The teaser image is a trailer, a *hook*; it advertises the paper to the potential reader. The authors want to promote their paper and showcase the best results they can because the sheer number and easy access to papers has made it harder to stand out. The visual organization of these figures echoes that theme. Notice the commonalities between the two teaser images in Figure 2 (d) and (e). Both show the output of several algorithms attempting to solve the same problem, but they depict the results in such a way that their method is clearly best. This visual effect mirrors that of advertisements, which depict two competing products in action (Figure 2 (f)). While the experiments in research papers are far more sophisticated than those in advertisements, they share a common visual design. Along these lines, we find a recurring theme of teaser images which rely on the iconography of the 3D-reconstructed, brightly colored human body as a particularly compelling visual. Several examples are shown in Figure 1. Human faces and bodies have been found to attract consumer attention to advertisements [78, 109]; a similar principle may be motivating computer vision authors.

We observe a similar advertising quality in titles. Figure 3 (right) shows the rise in popularity of a particular title construction where an acronym, which is usually the name of a model, is followed by a colon: "HOPE-Net: A Graph-Based Model for Hand-Object Pose Estimation" [31] or "DeMoN: Depth and Motion Network for Learning Monocular Stereo" [100]. These names both signal that the paper proposes a new model and brands the paper with a short, memorable name which is often a cultural reference or clever pun. An especially cheeky example is Joseph Redmon and Ali Farhadi's 2017 paper "YOLO9000: Better Faster Stronger" [88], which improves upon an earlier model called YOLO (short for You Only Look Once) [87], and references a variety of memes from the mid-2010s.[2]

4.1.2 Beyond the paper: arXiv, social media and videos. Why would many authors begin to engage in these teaser figure and title practices over the course of the 2010s? One explanation is a change in medium through which research reaches its audience, from conference and journal proceedings onto social media and preprint websites. P4 describes how his students have strategies to get their papers noticed on the preprint site arXiv: *"if they take your submission on Thursday and it goes up on the arXiv most recent publications list, it's up for all of Friday, Saturday, and Sunday...so it gets more days of exposure...It improves your odds that somebody will notice your thing."* P8 describes the pressure on her students to promote their work: *"social media, like promoting one's research has become such a big thing and I think students...are realizing, 'Oh it's not enough for me to, y'know, come up with a paper, post it on arXiv, get it accepted. I also need to tweet about it.' It's frankly quite exhausting...[before] the only way you promote your paper is it shows up at the conference and hopefully, y'know, some famous computer vision researchers will come up and look."* She talks about how her advisor would bring his friends over to her poster, and that was all the advertising she needed to get noticed, but that strategy no longer works as well in the modern crowded field of computer vision.

Again this pattern resembles one from computer graphics. P12 describes the importance of videos in SIGGRAPH: *"in graphics the conventional wisdom has been it's useful to have, not only do the paper...but to also show a video that really highlights and explains the work. And if you do a good job of explaining it, people find it compelling."* These videos were considered part of the paper submission and peer reviewed alongside the text, which led authors to invest heavily in the quality of their videos.

That attention translates into citations, as well as other benefits. P11, who works in an industry lab that hires recent PhDs, explains why his group publishes at all: *"exposure is actually really important. If you want to attract really top level talent, then having zero published papers is really going to work against you, right? Particularly if you're looking at people who are in positions that are for doing some sort of active innovation."* For this group, the publication is primarily a way to gather attention, they derive value from the attention paid to their work through hiring. Second, attention helps researchers to identify the value of their own work. P7 talks at length about his desire for impact. He switched fields from computational complexity to computer vision because there were more active researchers, and he could not tell if his work was having an impact in a small field. P9 tells the story of how attention from a senior scholar improved his relationship with his advisor: *"that email from [scholar], that's the beginning of my great relationship with my advisor was that one little email, because within five minutes [advisor] was up in the office, 'Oh, you got an email from [scholar]? Very good. Very good. How about a coffee?' "* Notice that the career benefits resulted not from the attention itself, but from the record of that attention in the form of an email from a senior scholar.

[2] YOLO itself was a meme, short for "you only live once," the number 9000 references a famous quote from the television show Dragon Ball Z and the phrase "better, faster, stronger" references a Daft Punk song. While unusual in computer vision, this kind of nerdy referential humor has been observed in other areas, for example, web design [43].

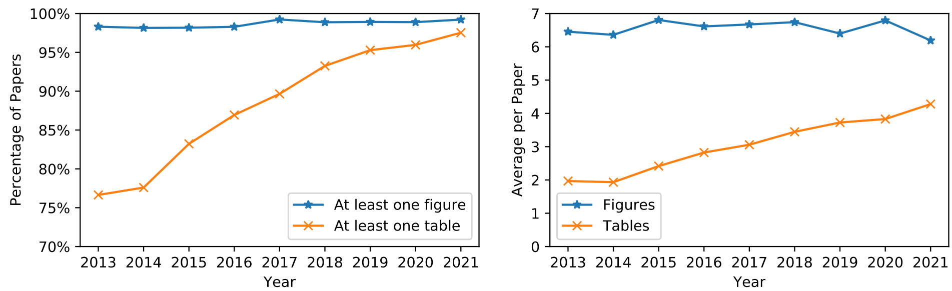


Fig. 4. Left: The fraction of CVPR papers with figures and tables over time. Right: The average number of figures and tables per CVPR paper over time.

