Tipos de publicaciones y métricas

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Types of publications

- Thesis
- Research paper
- Review
- Survey

Others:

- Extended abstract
- Poster

Thesis

- Document containing the research and findings that students submit to get the professional qualification or degree.
- In a thesis, the researcher puts forth his/her conclusion. The researcher also gives evidence in support of the conclusion.
- The thesis contains a **broader description of the subject matter**. In contrast, the research paper contains a **narrow description** of the subject matter.

Survey

- According to the definition of survey paper provided by IEEE Communications Surveys & Tutorials journal , "The term survey, as applied here, is defined to mean a survey of the literature. **A survey article should provide a comprehensive review of developments in a selected area**".
- In ACM Computing Survey , survey paper is described as “A paper that **summarizes and organizes recent research results** in a novel way that integrates and adds understanding to work in the field. A survey article emphasizes the **classification of the existing literature,** developing a perspective on the area, and evaluating trends.”
- In Elsevier journal of Computer Science Review, you will see here that “**Critical review of the relevant literature**“ is required a component of every typical survey paper.

Survey

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Survey paper

A comprehensive survey of clustering algorithms: State-of-the-art machine learning applications, taxonomy, challenges, and future research prospects

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A R T I C L E I N F O

Keywords:
Clustering
Clustering algorithms, partitioning
Data mining
Hierarchical clustering
Automatic clustering
K-Means
Optimization algorithms, Machine learning
Unsupervised learning
Supervised learning

A B S T R A C T

Clustering is an essential tool in data mining research and applications. It is the subject of active research in many fields of study, such as computer science, data science, statistics, pattern recognition, artificial intelligence, and machine learning. Several clustering techniques have been proposed and implemented, and most of them successfully find excellent quality or optimal clustering results in the domains mentioned earlier. However, there has been a gradual shift in the choice of clustering methods among domain experts and practitioners alike, which is precipitated by the fact that most traditional clustering algorithms still depend on the number of clusters provided a priori. These conventional clustering algorithms cannot effectively handle real-world data clustering analysis problems where the number of clusters in data objects cannot be easily identified. Also, they cannot effectively manage problems where the optimal number of clusters for a high-dimensional dataset cannot be easily determined. Therefore, there is a need for improved, flexible, and efficient clustering techniques. Recently, a variety of efficient clustering algorithms have been proposed in the literature, and these algorithms produced good results when evaluated on real-world clustering problems. This study presents an up-to-date systematic and comprehensive review of traditional and state-of-the-art clustering techniques for different domains. This survey considers clustering from a more practical perspective. It shows the outstanding role of clustering in various disciplines, such as education, marketing, medicine, biology, and bioinformatics. It also discusses the application of clustering to different fields attracting intensive efforts among the scientific community, such as big data, artificial intelligence, and robotics. This survey paper will be beneficial for both practitioners and researchers. It will serve as a good reference point for researchers and practitioners to design improved and efficient state-of-the-art clustering algorithms.

1. Introduction

Clustering (an aspect of data mining) is considered an active method of grouping data into many collections or clusters according to the similarities of data points features and characteristics (Jain, 2010; Abualigah, 2019). Over the past years, dozens of data clustering techniques have been proposed and implemented to solve data clustering problems (Zhou et al., 2019; Abualigah et al., 2018a,b). In general, clustering analysis techniques can be divided into two main groups: hierarchical and partitional (Tan, 2018). Although methods in these two groups have proved to be very effective and efficient, they generally depend on providing prior knowledge or information of the exact number of clusters for each dataset to be clustered and analyzed (Chang et al., 2010). More so, when dealing with real-world datasets, it is normal not to expect or have any prior information regarding the number of naturally occurring groups in the data objects (Liu et al., 2011). Therefore, the concept of automatic data clustering algorithms is introduced to address this limitation. Automatic clustering algorithms refer to any clustering techniques used to automatically determine

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Explainable Reinforcement Learning: A Survey

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Abstract. Explainable Artificial Intelligence (XAI), i.e., the development of more transparent and interpretable AI models, has gained increased traction over the last few years. This is due to the fact that, in conjunction with their growth into powerful and ubiquitous tools, AI models exhibit one detrimental characteristic: a performance-transparency trade-off. This describes the fact that the more complex a model's inner workings, the less clear it is how its predictions or decisions were achieved. But, especially considering Machine Learning (ML) methods like Reinforcement Learning (RL) where the system learns autonomously, the necessity to understand the underlying reasoning for their decisions becomes apparent. Since, to the best of our knowledge, there exists no single work offering an overview of Explainable Reinforcement Learning (XRL) methods, this survey attempts to address this gap. We give a short summary of the problem, a definition of important terms, and offer a classification and assessment of current XRL methods. We found that a) the majority of XRL methods function by mimicking and simplifying a complex model instead of designing an inherently simple one, and b) XRL (and XAI) methods often neglect to consider the human side of the equation, not taking into account research from related fields like psychology or philosophy. Thus, an interdisciplinary effort is needed to adapt the generated explanations to a (non-expert) human user in order to effectively progress in the field of XRL and XAI in general.

