

Dominance and Diversity in Artificial Intelligence Research:
A Scientometric Analysis of National Trends across Subdisciplines

Master Thesis

Digital Humanities



UNIVERSITÄT
LEIPZIG

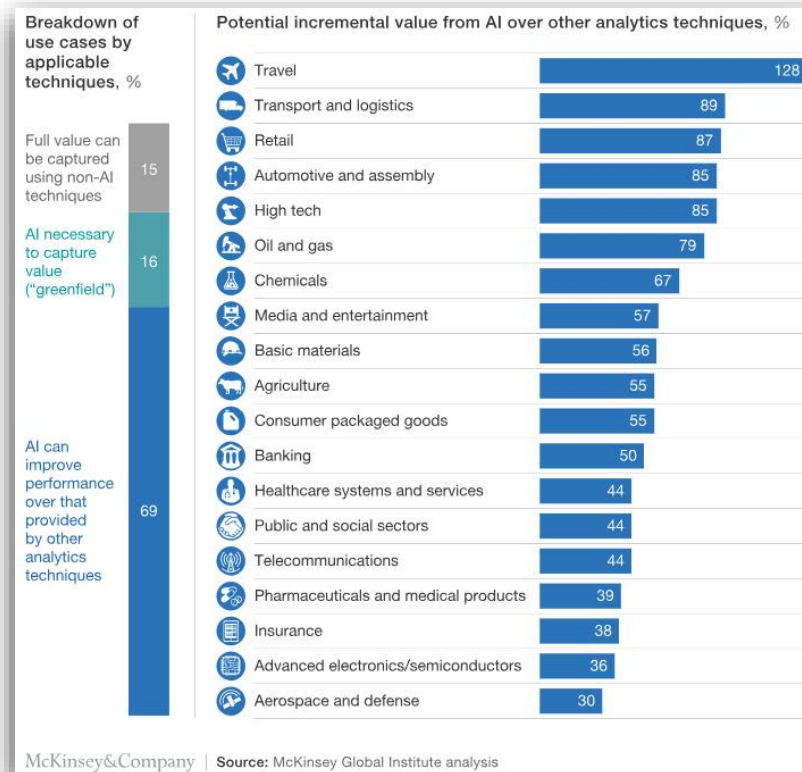
Julius Pfundstein

AI has become a central resource of geoeconomic power

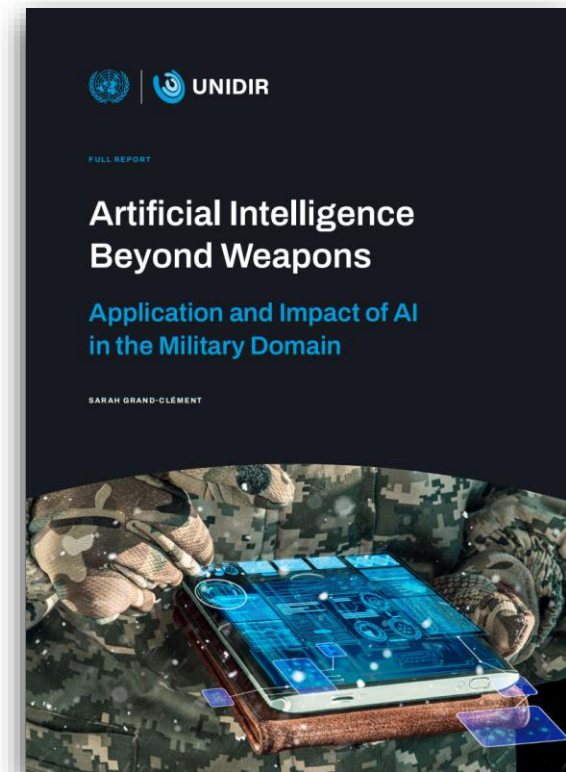
PWC estimates AI will add 17 trillion USD to the global economy by 2030