While the relationship between attention and prestige is not new, the unprecedented growth of computer vision over the past decade places pressure on the attention of senior researchers. There have been ongoing discussions in the computer vision community on how to react to this growth. Some of the proposed ideas are recorded in the passed motions of the annual meeting of the IEEE pattern analysis and machine intelligence technical committee (PAMI-TC), the governing body of the computer vision research community. In 2021–2022, motions changed the rules regarding double submission to reduce burden on reviewers, introduced punitive measures for missing or poor quality peer reviews from authors, and banned discussion of submitted papers on social media to avoid influencing peer reviewers (the last of which was repealed in 2023) [3, 9]. The rationale statement for the social media ban specifically highlights attention: "Groups with large followings and the resources to mount visible social media promotions received significant attention for work that is under review. Reviewers are exposed to this work and the attention it receives can bias their judgment—if so many people on social media are excited, mustn't it be good?" [9]. In addition to highlighting the valorizing role of attention, this statement showcases the view of peer review as an unbiased process for evaluating the quality of research.

We see two additional key themes starting to emerge. First, there are parallels between computer vision in the 2010s and computer graphics in the 1980s and 1990s, which many of our participants pointed out (P1, P2, P6, P9, P10, P12). Both disciplines rapidly grew due to industry investment, from the tech industry in vision and the entertainment industry in graphics, which created an attention economy, forcing papers to go above and beyond to attract attention. Second, research work is being commodified—treated as interchangeable, given some measure of its value. In computer vision, that means the particular ideas an author proposes are less important than their ability to grab attention and advance the author's career.

4.2 Measuring the Contribution

Today, the "table of results" in a computer vision paper fulfills a central function in both the written argument and the peer review process: evaluation. When proposing a new method for solving a vision problem, the authors must demonstrate that it works at least as well, if not better than, "SOTA" (state-of-the-art) existing methods. These tables often contain the values of standard evaluation metrics computed on a benchmark dataset, like top-1 or top-5 accuracy on the ImageNet test set [28] for image classification or mean average precision on the MS-COCO test set [69] for object detection.

While it is tempting to treat these tables as textual content, their effect on the paper, we argue, is primarily visual. A key feature of these tables is that they put the best result, which is almost always from the author's proposed method, in bold. This design feature is essential for readability, as a large table full of numbers is very difficult to interpret. These tables will sometimes also use arrows to indicate whether a column displays a metric where higher or lower numbers indicate better performance. More recently, as these tables have become more complex, authors have developed other readability innovations, like using colored numbers and subscripted or parenthetical percent improvements (Figure 5 (e)). These innovations serve to further visualize the quantified value of the paper's contribution.

But all of this was not the case a few decades ago. The vast majority of computer vision papers from the 1980s and 1990s rely on mathematical arguments based on, for example, pinhole camera geometry and do not contain any quantitative results. Empirical evaluation, if included at all, was primarily qualitative, in the form of figures showing sample results. As P8 explains, she had a combination of quantitative and qualitative evaluation in her paper from 2003, which was unusual: *"quantitative evaluation, you know, back in 2003 was still kind of in its infancy...I'm not sure that this [2003] paper has basically any comparison to competing methods which probably would be required today."* P3 explains that he was primarily concerned in 1990 with showing test examples to demonstrate his algorithm's effective handling of edge cases. P9 explains that in 1999, showing example output of his system was sufficient: *"instead of [Amazon] Mechanical Turk you just have the reviewers just eyeball the images."* In the satirical 2010 "Paper Gestalt" [103] paper, which attempts to use computer vision methods to distinguish between good and bad papers, large confusing tables were identified as a key feature of *bad* papers, not an essential feature of good ones.

So how did computer vision transform from a mathematical discipline based on geometry to an empirical, quantitative discipline based on benchmarks? This transition was gradual: we can see its seeds as early as a debate at ICCV 1999, referenced by P9, between Jitendra Malik and Olivier Faugeras [99]. In that debate, Malik argued that computer vision should focus more on probabilistic modeling and perception, rather than methods based in geometry, while Faugeras rejected empirical computer vision as unfalsifiable, advocating for the mathematical rigor of geometry.