Keywords: Machine learning · Explainable · Reinforcement Learning · Human-computer interaction · Interpretable

1 Introduction

Over the past decades, AI has become ubiquitous in many areas of our everyday lives. Especially Machine Learning (ML) as one branch of AI has numerous fields of application, be it transportation [57], advertisement [46], or medicine [38]. Unfortunately, the more powerful and flexible those models are, the more opaque they become, essentially making them black boxes (see Fig. 1). This trade-off is

A. Holzinger et al. (Eds.): CD-MAKE 2020, LNCS 12279, pp. 77–95, 2020.
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Review

Involves the collection of all the relevant literature on a topic. However, unlike a survey article, it additionally **discusses the metadata from the surveyed literature** to technically **compare different studies**, **draws conclusions on their weaknesses and strengths**, and **proposes future directions**.

Trustworthy Artificial Intelligence: A Review

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Artificial intelligence (AI) and algorithmic decision making are having a profound impact on our daily lives. These systems are vastly used in different high-stakes applications like healthcare, business, government, education, and justice, moving us toward a more algorithmic society. However, despite so many advantages of these systems, they sometimes directly or indirectly cause harm to the users and society. Therefore, it has become essential to make these systems safe, reliable, and trustworthy. Several requirements, such as fairness, explainability, accountability, reliability, and acceptance, have been proposed in this direction to make these systems trustworthy. This survey analyzes all of these different requirements through the lens of the literature. It provides an overview of different approaches that can help mitigate AI risks and increase trust and acceptance of the systems by utilizing the users and society. It also discusses existing strategies for validating and verifying these systems and the current standardization efforts for trustworthy AI. Finally, we present a holistic view of the recent advancements in trustworthy AI to help the interested researchers grasp the crucial facets of the topic efficiently and offer possible future research directions.

CCS Concepts: • **Computing methodologies → Cross-validation**; **Intelligent agents**;

Additional Key Words and Phrases: Artificial intelligence, machine learning, black-box problem, trustworthy AI, explainable AI, fairness, explainability, accountability, privacy, acceptance

ACM Reference format:
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https://doi.org/10.1145/3491209

1 INTRODUCTION

Artificial intelligence (AI) and algorithmic decision making are transforming our lives. In today's world, most of our day-to-day tasks are either done or guided by machines or algorithms. This area of algorithmic decision making is not new. We have been using machines for decision making for a long time. However, today these systems have become very efficient and complex because of the availability of vast data, advanced algorithms, and high computing power. It has

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Systematic Review

A systematic review is more exhaustive than a literature review as it includes both published and unpublished literature. Further, a systematic review sets out to address a question and does so by a **thorough review of existing literature** (based on an appropriate **search methodology** for a systematic search) and robust data extraction and analysis techniques.

Review

Characteristics of publicly available skin cancer image datasets: a systematic review

David Wen, Saad M Khan, Antonio Ji Xu, Hussein Ibrahim, Luke Smith, Jose Caballero, Luis Zepeda, Carlos de Blas Perez, Alastair K Denniston, Xiaoxuan Liu*, Rubeta N Matin*

Publicly available skin image datasets are increasingly used to develop machine learning algorithms for skin cancer diagnosis. However, the total number of datasets and their respective content is currently unclear. This systematic review aimed to identify and evaluate all publicly available skin image datasets used for skin cancer diagnosis by exploring their characteristics, data access requirements, and associated image metadata. A combined MEDLINE, Google, and Google Dataset search identified 21 open access datasets containing 106 950 skin lesion images, 17 open access atlases, eight regulated access datasets, and three regulated access atlases. Images and accompanying data from open access datasets were evaluated by two independent reviewers. Among the 14 datasets that reported country of origin, most (11 [79%]) originated from Europe, North America, and Oceania exclusively. Most datasets (19 [91%]) contained dermoscopic images or macroscopic photographs only. Clinical information was available regarding age for 81 662 images (76·4%), sex for 82 848 (77·5%), and body site for 79 561 (74·4%). Subject ethnicity data were available for 1415 images (1·3%), and Fitzpatrick skin type data for 2236 (2·1%). There was limited and variable reporting of characteristics and metadata among datasets, with substantial under-representation of darker skin types. This is the first systematic review to characterise publicly available skin image datasets, highlighting limited applicability to real-life clinical settings and restricted population representation, precluding generalisability. Quality standards for characteristics and metadata reporting for skin image datasets are needed.