Applicable across the entire value chain

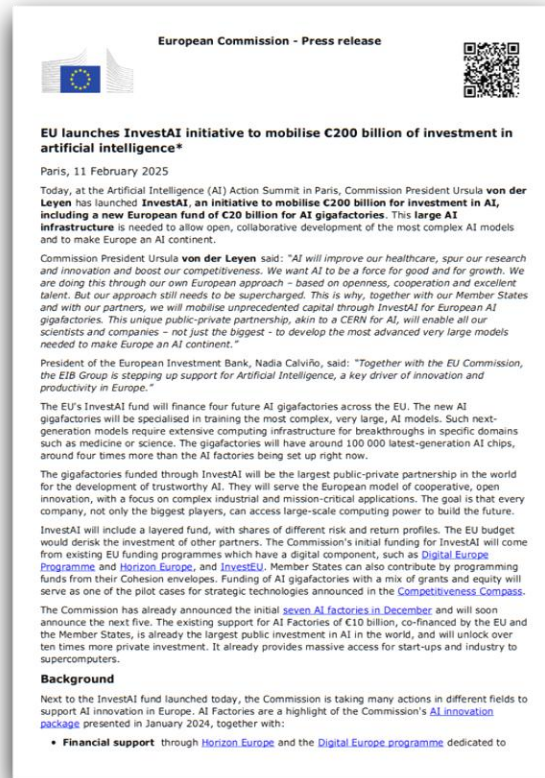


UNDIR considers AI (Automated Weaponry; Cyber-Security; Intelligence) to be indispensable in modern warfare



by now most governments have an official AI-roadmap

EU27 200 Billion Investment Strategy



US 500 Billion investment in AI & Semiconductors



China 1.86 Trillion for 10 industries (including AI)

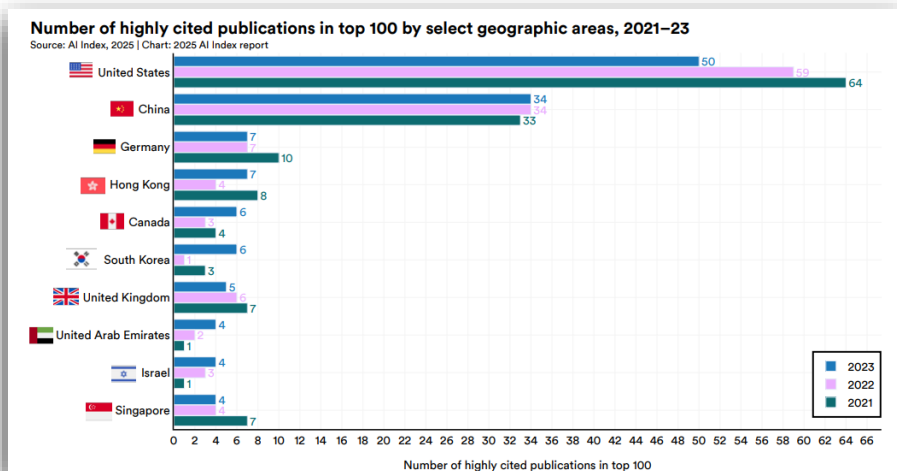


research is undercomplex in two ways

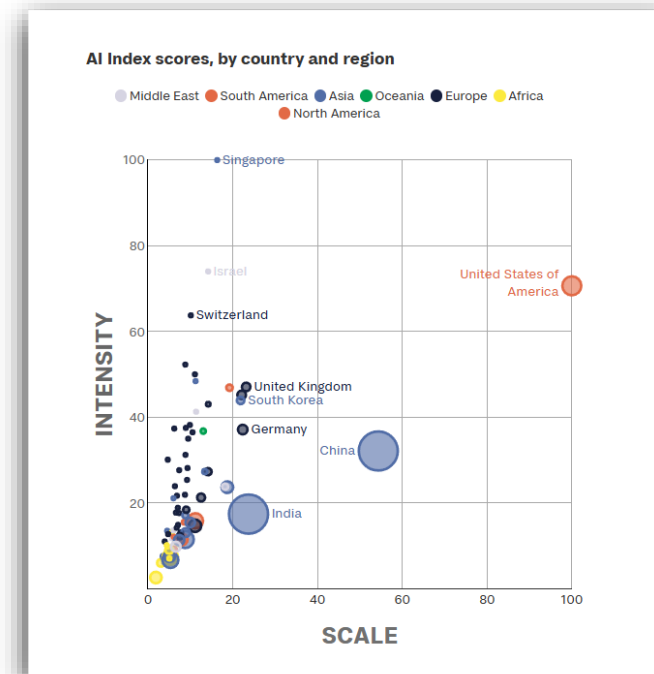
AI is considered as a singular Discipline


No distinction of Institutions (or institutional types) within countries

Artificial Intelligence Index Report 2025 Stanford University Human-Centered Artificial Intelligence