The publication of Krizhevsky, Sutskever, and Hinton's "ImageNet Classification with Deep Convolutional Neural Networks" in 2012 [62] marks a turning point for empirical evaluation. This paper is historically significant for setting off the deep learning revolution, and its design and writing served as a foundation for the thousands of deep learning-based computer vision papers that followed. The paper's central argument is that several "new and unusual features" lead deep convolutional neural networks to significantly outperform other methods. These features include rectified linear units (ReLU), GPU-based training, and regularization techniques like data augmentation and dropout. Crucially for our story, however, this argument is made by way of a table, shown in Figure 5 (c), with the best performance in bold. Neural network papers are obligated to use empirical evaluation, as there are insufficient theoretical guarantees for these models and they are difficult to evaluate otherwise. Over the following years, many papers followed Krizhevsky et al.'s lead, showing that deep convolutional neural networks outperform existing methods on other central problems like object detection and semantic segmentation. We can see a corresponding increase in both the average number of tables per paper, as well as the fraction of papers containing at least one table in Figure 4. While the prevalence of figures has remained relatively constant, tables have become significantly more common. While only 75% of CVPR 2013 papers had a table, 95% of CVPR 2021 papers did, and the average number of tables per paper has doubled from two to four. While not all of these tables are the kind of results table we are discussing, the change is striking.

Like teaser images, however, this style of table arises in computer graphics before entering computer vision; see Figure 5 (a) for an early example. Early graphics results tables primarily showed runtime comparisons, rather than accuracy or quality evaluations. These tables are used in

	L	LIC	RK	CK	DP
Hyperthermia 400 × 600	10	12.26	**3.36**	3.65	3.55
	20	21.93	**3.75**	4.15	3.99
	40	41.36	**4.60**	5.20	4.88
Dipole 500 × 500	10	18.35	4.35	4.41	**4.31**
	20	34.29	4.78	4.81	**4.60**
	40	71.14	5.61	5.61	**5.39**
Cylinder 600 × 200	10	7.76	**1.49**	1.54	1.57
	20	14.44	**1.62**	1.65	1.70
	40	27.01	**1.92**	1.99	2.00

Table 1: Performance of the original LIC algorithm compared to the new algorithm equipped with different numerical integrators: RK = adaptive Runge-Kutta scheme RK4(3), CK = Cash and Karp, DP = Dormand and Prince (cf. Sect. 4). The boldface entry gives the shortest time in each row.

(a) SIGGRAPH 1995 [94]

ρ	PA	CO	CU	CY	EL	PY	SP	PL	TO
NC	0.14	0.40	**0.05**	0.20	0.34	0.25	0.42	0.23	0.30
ED	0.21	0.16	**0.05**	0.07	0.12	0.21	0.17	0.17	0.17
HD	0.16	0.12	**0.03**	0.04	0.16	0.17	0.15	0.12	0.13

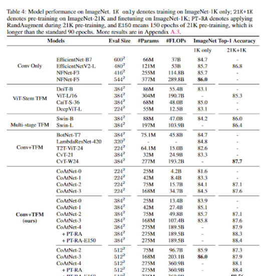
Table 2. Classification result for the Rubik's cube.

(b) 1999 edited volume [21]

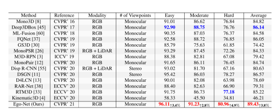
Model	Top-1 (val)	Top-5 (val)	Top-5 (test)
SIFT + FVs [7]	—	—	*26.2%*
1 CNN	40.7%	18.2%	—
5 CNNs	38.1%	16.4%	**16.4%**
1 CNN*	39.0%	16.6%	—
7 CNNs*	36.7%	15.4%	**15.3%**

Table 2: Comparison of error rates on ILSVRC-2012 validation and test sets. In *italics* are best results achieved by others. Models with an asterisk* were "pre-trained" to classify the entire ImageNet 2011 Fall release. See Section 6 for details.

(c) NeurIPS 2012 [62]



(d) NeurIPS 2021 [25]



(e) CVPR 2021 [67]

	5pt problem			4pt problem		
	ρ [%]	$\mu_t[\mu s]$	$\epsilon_t[\mu s]$	ρ[%]	$\mu_t[\mu s]$	$\epsilon_t[\mu s]$
B1, A_{50}	47.3	∞	∞	44.2	∞	∞
B1, A_{75}	74.2	∞	∞	72.0	∞	∞
B1, A_{90}	87.7	∞	∞	87.9	∞	∞
B2, A_{50}	9.9	11.8	119.5	5.2	16.1	310.5
B2, A_{75}	9.0	12.4	137.8	4.9	16.7	340.9
B2, A_{90}	8.4	12.1	144.5	5.0	16.3	324.5
B2, A	11.2	327.9	2927.7	9.8	150.1	1531.6
B3, A_{50}	14.0	12.2	87.3	5.1	15.9	312.2
B3, A_{75}	13.4	12.8	95.3	4.8	17.0	352.7
B3, A_{90}	4.2	19.5	460.2	4.8	19.9	413.5
MLP, A_{50}	29.3	15.7	53.5	21.6	19.7	91.3
MLP, A_{75}	38.8	15.0	38.7	27.8	20.3	73.0
MLP, A_{90}	39.9	14.3	35.8	29.2	19.6	66.9
MLP_T A_{50}	17.0	4.6	26.9	9.1	8.9	96.8
MLP_T A_{75}	29.0	7.6	**26.1**	19.0	13.5	71.1
MLP_T A_{90}	36.8	10.8	29.3	26.3	16.2	**61.6**