Lancet Digit Health 2022; 4: e64–74

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Introduction

Digital health innovation has the potential to improve health care by increasing access to specialist expertise.[1,2] Collaboration (ISIC) archive,[13] are increasingly used to develop machine learning algorithms for skin cancer diagnosis.[24–26] Additionally, although primarily aimed for

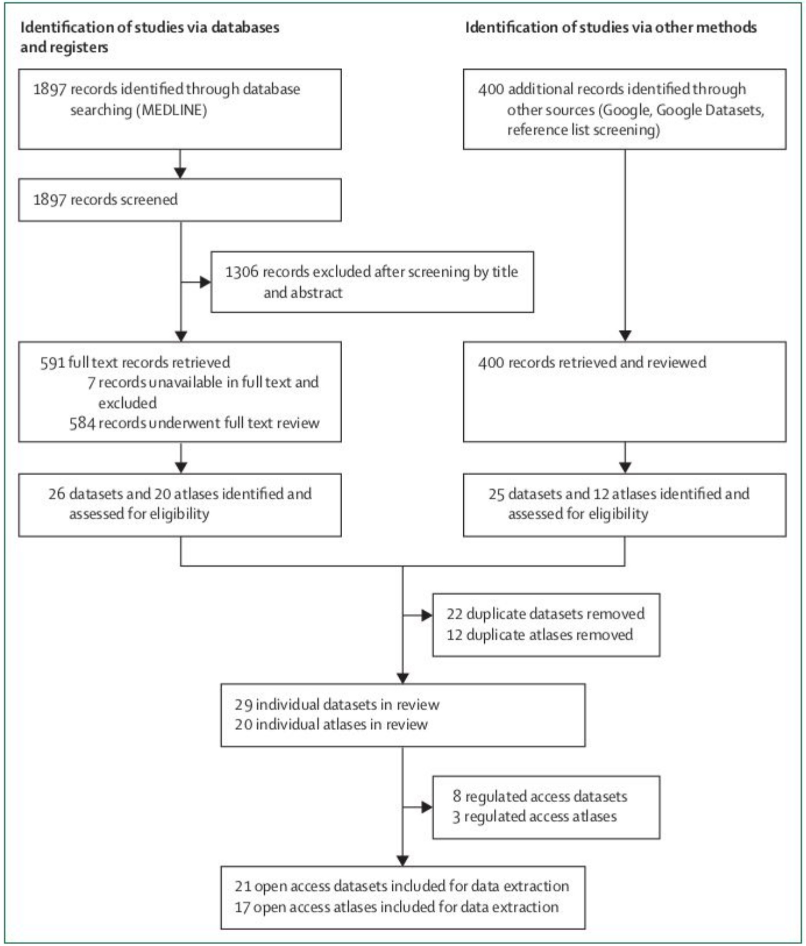

Figure 1: PRISMA flow diagram outlining dataset and atlas identification


Research Papers
Adapted from Stanford CS197

There are many genres

Even within areas, there exist many different genres of paper. Each genre is typically built around the claim you are making, and implies a structure to the sections and to the writing. For example:

We solve a problem: articulate the problem, explain what causes that problem and what others have done to deal with it, detail your approach, and prove that you make progress on the problem

We measure an outcome: explain that nobody has bothered understanding how a phenomenon behaves, explain how to create a study that sheds light, and report the outcomes of it

We introduce a technique: articulate a problem as above, but focus the narrative on the technique you've created, since it will generalize

Adapted from Stanford CS197

Genres imply structure

But, this will vary by area!

Common "We Solve A Problem" structure:

- Introduction: overview and thesis
- Related Work: situate your contribution relative to prior research
- Approach: describe your approach and important implementation details
- Evaluation: test whether your approach succeeds at its stated goals
    - Method
    - Results
- Discussion: reflect on limitations, implications, and future work
- Conclusion: summarize and restate your contribution

Adapted from Stanford CS197

Contribution Type

What type of contribution is your project making?

HCI: interaction technique, system, etc

AI: theory, system / architecture, etc.

Different contributions may have different paper structures or expectations for each paper section.

Adapted from Stanford CS197

Example: HCI (Interaction Technique)

Introduction

RW

System

User Study & Results

Discussion

Limitations & Future Work

Conclusion

In-Depth Mouse: Integrating Desktop Mouse into Virtual Reality

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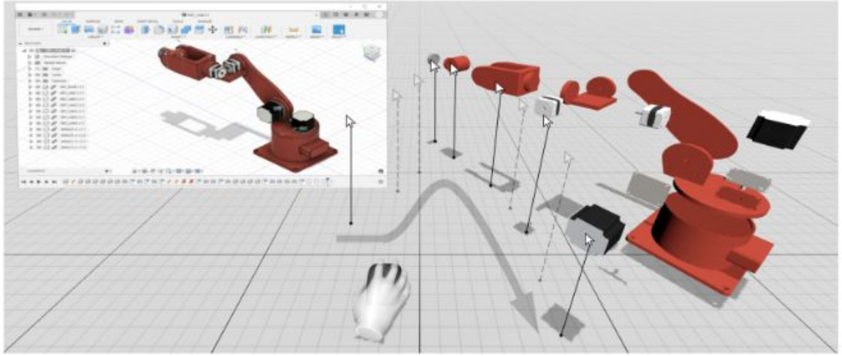


Figure 1: We investigate a technique that integrates a desktop mouse into VR to support productive knowledge work. Our approach uses *Depth-Adaptive Cursor*, a 2D-mouse driven pointing technique for 3D selection with depth-adaptation that continuously interpolates the cursor depth by inferring what users intend to select based on the cursor position, the viewpoint, and the selectable objects. Vertically dropped lines and arrow are added for illustration of depth.

