INFO4990/INFO5993
CS RESEARCH METHODS

Week 6: Becoming Effective Consumers and Producers of Research

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We recognise and pay respect to the Elders and communities – past, present, and emerging – of the lands that the University of Sydney's campuses stand on. For thousands of years they have shared and exchanged knowledges across innumerable generations for the benefit of all.

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Why Research Methods?

- Foundation of computer science research
- Guides you through the research cycle
- Reading = *understanding others' work* (e.g., new AI models, algorithms)
- Writing = *communicating your own work* (e.g., conference/journal papers)
- Builds **critical thinking** and **research ethics**

📖 (Reading) → "Input / Learning" ⇔ ✍️ (Writing) → "Output / Sharing"

The Computer Science Research Lifecycle

- **Literature Review** → learn what exists
- **Problem Identification & Motivation** → find gaps or challenges
- **Research Design & Methodology** → plan your approach
- **Research Execution** → experiments, proofs, prototypes
- **Data Analysis & Interpretation** → make sense of results
- **Dissemination & Publication** → share with community

How to Read a Paper

Types of Computer Science Papers

- **Conference Papers –** timely, competitive, peer-reviewed
- **Journal Papers –** in-depth, refined, peer-reviewed
- **Survey Papers –** broad overview of a field, highlight trends & gaps
- **Technical Reports –** early-stage work, often internal or preprints
- **Book Chapters –** foundational or background knowledge

A Sample Survey Paper

A Survey of 3D Reconstruction with Event Cameras

Chuanzhi Xu, Haoxian Zhou, Langyi Chen, Haodong Chen, Ying Zhou, Vera Chung, Qiang Qu†, Weidong Cai
School of Computer Science, The University of Sydney, NSW, Australia

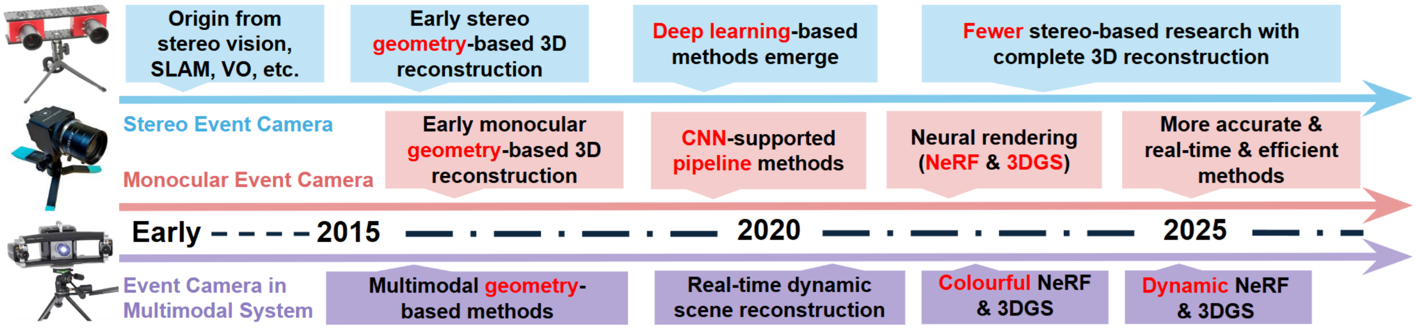

Fig. 1: **Roadmap of 3D reconstruction with event cameras.** It shows the development from event-based geometry to neural 3D rendering.

A Sample Survey Paper – Continued

TABLE X: Publicly available datasets for 3D reconstruction tasks with event cameras. (Abbr.: E = event stream, RGB = image frames, Li = LiDAR, IMU = inertial unit, Vcn = Vicon.)