Table 4. Classifier evaluation. Rows correspond to start problem selection strategies. The anchors are extracted from datasets *Office* and *Terrains* (Tab. 1). The strategies are evaluated on datasets *De-*

(f) CVPR 2022 [52]

Fig. 5. Six results tables with numbers in bold. (a) is the earliest example of this style we found, (b) is the earliest example from computer vision. (c) is from the highly influential 2012 AlexNet ImageNet classification paper [62], (d) is a 2021 state of the art result on ImageNet [25], (e) is a more trendy table from 2021, making use of grayscale background, colored numbers and subscript arrows showing improvement [67] and (f) is a table from a 2022 CVPR paper [52] from the geometric side of computer vision, which is historically more mathematical and usually has fewer such tables.

computer vision for showing machine learning performance at least as early as 1999 (Figure 5 (b)). Interestingly, tables from this era usually had methods in the columns and different data examples in the rows, in contrast to the later tables which have evaluation metrics in columns and methods in rows. This swap also aided readability, as it is easier to scan vertically than horizontally [71].

As competition has heated up, results tables have grown. For example, compare the table in Figure 5 (c), from a 2012 paper, to the table in Figure 5 (d), from a 2021 paper. The benchmark remains ImageNet, though performance has surged from 40% top-1 accuracy to over 85%, but the competing state-of-the-art includes dozens of models and differ by only fractions of a percent. Even highly geometric papers, like the example in Figure 5 (f), now involve empirical evaluation.

More broadly, in computer vision there is a widespread assumption that research inherently involves competition between technical methods. Several of our participants described academic publication using free market metaphors. P2 explains his research output: *"publication was really fast during that time because there was not a lot of competition."* P3 explained that CVPR has become inaccessible to students because *"supply and demand"* have raised the standards for publication. P4 described vision as *"very industrial"* and gave examples of techniques that students use to optimize their arXiv submissions to reach as many eyes as possible.

With these tables buried deep within the paper, it may seem like their effect on attention is minimal. However, a competitive benchmark result attracts attention on its own. Once a researcher has the lead, other papers must compare against their benchmark and cite them. P6 compares benchmarks to arcade game leaderboards: *"If it's an established benchmark... there's somebody who has the lead right? Like you would have on like a classic video game arcade machine, right? It's like I* *have to just get my initials at the top right? That's exactly what they're doing, and that's frustrating."* P5 and P8 advise their students to avoid working on research which forces them into competition with large companies. P5 explains, *"I tell them, don't work on problems that, you know, a lot of people are working on right now, you can't possibly compete with Facebook, Google, Amazon because you're not as computing heavy."* While students could still develop innovative ideas for those problems, they likely would not beat the benchmarks that large companies have set without leveraging similar computing power and would not attract attention. Because students will not be able to compete with large companies for attention on these problems, they are not worth studying.

In summary, the development of the results table shows the transition of computer vision from an applied mathematical discipline to a quantitative-empirical one. As vision started relying on empirical evaluation, it adopted a style of results table which was used for runtime benchmarking in computer graphics, and as evaluation benchmarks became established for vision problems, these tables grew in size and importance. Today, competition on benchmarks is the organizing principle of the discipline; new methods must demonstrate that they are empirically more effective than existing methods to be accepted, and the results table is an essential part of the paper. This element showcases several of the same themes as teaser images: influence from computer graphics, and commodification, in the form of measurable improvements over prior work. It also echoes patterns observed in HCI more broadly regarding quantification: once a phenomenon, in this case the quality of a method, has been measured, that measurement creates and constrains possibilities for action [83].