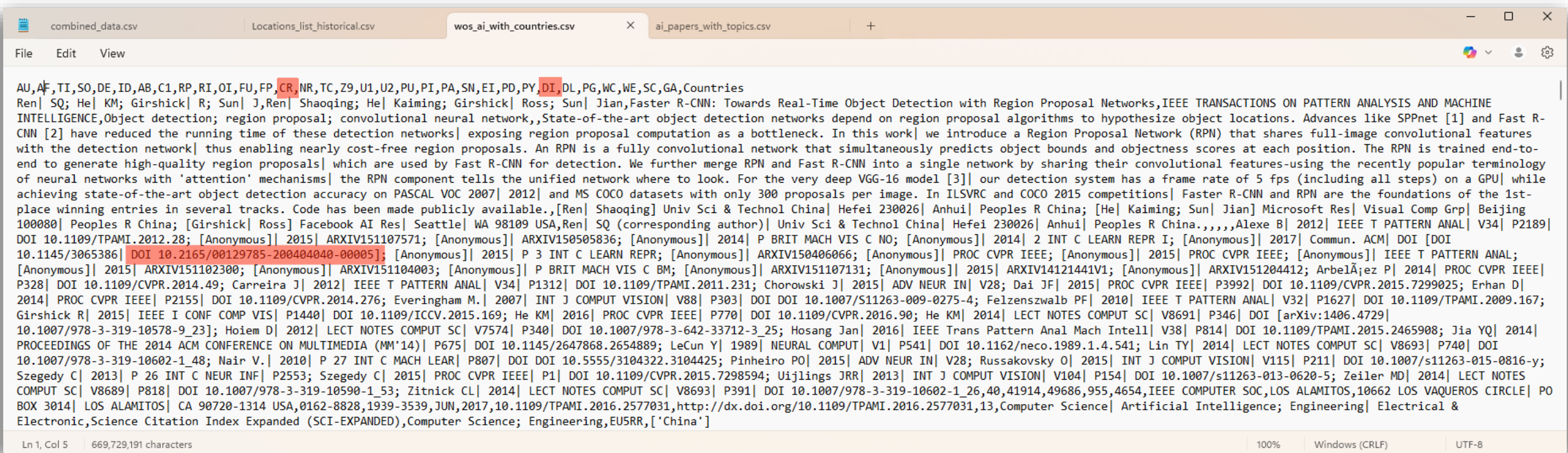
The Global Artificial Intelligence Index 2024 Tortoisemedia





-

5

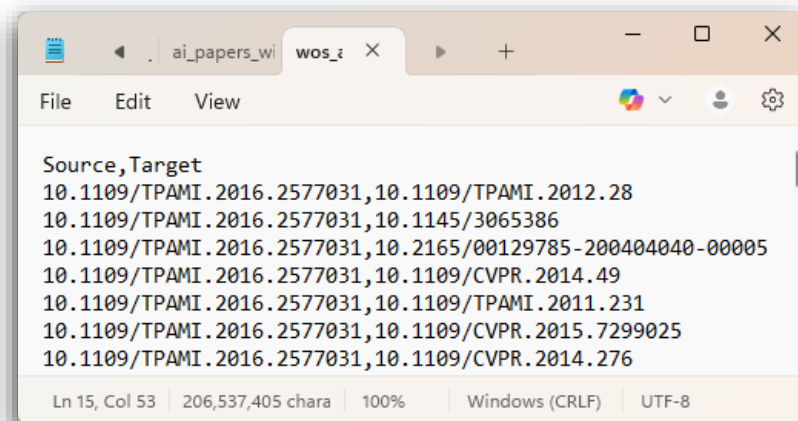
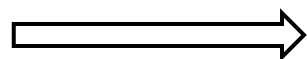


combined_data.csv Locations_list_historical.csv wos_ai_with_countries.csv ai_papers_with_topics.csv