ABSTRACT

Virtual Reality (VR) has potential for productive knowledge work, however, midair pointing with controllers or hand gestures does not offer the precision and comfort of traditional 2D mice. Directly integrating mice into VR is difficult as selecting targets in a 3D space is negatively impacted by binocular rivalry, perspective mismatch, and improperly calibrated control-display (CD) gain. To address these issues, we developed *Depth-Adaptive Cursor*, a ... that *Depth-Adaptive Cursor* significantly improved performance compared with an existing mouse-based pointing technique without depth-adaption in terms of time (21.2%), error (48.3%), perceived workload, and user satisfaction.

CCS CONCEPTS

• **Human-centered computing → Pointing; Virtual reality.**

Adapted from Stanford CS197

Example: HCI (Interaction Technique)

- Introduction
- RW
- System
- **User Study** & **Results**
- Discussion
- Limitations & Future Work
- Conclusion

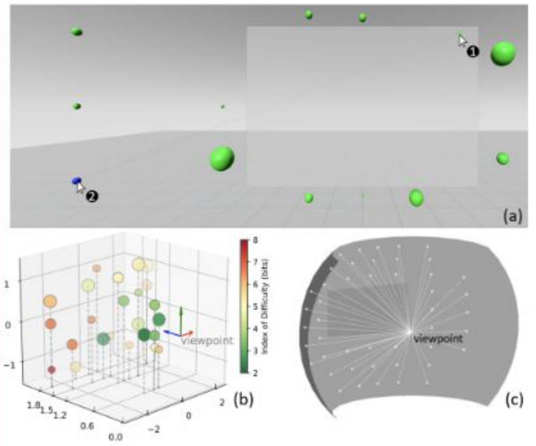
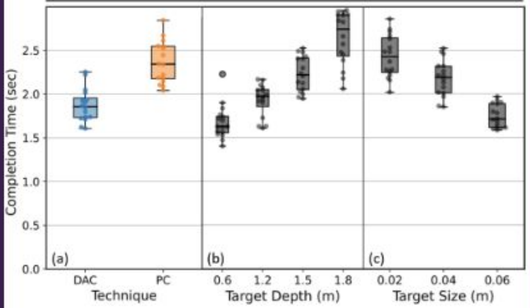


Figure 6: Setup of the 3D Pointing Task: (a) The task is to select an origin 2D target (a square on a 2D plane) and then again in a destination 3D target (a blue sphere in a 3D space). We use the combination of 2D and 3D targets to represent

Illustrate User Task

	F	p	η_p^2	Level	Mean	SE
(a) Technique	57.52	<.001	0.793	DAC	1.872	0.048
				PC	2.376	0.060
(b) Target Depth	86.12	<.001	0.852	0.6	1.676	0.049
				1.2	1.929	0.046
				1.5	2.231	0.051
				1.8	2.669	0.080
(c) Target Size	131.32	<.001	0.897	0.02	2.445	0.060
				0.04	2.179	0.052
				0.06	1.747	0.034



Statistical Results

Example: AI

Introduction

RW

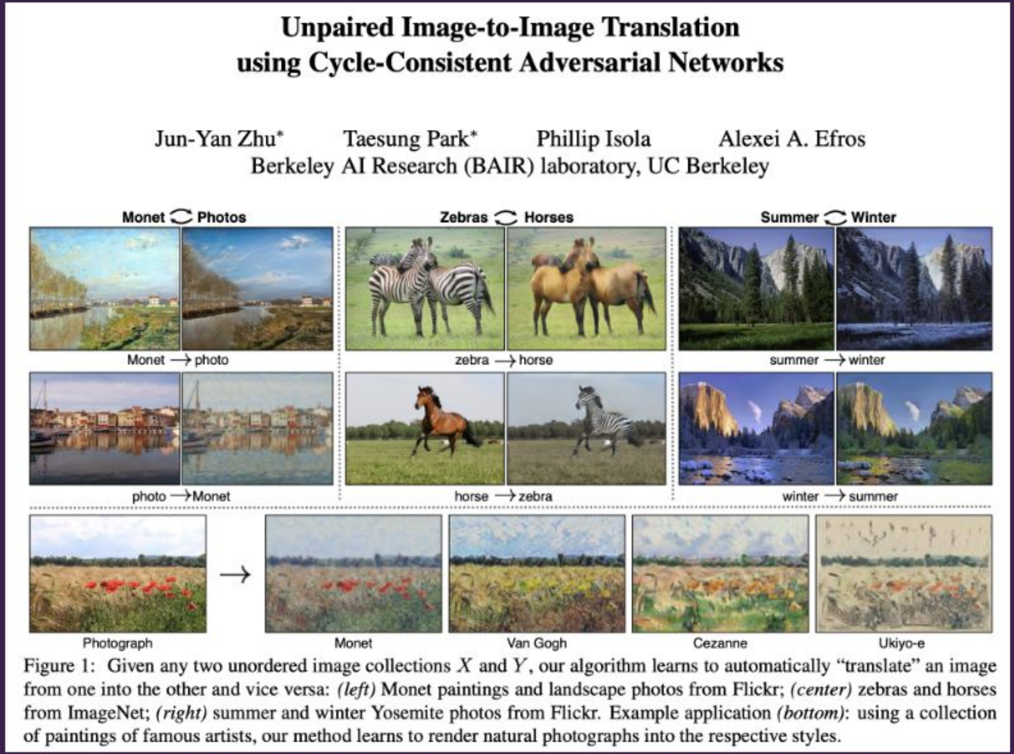
Method

Implementation

Evaluation

Limitations & Discussion

Conclusion


Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

Jun-Yan Zhu* Taesung Park* Phillip Isola Alexei A. Efros
Berkeley AI Research (BAIR) laboratory, UC Berkeley