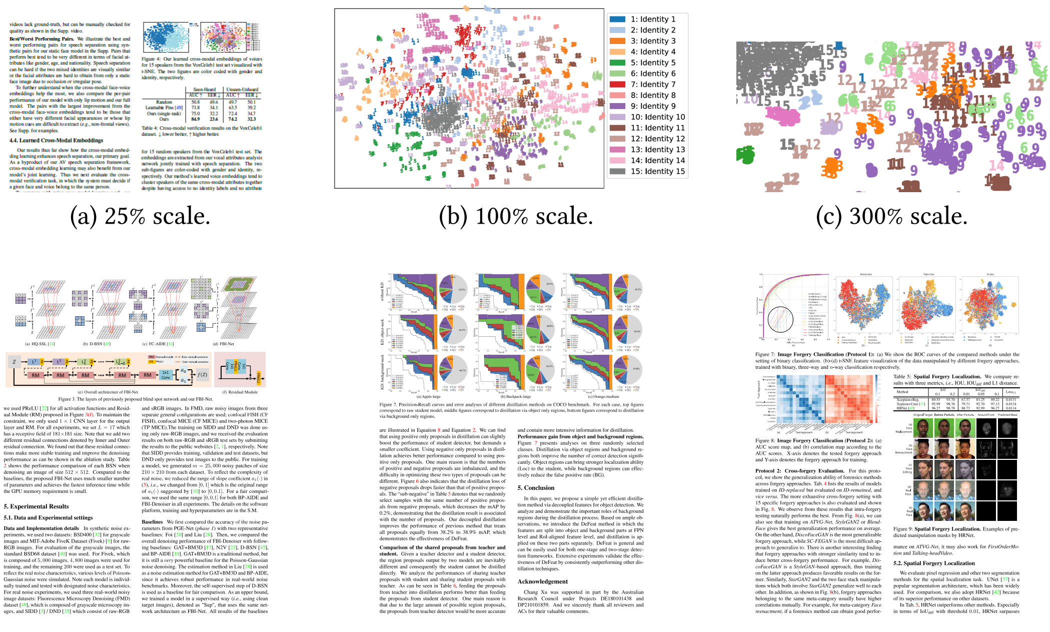
4.3 Disseminating the Contribution

4.3.1 The PDF and digital proceedings. The final element we explore is the Portable Document Format (PDF) itself, and the way that authors engage with it as a medium. PDF was a derivative of Adobe's already-successful Postscript language for specifying documents, and a proprietary file format until 2008. In an article from 1998, Kasdorf compares the PDF format to SGML (Standard Generalized Markup Language), and argues that both formats should be used on the web: markup languages for screen-based content and page-based languages for printed content [58].

However, in the context of computer vision research, the PDF is now more of a screen-based format than a printed one. The PDF viewer has steadily replaced paper as the medium for reading research articles, which has led researchers to design their articles for viewing on screens, rather than as physical, printed research papers.

Our participants ascribe this shift to an aesthetic factor: color. P9 explains that a huge draw of a conference like SIGGRAPH was its color proceedings: *"SIGGRAPH was always in color. It was absolutely beautiful color. Much more expensive."* P10 points to a turning point where researchers started preparing all of their figures in color: *"There was also a turning moment at some point, I think it was around 2004-5-6 something like that. So before that, it was black and white plus color images at the end. Like in a set of separate full color plates as they call them. It was difficult to decide which figures to put in color, since visualizations had to be fully redesigned for black and white."* Once some figures could be in color, authors had to choose which of their figures to leave in black and white, which was a difficult choice. P10 explains his solution: *"the only simple solution I found is you don't decide. You just leave it like this and then they complain, well this is not visible...[so] you insert the URL of your webpage."*

But the existence of URLs, and particularly hyperlinked URLs, points towards another motivating factor for digital proceedings. Before the web, articles were written, submitted, and published on paper. But through the 1990s and 2000s, a series of rapid technological changes took place, transitioning to digital submission and dissemination. The transition to digital proceedings, like other trends, started in SIGGRAPH, which produced the first fully digital proceedings on CD-ROM



(a) 25% scale. (b) 100% scale. (c) 300% scale.

(d) A page from [18] (e) A page from [45] (f) A page from [49]

Fig. 6. Top: three screenshots at different sizes of a figure from [38] which is too small to reproduce using a standard office printer. Bottom: three examples pages from CVPR papers with highly information-dense figures in small page regions, shown at 20% of original size.

in 1993 [13]. CVPR distributed digital proceedings as early as 2005, allowing color figures without the cost of color printing. P9 explains that in 1999, digital versions of papers were hard to read: *"most papers were in postscript and the postscript viewer was kind of sucky. Didn't really look very good on the screen."* P7 found the transition to PDF freeing: *"I've seen figures have become a whole lot more common...the PDFs are now in color so you have a whole bunch of other choices."*

One such choice is the high resolution figure, which exploits the scalable nature of vector graphics and the zoom feature of PDF viewers to put more data in a PDF without exceeding the page limit. Several examples of this trend from CVPR 2021 are shown in Figure 6. While these figures are not overly complex or poorly designed, they are too small to be readable on a 300-dpi printed page.

Several of our participants mentioned these high resolution figures. P6 and P10 are frustrated that they cannot print some PDFs because the figures are too small. P10 ascribes these figures to the increasing complexity of research: *"the tendency of grouping more small figures into a kind of collection... I wonder, is this because of the limited page count that people try to avoid the whitespace around the figures and then they put everything in one big figure because then you can save on the whitespace? Or is it simply because really...the techniques that we're describing nowadays are so, so much more complicated? So you need them to...put the architecture of the whole thing in detail there. Otherwise nobody understands it."* P7, on the other hand, ascribes it to digital submissions: *"In '94, you turned in your paper by actually having a piece of large paper that was probably 24" wide by 30" or something...you had columns of text from LaTeX and then your figures had to be glued in place in what's called 'screen,' right? So you actually have to make sure that they didn't copy badly."*

When papers were submitted by mail, the medium of the "camera-ready" draft was a significant limitation on the kinds of visual content that could be included, but now the only limitation is on the number of pages, so authors use smaller figures to include more content. The small size of these figures, especially in comparison with the large front page teaser image, creates a visual hierarchy, highlighting the differences in purpose between these figures. The teaser attracts attention, the dense figures provide details for those who zoom in, and the impression of details for those who do not.