File Edit View

AU,AF,FI,SO,DE,ID,AB,C1,RP,RI,OI,FU,FP,CR,NR,TC,Z9,U1,U2,PU,PI,PA,SN,EI,PD,PY,DI,DL,PG,WC,WE,SC,GA,Countries
Ren| SQ; He| KM; Girshick| R; Sun| J,Ren| Shaoqing; He| Kai ming; Girshick| Ross; Sun| Jian,Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks,IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE
INTELLIGENCE,Object detection; region proposal; convolutional neural network,,State-of-the-art object detection networks depend on region proposal algorithms to hypothesize object locations. Advances like SPPnet [1] and Fast R-
CNN [2] have reduced the running time of these detection networks| exposing region proposal computation as a bottleneck. In this work| we introduce a Region Proposal Network (RPN) that shares full-image convolutional features
with the detection network| thus enabling nearly cost-free region proposals. An RPN is a fully convolutional network that simultaneously predicts object bounds and objectness scores at each position. The RPN is trained end-to-
end to generate high-quality region proposals| which are used by Fast R-CNN for detection. We further merge RPN and Fast R-CNN into a single network by sharing their convolutional features-using the recently popular terminology
of neural networks with 'attention' mechanisms| the RPN component tells the unified network where to look. For the very deep VGG-16 model [3]| our detection system has a frame rate of 5 fps (including all steps) on a GPU| while
achieving state-of-the-art object detection accuracy on PASCAL VOC 2007| 2012| and MS COCO datasets with only 300 proposals per image. In ILSVRC and COCO 2015 competitions| Faster R-CNN and RPN are the foundations of the 1st-
place winning entries in several tracks. Code has been made publicly available.,[Ren| Shaoqing] Univ Sci & Technol China| Hefei 230026| Anhui| Peoples R China; [He| Kai ming; Sun| Jian] Microsoft Res| Visual Comp Grp| Beijing
100080| Peoples R China; [Girshick| Ross] Facebook AI Res| Seattle| WA 98109 USA,Ren| SQ (corresponding author)| Univ Sci & Technol China| Hefei 230026| Anhui| Peoples R China.,,,,Alexe B| 2012| IEEE T PATTERN ANAL| V34| P2189|
DOI 10.1109/TPAMI.2012.28; [Anonymous]| 2015| ARXIV151107571; [Anonymous]| ARXIV150505836; [Anonymous]| 2014| P BRIT MACH VIS C NO; [Anonymous]| 2014| 2 INT C LEARN REPR I; [Anonymous]| 2017| Commun. ACM| DOI [DOI
10.1145/3065386| DOI 10.2165/00129785-200404040-00005]; [Anonymous]| 2015| P 3 INT C LEARN REPR; [Anonymous]| ARXIV150406066; [Anonymous]| PROC CVPR IEEE; [Anonymous]| 2015| PROC CVPR IEEE; [Anonymous]| IEEE T PATTERN ANAL;
[Anonymous]| 2015| ARXIV151102300; [Anonymous]| ARXIV151104003; [Anonymous]| P BRIT MACH VIS C BM; [Anonymous]| ARXIV151107131; [Anonymous]| 2015| ARXIV14121441V1; [Anonymous]| ARXIV151204412; ArbelÃ¡ez P| 2014| PROC CVPR IEEE|
P328| DOI 10.1109/CVPR.2014.49; Carreira J| 2012| IEEE T PATTERN ANAL| V34| P1312| DOI 10.1109/TPAMI.2011.231; Chorowski J| 2015| ADV NEUR IN| V28; Dai JF| 2015| PROC CVPR IEEE| P3992| DOI 10.1109/CVPR.2015.7299025; Erhan D|
2014| PROC CVPR IEEE| P2155| DOI 10.1109/CVPR.2014.276; Everingham M.| 2007| INT J COMPUT VISION| V88| P303| DOI DOI 10.1007/S11263-009-0275-4; Felzenszwalb PF| 2010| IEEE T PATTERN ANAL| V32| P1627| DOI 10.1109/TPAMI.2009.167;
Girshick R| 2015| IEEE I CONF COMP VIS| P1440| DOI 10.1109/ICCV.2015.169; He KM| 2016| PROC CVPR IEEE| P770| DOI 10.1109/CVPR.2016.90; He KM| 2014| LECT NOTES COMPUT SC| V8691| P346| DOI [arXiv:1406.4729|
10.1007/978-3-319-10578-9_23]; Hoiem D| 2012| LECT NOTES COMPUT SC| V7574| P340| DOI 10.1007/978-3-642-33712-3_25; Hosang Jan| 2016| IEEE Trans Pattern Anal Mach Intell| V38| P814| DOI 10.1109/TPAMI.2015.2465908; Jia YQ| 2014|
PROCEEDINGS OF THE 2014 ACM CONFERENCE ON MULTIMEDIA (MM'14)| P675| DOI 10.1145/2647868.2654889; LeCun Y| 1989| NEURAL COMPUT| V1| P541| DOI 10.1162/neco.1989.1.4.541; Lin TY| 2014| LECT NOTES COMPUT SC| V8693| P740| DOI
10.1007/978-3-319-10602-1_48; Nair V.| 2010| P 27 INT C MACH LEAR| P807| DOI DOI 10.5555/3104322.3104425; Pinheiro PO| 2015| ADV NEUR IN| V28; Russakovsky O| 2015| INT J COMPUT VISION| V115| P211| DOI 10.1007/s11263-015-0816-y;
Szegedy C| 2013| P 26 INT C NEUR INF| P2553; Szegedy C| 2015| PROC CVPR IEEE| P1| DOI 10.1109/CVPR.2015.7298594; Uijlings JRR| 2013| INT J COMPUT VISION| V104| P154| DOI 10.1007/s11263-013-0620-5; Zeiler MD| 2014| LECT NOTES
COMPUT SC| V8689| P818| DOI 10.1007/978-3-319-10590-1_53; Zitnick CL| 2014| LECT NOTES COMPUT SC| V8693| P391| DOI 10.1007/978-3-319-10602-1_26,40,41914,49686,955,4654,IEEE COMPUTER SOC,LOS ALAMITOS,10662 LOS VAQUEROS CIRCLE| PO
BOX 3014| LOS ALAMITOS| CA 90720-1314 USA,0162-8828,1939-3539,JUN,2017,10.1109/TPAMI.2016.2577031,http://dx.doi.org/10.1109/TPAMI.2016.2577031,13,Computer Science| Artificial Intelligence; Engineering| Electrical &
Electronic,Science Citation Index Expanded (SCI-EXPANDED),Computer Science; Engineering,EU5R9,['China']