Figure 1: Given any two unordered image collections X and Y, our algorithm learns to automatically "translate" an image from one into the other and vice versa: *(left)* Monet paintings and landscape photos from Flickr; *(center)* zebras and horses from ImageNet; *(right)* summer and winter Yosemite photos from Flickr. Example application *(bottom)*: using a collection of paintings of famous artists, our method learns to render natural photographs into the respective styles.

Example: AI

- Introduction
- RW
- **Method**
- Implementation
- Evaluation
- Limitations & Discussion
- Conclusion

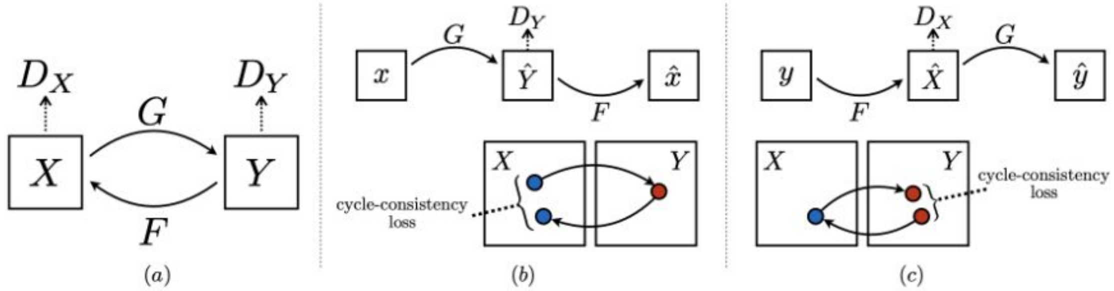


Figure 3: (a) Our model contains two mapping functions $G : X \rightarrow Y$ and $F : Y \rightarrow X$, and associated adversarial discriminators D_Y and D_X. D_Y encourages G to translate X into outputs indistinguishable from domain Y, and vice versa for D_X and F. To further regularize the mappings, we introduce two *cycle consistency losses* that capture the intuition that if

$$\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) = \mathbb{E}_{y \sim p_{\text{data}}(y)}[\log D_Y(y)] + \mathbb{E}_{x \sim p_{\text{data}}(x)}[\log(1 - D_Y(G(x)))], \quad (1)$$

$$\mathcal{L}_{\text{cyc}}(G, F) = \mathbb{E}_{x \sim p_{\text{data}}(x)}[\|F(G(x)) - x\|_1] + \mathbb{E}_{y \sim p_{\text{data}}(y)}[\|G(F(y)) - y\|_1].$$

$$\mathcal{L}(G, F, D_X, D_Y) = \mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) + \mathcal{L}_{\text{GAN}}(F, D_X, Y, X) + \lambda \mathcal{L}_{\text{cyc}}(G, F),$$

Adapted from Stanford CS197

Example: AI

Introduction

RW

Method

Implementation

Evaluation

Limitations & Discussion

Conclusion

Adapted from Stanford CS197

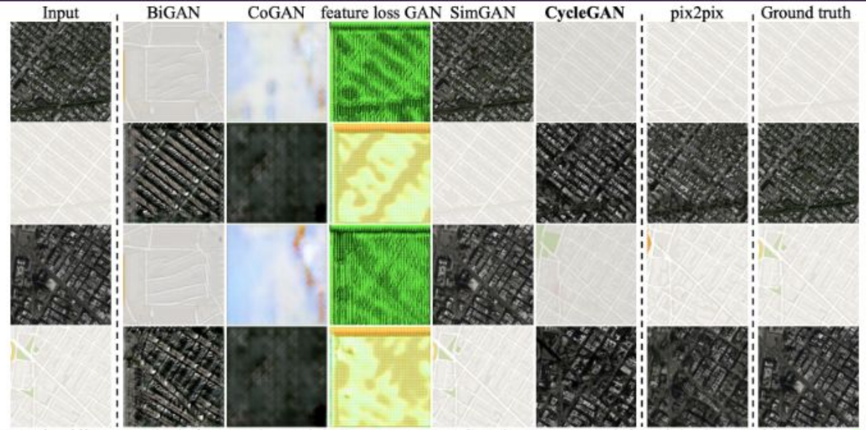


Figure 6: Different methods for mapping aerial photos↔maps on Google Maps. From left to right: input, BiGAN/ALI [7, 9], CoGAN [32], feature loss + GAN, SimGAN [46], CycleGAN (ours), pix2pix [22] trained on paired data, and ground truth.