Dataset	Venue (Year)	Type	Sensors / Resolution	Label	Size
MVSEC [80]	RA-L (2018)	Real	Stereo 346×260 E, Li, IMU, GPS	Point Cloud	30 GB
DHP19 [185]	CVPR (2019)	Real	4×346×260 E, Vcn	13-joint skeleton	30 GB
DSEC [93][83]	RA-L (2021)	Real	2×640×480 E, 2×1.4 MP RGB, Li, IMU	Depth Map (LiDAR)	150 GB
TUM-VIE [124]	IROS (2021)	Real	Stereo 1280×720 E, IMU 200 Hz, Vcn	Grayscale Frames	300 GB
ViViD++ [186]	RA-L (2022)	Real	Mono E + Thermal + Li	Pose	200 GB
MOEC-3D [106]	ECCV (2022)	Real	Mono E, laser mesh	Mesh	30 GB
EVIMO-2 [164]	Arxiv (2022)	Real	3×640×480 E, RGB, 2 IMU, Vcn	Object Pose	350 GB
EventScape [187]	RA-L (2021)	Synthetic	CARLA (E+RGB)	Dense Depth Maps	70 GB
EventNeRF [35]	CVPR (2023)	Synthetic	Mono E + RGB Refs	RGB Frame	18 GB
SynthEVox3D [95]	ICVR (2023)	Synthetic	Mono E (E2V) from Blender Simulator	Voxel Grid	32 GB
SEVD [188]	Arxiv (2024)	Synthetic	CARLA multiview E+RGB	Depth Map, Masks	300 GB
DAVIS240C [101]	IJRR (2017)	Real + Synthetic	Mono 240×180 E, IMU	Pose	10 GB

VII. Research Gaps & Future Direction

Despite recent advances, event-driven 3D reconstruction still faces key challenges across simulation, evaluation, modelling, and deployment.

Standardised datasets and benchmarks: The lack of standardised datasets poses significant challenges. Existing datasets are either too limited, private, or inconsistent in terms of data formats, annotations, and scenarios. Consequently, researchers face difficulties in fair method comparison and reproducibility [26]. Future research should focus on developing comprehensive, publicly available datasets tailored

Should I Read This Paper?

- **Relevance –** Does it address your research question?
- **Field –** Even outside your area, can it inspire methods or ideas?
- **Authors –** Are they well-known or active in the field? (Top Uni/Lab)
- **Venue –** Conference, journal, or technical report? (Check CORE ranking if applicable)
- **Publication Date & Impact –** Recent work or classic? How often cited?

Not Relevant	Read Briefly	Read In-depth	Read deeply enough to replicate

Structure of a CS Research Paper

- 📜 **Abstract** – summary of problem, approach, results
- ✍️ **Introduction –** motivation, scope, research questions
- 🔗 **Related Work** – what others have done, gaps in literature
- ⚙️ **Methodology** – approach, algorithms, system design, or framework
- 📊 **Experiments / Results** – evaluation, benchmarks, comparisons
- 🎯 **Conclusion & Future Directions –** key contributions, limitations, next steps

Abstract: The Heart of a Paper

- **Purpose:** captures the essence of the research
- Should answer:
  - What problem is being addressed?
  - What approach is proposed?
  - What are the results?

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

An experienced researcher should grasp the paper's main idea from the abstract alone

The Introduction: Setting the Stage

- Welcomes **and guides the reader**
- Explains **why the problem matters**
- Frames the **scope** and **definitions**
- Outlines the **research questions/objectives**
- Provides a **personal story or motivation**