Ln 1, Col 5 669,729,191 characters 100% Windows (CRLF) UTF-8

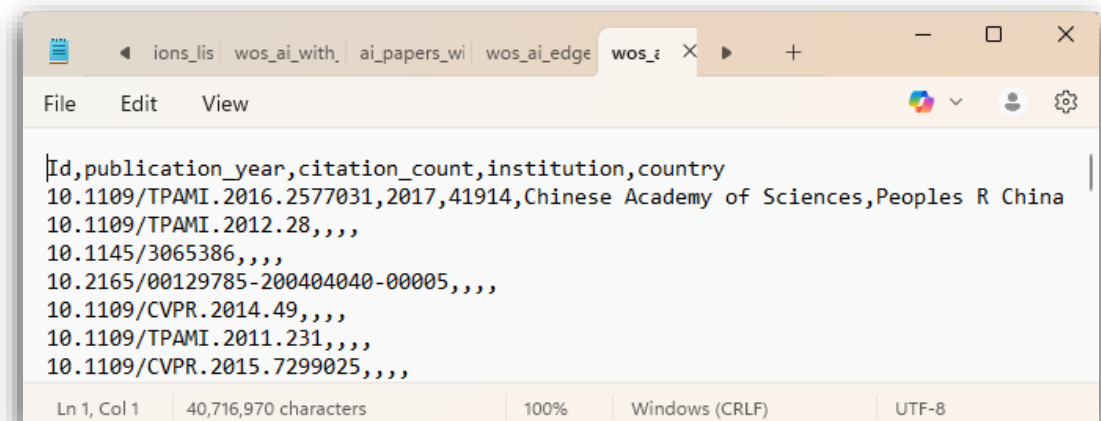


ai_papers_wi wos_z

File Edit View

Source,Target
10.1109/TPAMI.2016.2577031,10.1109/TPAMI.2012.28
10.1109/TPAMI.2016.2577031,10.1145/3065386
10.1109/TPAMI.2016.2577031,10.2165/00129785-200404040-00005
10.1109/TPAMI.2016.2577031,10.1109/CVPR.2014.49
10.1109/TPAMI.2016.2577031,10.1109/TPAMI.2011.231
10.1109/TPAMI.2016.2577031,10.1109/CVPR.2015.7299025
10.1109/TPAMI.2016.2577031,10.1109/CVPR.2014.276