Loss	Map → Photo % Turkers labeled *real*	Photo → Map % Turkers labeled *real*
CoGAN [32]	0.6% ± 0.5%	0.9% ± 0.5%
BiGAN/ALI [9, 7]	2.1% ± 1.0%	1.9% ± 0.9%
SimGAN [46]	0.7% ± 0.5%	2.6% ± 1.1%
Feature loss + GAN	1.2% ± 0.6%	0.3% ± 0.2%
CycleGAN (ours)	**26.8% ± 2.8%**	**23.2% ± 3.4%**

Table 1: AMT “real vs fake” test on maps↔aerial photos at 256 × 256 resolution.

Loss	Per-pixel acc.	Per-class acc.	Class IOU
CoGAN [32]	0.40	0.10	0.06
BiGAN/ALI [9, 7]	0.19	0.06	0.02
SimGAN [46]	0.20	0.10	0.04
Feature loss + GAN	0.06	0.04	0.01
CycleGAN (ours)	**0.52**	**0.17**	**0.11**
pix2pix [22]	0.71	0.25	0.18

Table 2: FCN-scores for different methods, evaluated on Cityscapes labels→photo.

Loss	Per-pixel acc.	Per-class acc.	Class IOU
CoGAN [32]	0.45	0.11	0.08
BiGAN/ALI [9, 7]	0.41	0.13	0.07
SimGAN [46]	0.47	0.11	0.07
Feature loss + GAN	0.50	0.10	0.06
CycleGAN (ours)	**0.58**	**0.22**	**0.16**

Loss	Per-pixel acc.	Per-class acc.	Class IOU
Cycle alone	0.22	0.07	0.02
GAN alone	0.51	0.11	0.08
GAN + forward cycle	**0.55**	**0.18**	**0.12**
GAN + backward cycle	0.39	0.14	0.06
CycleGAN (ours)	0.52	0.17	0.11

Table 4: Ablation study: FCN-scores for different variants of our method, evaluated on Cityscapes labels→photo.

Loss	Per-pixel acc.	Per-class acc.	Class IOU
Cycle alone	0.10	0.05	0.02
GAN alone	0.53	0.11	0.07
GAN + forward cycle	0.49	0.11	0.07
GAN + backward cycle	0.01	0.06	0.01
CycleGAN (ours)	**0.58**	**0.22**	**0.16**

Table 5: Ablation study: classification performance of photo→labels for different losses, evaluated on Cityscapes.

method, on the other hand, can produce translations that are often of similar quality to the fully supervised pix2pix.

Table 1 reports performance regarding the AMT perceptual realism task. Here, we see that our method can fool participants on around a quarter of trials, in both the

Typical gold standard: conference

Computer Science, unlike other fields, is a conference-oriented field.

There are a small set of top-tier conferences for each area. These are generally known to be the venues that publish the best work in the area.

There also exist a variety of second-tier and other conferences, which are less prestigious and often easier to get into.

Journals, and conference-journal hybrids, fit into this category too.

Adapted from Stanford CS197

Work-in-progress venues

You can only publish a research result once. Conferences and journals are known as **archival**, meaning that they are archived permanently in the academic record.

There also exist a variety of **non-archival venues** that are intended for feedback and exposure.

- Workshops
- Posters
- Demos
- arXiv.org

Adapted from Stanford CS197

Work-in-progress venues

You can only publish a research result once. Conferences and journals are known as **archival**, meaning that they are archived permanently in the academic record.

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- Workshops
- Posters
- Demos
- arXiv.org

Top conferences and journals

- Databases and Data Management:
  - VLDB, SIGMOD, ICDE
- Data Mining:
  - KDD, WWW
- HCI:
  - CHI, UIST, InfoVis
- Machine Learning:
  - NeurIPS (formerly NIPS), ICML, ICLR, AAAI
  - CVPR (vision), ACL (NLP), EMNLP (NLP)

[Conference Ranks]()

Conference Data

Search: eccv

Name	Abbrv.	Rank	Source
European Conference on Computer Vision	ECCV	A	ERA
European Conference on Computer Vision	ECCV	A1	Qualis
Name	**Abbrv.**	**Rank**	**Source**

Research metrics

- Research metrics are quantitative measurements designed to evaluate research outputs and their impacts.
  - journal, a journal article, a book, book chapter or the overall research productivity
- Metrics include a variety of measures and statistical methods for assessing the **quality** and **broader impact** of scientific and scholarly research.

Research metrics

They fall into 2 categories, bibliometrics and altmetrics.

- **Bibliometrics** are the traditional **citation** based metrics. They are based on citation counts, counting how many times a publication has been cited in another publication.
- **Altmetrics** are **web based metrics**. They are used for measuring the attention or the interest of a scholarly work on various types of online platforms that includes social media, research blogs, forums, etc.