Methodology: The Core Contribution

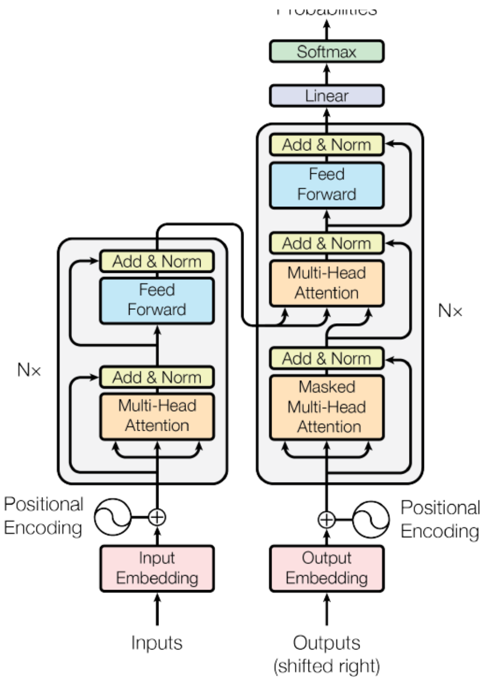

Figure 1: The Transformer - model architecture.

- Explains the **main contribution** of the paper
- Details the **approach, algorithms, or framework**
- May include **mathematical models, pseudocode, or system design**
- If available: **source code** to support reproducibility
- Readers should understand **how** the research was done, not just **what** was done

Experiments & Results: Evidence for Claims

- Demonstrates whether the approach **works in practice**
- Includes:
    - **Performance metrics** (e.g., accuracy, latency)
    - **Benchmarks** vs. existing methods
    - **Comparative analysis** (tables, graphs, ablation studies)
- Should show both **strengths and weaknesses**
- Results must be **interpretable and reproducible**

How to Read a Paper Effectively

- Don't read linearly from start to finish
- Use multiple passes:
  - **First pass –** skim (title, abstract, figures, conclusion)
  - **Second pass –** read methods & results carefully
  - **Third pass –** deep critical read (verify claims, question assumptions)
- Highlight and leave comments
- Focus on **understanding the story**, not every technical detail on first read

Questions to Ask While Reading

- What is the **topic** and **purpose** of the research?
- What do I already know about this topic?
- What **methods** were used — are they appropriate?
- Do the **results** agree with or challenge prior work?
- Do I agree with the authors' **conclusions**? Why or why not?

Turning Results into Research Questions

- Don’t stop at “this paper is perfect” — **look for gaps**
- Ask:
  - If results are strong → what about **efficiency**?
  - If efficiency is high → what about **robustness**?
  - If robustness is shown → what about **generalization**?
- Every result opens new questions → opportunities for research

Activity: Should I Read This Paper?

- Read the **abstracts** provided (2–3 short samples).
- Decide:
  - **Not Relevant** ❌
  - **Read Briefly** 🟡
  - **Read In-depth** ✅
  - **Read Deeply Enough to Replicate** 🔁
- Discuss in pairs: *Why did you classify it that way?*

Sample abstracts – Adam, MoCo, DDPM

Abstract

We introduce *Adam*, an algorithm for first-order gradient-based optimization of stochastic objective functions, based on adaptive estimates of lower-order moments. The method is straightforward to implement, is computationally efficient, has little memory requirements, is invariant to diagonal rescaling of the gradients, and is well suited for problems that are large in terms of data and/or parameters. The method is also appropriate for non-stationary objectives and problems with very noisy and/or sparse gradients. The hyper-parameters have intuitive interpretations and typically require little tuning. Some connections to related algorithms, on which *Adam* was inspired, are discussed. We also analyze the theoretical convergence properties of the algorithm and provide a regret bound on the convergence rate that is comparable to the best known results under the online convex optimization framework. Empirical results demonstrate that Adam works well in practice and compares favorably to other stochastic optimization methods. Finally, we discuss *AdaMax*, a variant of *Adam* based on the infinity norm.