The digital nature of contemporary research papers was a sensitive topic in our interviews. Half of our participants (P1, P2, P3, P4, P5, and P8) expressed attachment to and nostalgia for their printed papers, and were saddened when asked when they stopped reading on paper. For P1, the time spent at the library made the papers physically significant: *"[the papers] were all me standing at a Xerox machine with a journal...I didn't find it as annoying. I found that it gave me something like a kind of a physical connection to the paper. This was sort of like, it's mine. I've watched it go by, you know."* P2 remembers that the SIGGRAPH proceedings *"were like flipped to the point where like it's the threads were like bare."* He's kept all of the papers he printed during his master's degree and revisits them from time to time: *"I still go back, you know, look at like oh this crap that I thought about these things, right?"* Finding and photocopying papers made them precious; he thinks there is *"a kind of a correlation between that sense of, like scarcity of it, like how precious the paper was, because it's so hard to find versus the amount of care you give it."* P4 fondly recalls his advisor taking papers out of a filing cabinet and photocopying them for him: *"the amazing thing about your advisor is you have this filing cabinet of stuff that's already pre-copied, you know, every paper he thought was interesting."*

These sorts of relationships to printed papers are interesting from a design perspective. They echo the findings of Odom et al. that we preserve designed objects which have functional, symbolic and material-aesthetic value [77]. When a researcher prints out and writes on a paper, the paper gains symbolic significance, a *"physical connection"* which endures over time. That makes printed pages less disposable than digital ones; there is a more tangible opportunity cost to creating them. From this perspective, digitization is an essential component of commodification, as it separates the research from its paper and thus its role as symbolic object. While reading digitally is significantly more environmentally sustainable than printing, shipping, and photocopying paper [4], many of our participants who primarily read on screens miss the era of physical papers.

In contrast, P7 prefers PDFs because they allow him to use a screenreader: *"I use an app that reads the pdf aloud to me...I can get most of the paper from that, I still have to read equations."* Despite being an advocate for making computer vision papers more accessible for the community, he explains that conferences are reluctant to put accessible equations in their templates because of its impact on file size: *"basically the conferences keep using templates that—so there's a trade off by adding this stuff to your file, your file gets bigger. And it turns out that the package, that one of the packages is pretty good for this, if you do it badly, it blows files up huge...I tried to get the guys from CVPR to use it and it just didn't happen, right?...I've just lived with the fact that it's not there."*

The juxtaposition between high resolution figures and inaccessible equations is ironic. These figures can have surprisingly large file sizes—the PDF shown in Figure 6 (a) is a stunning 36MB, more than 10 times the size of a typical CVPR PDF. But computer vision proceedings remain inaccessible, justified based on file size concerns. These figures also point to the vestigial nature of the page limit. Originally, page limits were put in place to minimize printing costs. But in the era of online-only proceedings, there is no financial reason to keep papers page-limited. In fact, the main limiting factor on conferences is the number of reviewers, rather than the lengths of accepted papers. As P8 describes: *"for the last...five years or more, there has been talk every single cycle, oh,* *you know, we don't have enough qualified reviewers. We have way too many submissions. Everyone's way too overwhelmed to do the reviewing."*

4.3.2 Faster publication through arXiv. The digital materiality of the PDF affords an alternative publication process that came up in several of our interviews (P4, P5, P8): the preprint server arXiv. P5 says arXiv is a major source of anxiety for his students: *"So my students...had the unpleasant experience of, you know, finishing a paper when they're just about to submit and they saw a paper on arXiv that did almost the same thing. Like, oh my, months of work just went down the drain."* This emotion, the sense of loss when a project becomes unpublishable because someone else got there first, echoes Su and Crandall's observation of "selective amnesia" [96], except in addition to old papers quickly becoming obsolete because something else is better, current papers may become obsolete because they are no longer first.

Conferences originally gained popularity in computer vision because they allowed research to make it to print faster than journals. According to P3, *"it used to take almost two years from the time a research is done and the PAMI [Pattern Analysis and Machine Intelligence journal] paper would appear. And so the conference has started becoming more and more important at that time. So that's the origins of ICCV and CVPR conferences becoming far more popular than journals. So during the 1980s and early 90s, the journal was the thing."* But now, if research is primarily disseminated by PDFs posted on arXiv, it seems like the same process is occurring again: conferences behave like journals and arXiv behaves like a conference. As P8 explains, researchers still submit to conferences for prestige: *"In order to get promoted in order to get a job, you need that stamp of approval. And it's a pretty strong signal to get papers accepted to a selective conference...this is really kind of the, you know, biggest marker, you know, the biggest benchmark by which you are evaluated."* As arXiv replaces conference proceedings as the fastest communication medium, the conference is left primarily to evaluate papers.