The use of both types of metrics contribute to evaluate and understand the impact of a research

Example:

https://www.nature.com/articles/s42256-019-0048-x

Access & Citations

67k	1990	2329
Article Accesses	Web of Science	CrossRef

Online attention

- 391 tweeters
- 30 news outlets
- 8 Wikipedia page
- 3342 Mendeley
- 12 blogs
- 1 F1000
- 1 Facebook pages
- 1 Video uploaders

This article is in the 99th percentile (ranked 1,007th) of the 355,676 tracked articles of a similar age in all journals and the 96th percentile (ranked 2nd) of the 27 tracked articles of a similar age in *Nature Machine Intelligence*

View more on Altmetric

Metrics for Journals: Journal Impact Factor

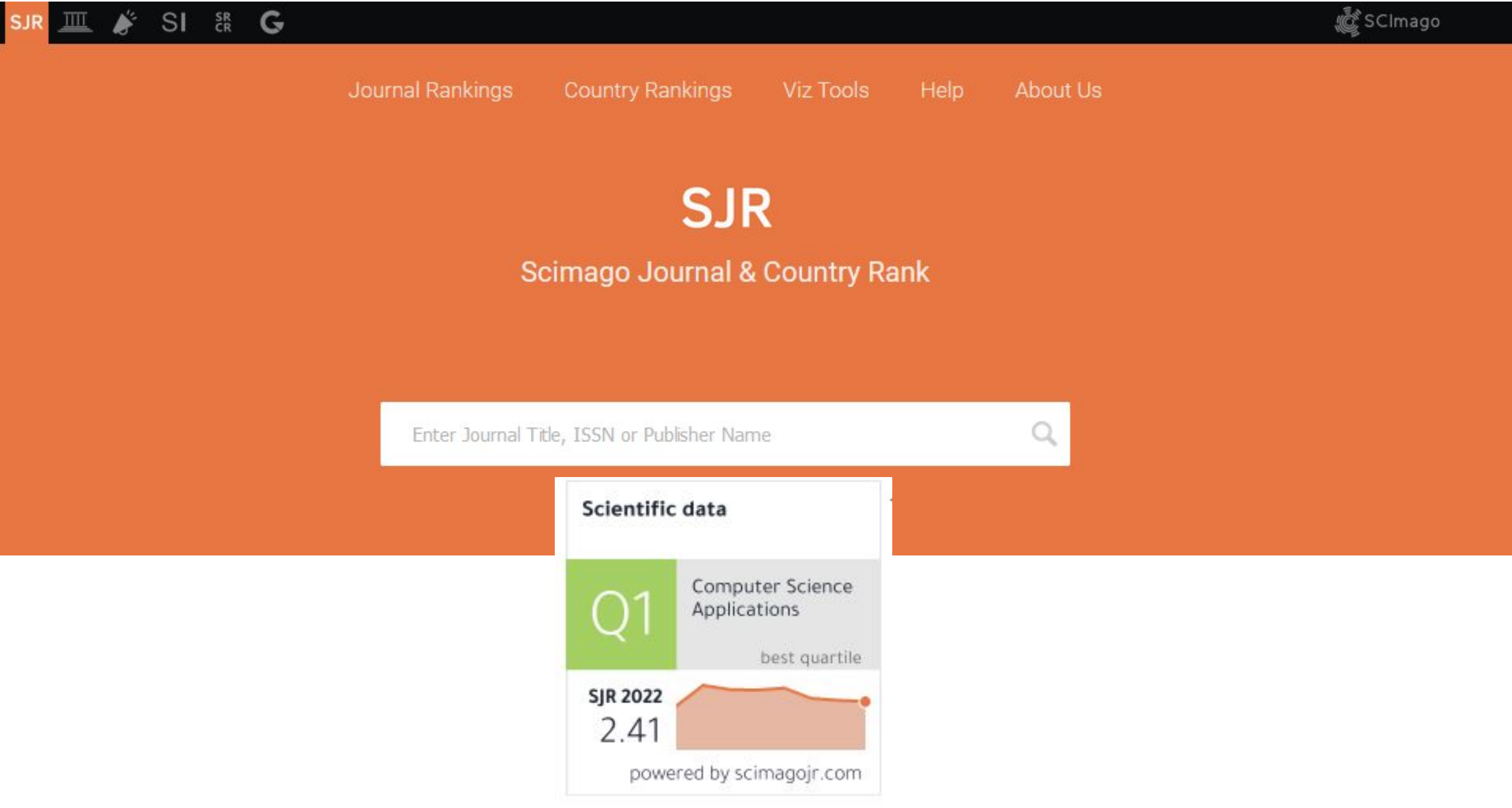
The most established metric for journal is the Journal Impact factor or JIF. It applies to academic journals. It’s the very first metric designed for journal evaluation.

The main element of the JIF calculation are the average number of citations a paper receives- in a journal-in a given period of time. When a journal has an impact factor of 5 it means that in the last three years, this journal averaged 5 citations per published article.

- This metric is also described an indicator of a journal citedness.
- Journals are arranged in a ranking order from high to low JIF in their relevant field categories.
- JIF is calculated from the selected journals indexed in a source, for the JIF, its source is the major database Web of Science that contains the science, social sciences and art and humanities indexes.
- The ranking of journals are presented in quartiles and percentiles. Some journals appear in more than one categories.