Abstract

We present Momentum Contrast (MoCo) for unsupervised visual representation learning. From a perspective on contrastive learning [29] as dictionary look-up, we build a dynamic dictionary with a queue and a moving-averaged encoder. This enables building a large and consistent dictionary on-the-fly that facilitates contrastive unsupervised learning. MoCo provides competitive results under the common linear protocol on ImageNet classification. More importantly, the representations learned by MoCo transfer well to downstream tasks. MoCo can ***outperform*** *its supervised pre-training counterpart in* ***7*** *detection/segmentation tasks on PASCAL VOC, COCO, and other datasets, sometimes surpassing it by large margins. This suggests that the gap between unsupervised and supervised representation learning has been largely closed in many vision tasks.*

Abstract

We present high quality image synthesis results using diffusion probabilistic models, a class of latent variable models inspired by considerations from nonequilibrium thermodynamics. Our best results are obtained by training on a weighted variational bound designed according to a novel connection between diffusion probabilistic models and denoising score matching with Langevin dynamics, and our models naturally admit a progressive lossy decompression scheme that can be interpreted as a generalization of autoregressive decoding. On the unconditional CIFAR10 dataset, we obtain an Inception score of 9.46 and a state-of-the-art FID score of 3.17. On 256x256 LSUN, we obtain sample quality similar to ProgressiveGAN. Our implementation is available at `https://github.com/hojonathanho/diffusion`.

Decide:

- **Not Relevant**
- **Read Briefly**
- **Read In-depth**
- **Read Deeply Enough to Replicate**

How to Write a Paper

Why Do We Write Research Papers?

- **Who is the audience?**
  - Supervisor 👨‍🏫
  - Research group 👩‍🔬 👨‍💻
  - Conference / Journal community 🌍
- **What are you trying to achieve?**
  - To **inform** (share findings)
  - To **analyze & evaluate** (place work in context)
  - To **persuade** (convince others of importance)

Tailoring Your Paper to the Audience

- **Supervisor –** knows your field, but expects clarity & rigor
- **Research Group –** mixed expertise; provide context & background
- **Conference / Journal –** diverse, international; assume less prior knowledge
- Don’t assume **everyone is an expert**
- Provide background in manageable “chunks”

Structure of a CS Research Paper

- 📜 **Abstract –** summary of problem, approach, results
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- 🔗 **Related Work –** what others have done, gaps in literature
- ⚙️ **Methodology –** approach, algorithms, system design, or framework
- 📊 **Experiments / Results –** evaluation, benchmarks, comparisons
- 🎯 **Conclusion & Future Directions –** key contributions, limitations, next steps

Abstract vs. Introduction: What’s the Difference?

- 📜 **Abstract**
  - Short (150–250 words)
  - Snapshot of the entire paper
  - Answers: Problem, Approach, Results
  - Read independently

- ✍️ **Introduction**
  - Longer (1–2 pages)
  - Motivates why the problem matters
  - Defines scope, context, research questions
  - Outlines structure of the paper

Related Work: Placing Your Research in Context

- Summarizes **prior work directly relevant** to your research
- Organized by **themes**, not just chronological listing
- Shows **what has been done** and **what gaps remain**
- Avoid value judgments (e.g., don’t say “poor work”)
- Helps readers see **your contribution’s novelty**

Results: Showing the Evidence

- Present results **clearly & accurately**
- Use **tables, graphs, and figures** to highlight findings
- Report **measurement uncertainties** (e.g., 3.24 ± 0.01)
- Show both **quantitative results (**metrics, numbers, benchmarks) and **qualitative results** (examples, case studies, visualizations)
- Avoid cherry-picking → include both positive and negative results
- Follow **widely used evaluation protocols** (datasets, metrics, baselines) for fair comparisons

Results: Quantitative Results and Qualitative Results

TABLE I

QUANTITATIVE EVALUATION OF VARIOUS NO-REFERENCE QUALITY ASSESSMENT METHODS ACROSS THE FIELDWORK, LLFF, AND LAB DATASETS, INCLUDING MEANS AND STANDARD DEVIATIONS OF SRCC, PLCC, AND KRCC. FOR EACH COLUMN, THE BEST RESULTS ARE HIGHLIGHTED IN BOLD, WITH THE CONCLUDING ROW INDICATING THE ENHANCEMENT RELATIVE TO THE SECOND-BEST RESULT.