ArXiv changes the writing process as well. As P9 explains, *"I find that the amount of time and effort put into each paper has gone downhill. For my papers, I would put a huge amount of time, especially in the intro...And recently I have been doing less and less of that and basically because the students are saying, ah you know, the new kids they don't even, they just skip the intro, they just go directly to the method. So I feel like, oh my god, nobody's even gonna read my beautiful prose!...But also I think because the field progresses faster, papers become obsolete much quicker. So it might be reasonable not to spend so much effort on a single paper if you know that in a year it will be obsolete."* In other words, the author now writes differently in order to better fit the faster publication system, spending less time on introductions in order to spend less effort on a paper which might quickly become obsolete.

To summarize, the technologies underlying the publishing process in computer vision have changed rapidly over the past three decades. Today, proceedings are published online, and most researchers read PDFs on a screen, rather than research papers in print. The loss of physical research papers affects readers' attachment to those documents, as virtual papers cannot hold significance as domestic objects in the same way. Meanwhile, authors have taken advantage of this fact and increased the resolution of their figures to bend conference page limits, and started publishing on arXiv to quickly attract attention to their new results. Again, we see the same themes: a pattern in computer vision was preceded by a similar shift in computer graphics, which has contributed to commodification. In this case, the conference publishing system has shifted from a means of scholarly communication to a means of evaluating research. Acceptance to a computer vision conference serves as a marker, not just of peer-reviewed technical correctness, but of sufficient novelty and significance to warrant high scores from reviewers, a *"stamp of approval"* for employment or promotion. In other words, improvements in writing tools have shifted the burden of evaluating new research work from the authors to the peer reviewers, placing significant labor burdens on the peer review process.

5 Discussion

Using a media archaeology approach, we have described the development of three aspects of the design of the contemporary computer vision research paper. First, we saw how teaser images, titles with acronyms, and videos advertise the contribution of a paper, and how attention from arXiv and social media has become more important. Second, we saw how the results table was introduced for measuring the significance of a contribution, and became ubiquitous. Finally, we looked at the transition from paper to PDF as a medium for disseminating research contributions and its new affordances for figure color and density. These trends have a key commonality: they make research papers easier to consume visually and more readily disposable.

These shifts showcase the changing material reality of academic publishing. The negligible reproduction cost of digital documents has reduced the labor required to communicate research. That has shifted the labor burden onto the attention of peer reviewers and online communities of scholars. The peer review process is now governed by self-imposed limiting factors, born of a desire by conferences to signal prestige through low acceptance rates. While we observe these changes in computer vision, they may soon appear in other disciplines as well.

When we treat online attention from peers as a kind of labor—something which allows authors to generate value from the research activities of their peers—we see a clear explanation for our visual trends. Authors who write more papers which are easy to understand at a glance, easy to promote on social media, more obviously novel, and more significant in the eyes of reviewers attract more attention. Attention confers a variety of benefits including citations, interest from future mentors, students, employers, and employees, and increased progress on specific research problems. These benefits increase the value of the author's research.

Authors seeking attention can develop design innovations, like more readable tables, but the attention economy ultimately privileges large industry labs. Discussion around the CVPR social media ban echoes these attempts to prevent competition between large industry labs and graduate students. But even social media bans cannot prevent the design of the paper itself from attracting attention. In reality, the value of that attention is great enough to motivate industry labs to invest in publishing. In addition to the marketing benefits, those companies can leverage scholarly attention to signal [35] the innovation and pedigree needed to recruit the best computer vision researchers.

We believe this pattern exemplifies a broader trend of exploiting the attention of researchers. While authors derive prestige and career progress from online attention, the researchers who read those papers do not. Instead, paying attention to the state of the discipline is essential for doing career-progressing research of their own. While staying current has always been a part of academic work, the growth of the discipline puts pressure on readers, increasingly treating them like a crowd of interchangeable peers whose attention is needed to make new research prestigious. This process resembles proletarianization[3] [15, Ch. 3], and may cause the "malaise" observed by Su and Crandall [96]. Just as these trends in computer vision were foreshadowed by trends in computer graphics, similar trends may follow in other fields. In a recent paper examining paper titles and abstracts, Ken Hyland argues that an attention economy has begun to form widely throughout academic publishing [56]. We encourage future study of the attention economy to focus on both the labor performed by peers, as well as the sort of visual evidence we have discussed.

These problems become more egregious when considered alongside the much broader labor issues involving data labeling in computer vision [29, 81, 90]. Workers have their intelligence

[3] In Marxist theory, the process by which people are assimilated into the working class, causing alienation.

commodified and exploited by researchers who are themselves responding to the commodification of their work. In this way, commodifying the labor of relatively privileged academics can exacerbate widespread exploitation of a less privileged workforce.