Other Journal Metrics

- The Scimago Journal Rank or SJR that differentiates a **citation coming from an important journal into its formula**.
- The immediacy index that indicates journals that publish cutting-edge research.
- The Eigenfactor score that removes self-citations and calculates article citations in a journal in the past five years.
- The CiteScore that includes citations to all documents, not only articles and reviews, published in a journal in the past 3 years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What research is not

1. Figure out what to do.
2. Do it.
3. Publish.

What research is

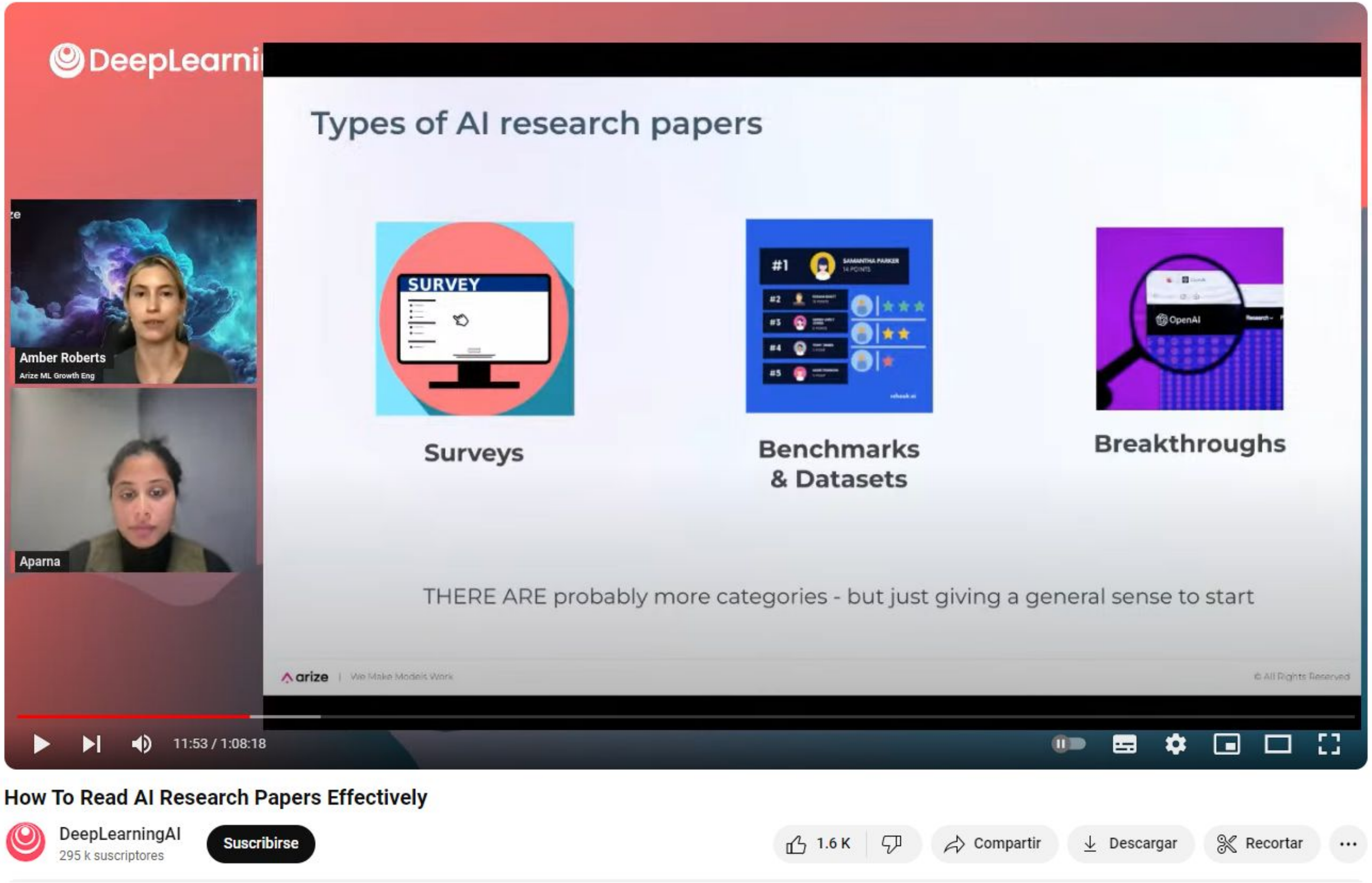
Research is an iterative process of exploration, not a linear path from idea to result [Gowers 2000]

Adapted from Stanford CS197

Thesis vs. Research Paper

Research Paper	Thesis
• Limited space	• “Unlimited” space
• Specialized context	• Broad context
• Tackles a specific question	• Tackles a large question

https://www.youtube.com/watch?v=K6Wui3mn-uI



Tipos de publicaciones y métricas

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How to do a literature review

1. Pick your favorite academic search engine (e.g., Google scholar) and start with keywords
2. Find 3-5 recent and highly cited papers
    - From reputable venues and by reputable institution/author
    - If you find a survey paper, start from the survey paper
3. Do the first pass to identify key papers and researchers that these works cite
4. Track down these papers/researchers
5. Iterate as needed