	Fieldwork			LLFF			Lab		
Method	SRCC ↑ (std)	PLCC ↑ (std)	KRCC ↑ (std)	SRCC ↑ (std)	PLCC ↑ (std)	KRCC ↑ (std)	SRCC ↑ (std)	PLCC ↑ (std)	KRCC ↑ (std)
TV	0.378 (0.64)	0.423 (0.58)	0.311 (0.62)	0.087 (0.65)	0.050 (0.61)	0.075 (0.52)	0.200 (0.48)	0.136 (0.30)	0.229 (0.36)
BRISQUE	0.089 (0.58)	0.152 (0.58)	0.067 (0.53)	−0.037 (0.54)	−0.103 (0.45)	−0.050 (0.44)	0.214 (0.83)	0.204 (0.72)	0.171 (0.70)
NIQE	0.467 (0.63)	0.331 (0.66)	0.400 (0.56)	0.025 (0.50)	−0.077 (0.43)	0.025 (0.42)	−0.357 (0.16)	−0.329 (0.12)	−0.314 (0.17)
PIQE	0.079 (0.49)	−0.079 (0.55)	0.273 (0.57)	0.047 (0.56)	−0.079 (0.47)	−0.021 (0.44)	−0.364 (0.65)	−0.060 (0.70)	−0.302 (0.49)
CLIP-IQA	0.233 (0.63)	0.178 (0.57)	0.200 (0.54)	0.025 (0.47)	−0.046 (0.36)	0.025 (0.34)	−0.057 (0.50)	−0.240 (0.47)	−0.086 (0.36)
CONTRIQUE	0.689 (0.28)	0.759 (0.29)	0.622 (0.29)	0.350 (0.40)	0.400 (0.50)	0.275 (0.33)	0.086 (0.43)	0.200 (0.53)	0.057 (0.36)
Re-IQA	0.589 (0.53)	0.585 (0.48)	0.489 (0.44)	0.062 (0.71)	−0.018 (0.71)	0.025 (0.61)	0.143 (0.16)	0.213 (0.30)	0.200 (0.10)
VIIDEO	0.022 (0.37)	0.070 (0.44)	0.022 (0.28)	−0.050 (0.49)	0.002 (0.49)	−0.000 (0.39)	0.000 (0.27)	0.061 (0.47)	−0.029 (0.30)
Video-BIIINDS	0.189 (0.39)	0.148 (0.41)	0.156 (0.31)	0.162 (0.44)	0.051 (0.40)	0.175 (0.38)	−0.314 (0.33)	−0.113 (0.42)	−0.286 (0.33)
FAST-VQA	0.167 (0.59)	0.106 (0.59)	0.122 (0.46)	0.112 (0.55)	0.255 (0.55)	0.185 (0.41)	−0.171 (0.65)	−0.191 (0.63)	−0.186 (0.52)
FasterVQA	0.186 (0.51)	0.245 (0.55)	0.172 (0.47)	0.162 (0.58)	0.176 (0.49)	0.125 (0.48)	−0.129 (0.46)	−0.175 (0.44)	−0.186 (0.38)
DOVER	0.200 (0.56)	0.267 (0.65)	0.267 (0.50)	0.150 (0.61)	0.153 (0.47)	0.125 (0.48)	−0.129 (0.26)	−0.209 (0.18)	−0.214 (0.22)
DOVER-Mobile	0.344 (0.60)	0.341 (0.61)	0.311 (0.47)	0.200 (0.47)	0.254 (0.36)	0.125 (0.40)	−0.071 (0.47)	−0.097 (0.32)	−0.143 (0.46)
NR-LFQA	0.207 (0.52)	0.157 (0.56)	0.149 (0.42)	0.088 (0.47)	0.106 (0.34)	0.114 (0.37)	−0.094 (0.59)	−0.067 (0.57)	−0.039 (0.51)
Tensor-NLFQ	0.282 (0.42)	0.290 (0.49)	0.202 (0.43)	0.223 (0.38)	0.210 (0.36)	0.125 (0.29)	−0.061 (0.64)	−0.064 (0.57)	−0.072 (0.55)
ALAS-DADS	0.356 (0.49)	0.183 (0.54)	0.244 (0.40)	0.138 (0.35)	0.125 (0.34)	0.050 (0.38)	0.043 (0.59)	0.166 (0.59)	0.029 (0.48)
LFACon	0.333 (0.44)	0.310 (0.47)	0.242 (0.33)	0.412 (0.48)	0.395 (0.31)	0.325 (0.36)	0.157 (0.60)	0.132 (0.53)	0.086 (0.51)
Proposed	**0.911** (0.08)	**0.883** (0.11)	**0.822** (0.16)	**0.700** (0.28)	**0.644** (0.39)	**0.625** (0.19)	**0.700** (0.04)	**0.678** (0.10)	**0.571** (0.09)
V.S. 2nd Best	**+0.222 +32.3%**	**+0.124 +16.4%**	**+0.200 +32.1%**	**+0.287 +69.7%**	**+0.245 +61.2%**	**+0.300 +92.3%**	**+0.486 +226.7%**	**+0.465 +218.3%**	**+0.343 +150.0%**