These problems also echo recent discussions regarding generative artificial intelligence. These technologies (some of which originate from CVPR, e.g. [68]) show risk of producing online disinformation [104], displacing artists and writers [57], and creating problems for future curators and historians regarding provenance and authenticity of historical images [48]. For example, as Jiang et al. discuss, the science fiction magazine Clarkesworld was forced to pause submissions due to excessive AI-generated submissions after ChatGPT went public in 2023 [57]. While authors submitting to computer vision conferences are not yet producing their papers using AI text generators, there are parallels regarding a deluge of content that places the burden of evaluation on the attention of reviewers. While bans on AI-generated content may slow the growth in the short-term, they do not resolve the fundamental commodification of attention, and may fail as new tools continue to blur the boundary between human and AI-generated writing.

The main implication is that *ad hoc* responses to symptoms of the attention economy, like banning discussion on social media or punishing low effort peer reviews, will not change the pressures which are at play. Instead, computer vision is faced with a wicked problem [14], spanning peer review, hiring, promotion, and tenure, in addition to academic discourse, which demands a larger-scale rethinking of the inherent tensions between facilitating scholarly communication and evaluating scholarship. Removing barriers to research communication appears to speed up the pace of research, but also changes disciplinary practices by forcing scholars into an arms race, competing for the attention of their peers.

Our inquiry also carries implications both for the design of the technologies which support publication and literature reviewing. As conferences continue to move beyond compatibility with paper, there is growing need for a LaTeX-compatible, digital-first document file format which gives authors control of the look and feel of their publication, but is machine-readable and supports accessibility tools. There is also a growing need for tools to help scholars collect and curate relevant literature. But rather than make this process as fast and frictionless as possible, we encourage work grounded in “slow design” [76] and “slow science” [95] which attempts to recreate the preciousness, uniqueness, and care that our participants ascribed to the hardcopy papers they photocopied by hand. We also encourage, in line with the view of attention as labor, top conferences to consider compensating peer reviewers for the essential labor they perform.

Our work carries significant limitations. Our visual analysis is not systematic, and is likely biased towards visibly obvious trends, as well as trends which are present in published papers that have been digitized, ignoring the visual culture of posters, presentations, and rejected papers. As with any study of recent history, we cannot take a fully objective approach, as our personal experiences will skew our judgment. Our interview participants also only represent the views of senior researchers. A study of current students, junior faculty, and other younger authors and the “tricks” and “hacks” they use in their papers would be excellent future work.

Additionally, we have only scratched the surface of the media archaeology of the research paper, and there are numerous opportunities for future work. Alongside the patterns we analyze, sophisticated visual languages for system diagrams and renderings of visual features have developed. We encourage researchers to study these visual languages more systematically. We have also neglected to discuss the relationship between these sorts of readings of research papers with the much larger field of information science and bibliometrics [6]. A more quantitative study which measures the relationships between visual features of research papers and the structures of citation graphs, or a modeling study like Weng et al. conduct on internet memes [108], may prove fruitful.

We worry that the stylistic conventions of the field may be constraining the types of ideas students and faculty are willing to pursue. While this is true for any set of disciplinary norms, the culture of benchmarks in computer vision fosters a particular mindset of technological determinism, where research becomes a matter of either finding the best performing model for an existing task or proposing a new task and constructing a benchmark dataset for it. Within this mindset, it seems inevitable that all possible visual perception tasks have computational solutions, and research is only a matter of finding them first.

We also worry that these stylistic conventions may be contributing to the safety and injustice issues which currently surround machine learning [16, 74]. If authors are under pressure to publish more and faster, it is easiest to do that by overstating the significance of completed work. There are a range of behaviors which contribute to this problem: from neglecting to explore the limitations of a method, to only showing favorable evaluations, to outright fabrication of results. While we do not claim that authors are engaging in such behaviors, we do observe a tendency to write papers like advertisements and only minimally discuss the downsides of advertised methods. These behaviors become problematic when engineers, stakeholders, and researchers in other fields who are unfamiliar with the reality of conference publishing may take the claims in papers at face value, and put minimally tested systems into production based on a general trust of computation and data.

6 Conclusion

In this paper, we have examined the commodification of researcher attention through the visual evidence in computer vision research papers. These changes lead authors to include teaser images, and the presence of teasers leads researchers to develop methods which can more easily be presented as products, ready-made for readers to download, use, and cite. Second, the results table allows researchers to demonstrate the effectiveness of their neural network methods, but then the expectation of comparison to other methods forces other kinds of papers into the same evaluation paradigm. Finally, desire for color figures led conferences to adopt digital proceedings, which has led authors to create content which cannot be viewed on paper, necessitating screen-based reading. Through Bueno, we interpret attention as a necessary form of labor in academic publishing. These trends shift that labor onto the attention of researchers and especially peer reviewers. While better tools to support paper-reading (e.g. [20, 51, 85]) can help streamline this process and reduce the burden on individual scholars, the problem will persist unless scholarly communities address the commodification of scholarly attention. Generally, we recommend that conference organizers approach this situation as a systemic problem, and investigate measures to avoid competition between authors, slow the submission and peer review process, and search for more equitable and efficient ways of distributing attention and prestige.

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