Scene [Giraffe] Synthesized by NVS methods (NeRF) and (IBRNet-C)

Human, and NVS-SQA Preferences | *PSNR, SSIM, and LPIPS Preferences*

Reason: The right NSS exhibits noticeable blurring and missing content.

Scene [Intr-Animals] Synthesized by NVS methods (DVGO) and (LFNR)

PSNR, SSIM, and LPIPS Preferences | *Human, and NVS-SQA Preferences*

Reason: The left NSS shows clear artifacts highlighted by red boxes.

Scene [Orchids] Synthesized by NVS methods (GNT-C) and (NeX)

PSNR, SSIM, and LPIPS Preferences | *Human, and NVS-SQA Preferences*

Reason: The left NSS displays inconsistent color hues across views.

Fig. 8. **Example NSS generated by various NVS methods.** In all cases, the proposed NeRF-NQA aligns with human preferences without references, whereas the prevalent full-reference methods PSNR, SSIM, and LPIPS fall short. (zoom in for a clearer view)

Conclusion & Future Directions

- **Summarize key contributions** clearly and concisely
- Reflect on the **significance** of your results
- Acknowledge **limitations** honestly
- Suggest **future directions** and open problems
- Leave readers with a **final takeaway message**

Writing Tips for Clear & Effective Papers

- 🎯 **Know your audience –** tailor explanations & background
- 📝 **Use clear structure –** each section has a distinct role
- ✍️ **Strong paragraphs –** topic sentence + support + conclusion
- 🔤 **Define terms & abbreviations** on first use
- 🧩 **Use CS terminology correctly –** don’t invent new terms unnecessarily
- 🔎 **Check spelling & grammar –** small errors reduce credibility

Common Traps to Avoid

- ❌ **Poor paraphrasing –** copying too closely without originality
- ⚠️ **Plagiarism –** unclear about what’s yours vs. others’ work
- 📚 **Bad citations –** missing, incorrect, or inaccurate references
- 🕓 **Procrastination –** delaying writing until the last minute
- 🤖 **Misuse of AI tools –** unverified outputs, hallucinated references, blind trust

Becoming a Researcher in Computer Science

- 🔍 **Read with purpose –** don’t just absorb, question and critique
- ✍️ **Write with clarity –** your ideas are only as strong as your communication
- ⚖️ **Respect ethics –** originality, honesty, reproducibility
- 🌍 **Engage the community –** research is a conversation, not a monologue
- 🚀 **Think beyond results –** every paper is a stepping stone to new questions