Ln 15, Col 53 206,537,405 chara 100% Windows (CRLF) UTF-8

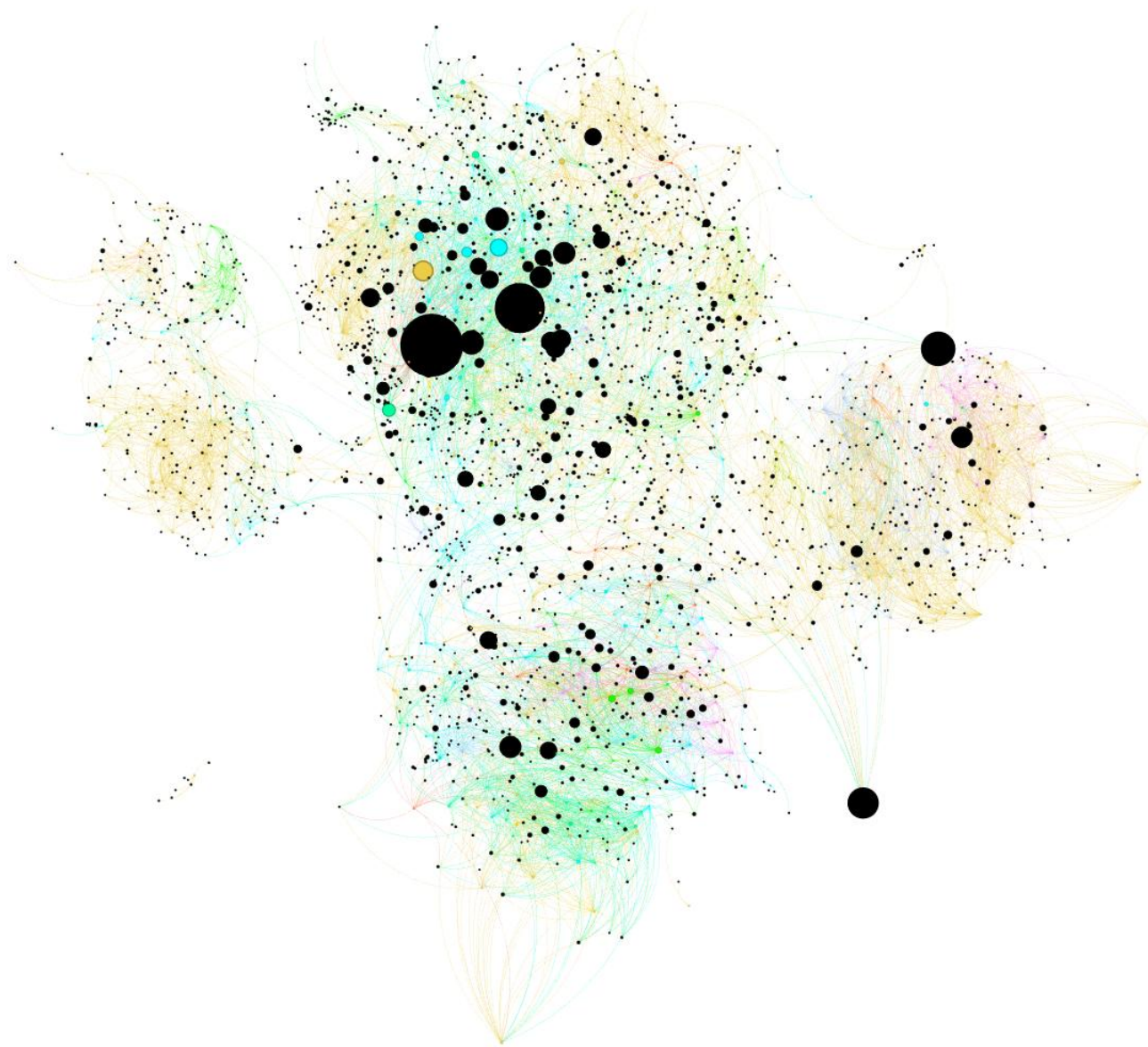


ions_lis wos_ai_with ai_papers_wi wos_ai_edge wos_z

File Edit View

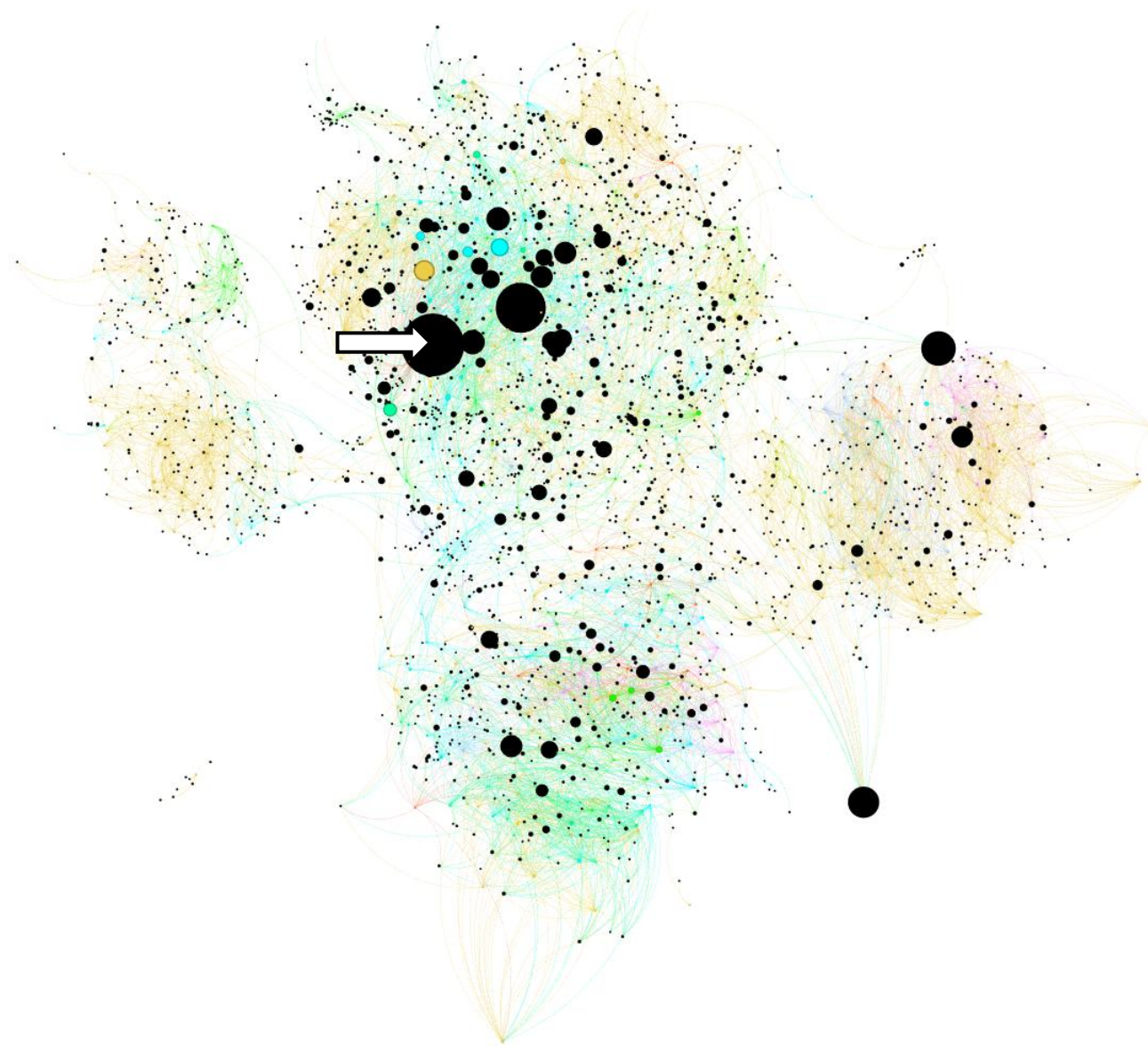
Id,publication_year,citation_count,institution,country
10.1109/TPAMI.2016.2577031,2017,41914,Chinese Academy of Sciences,Peoples R China
10.1109/TPAMI.2012.28,,,,
10.1145/3065386,,,,
10.2165/00129785-200404040-00005,,,,
10.1109/CVPR.2014.49,,,,
10.1109/TPAMI.2011.231,,,,
10.1109/CVPR.2015.7299025,,,,

Ln 1, Col 1 40,716,970 characters 100% Windows (CRLF) UTF-8



Gephi

- Node size displays eigenvector centrality
- Edge color displays country of origin of referencing country
- Filtered to contain only nodes with eigenvector centrality bigger than 1 percent of the biggest (index) and all edges between remaining nodes



Gephi

- Node size displays eigenvector centrality
- Edge color displays country of origin of referencing country
- Filtered to contain only nodes with eigenvector centrality bigger than 1 percent of the biggest (index) and all edges between remaining nodes

Deep Residual Learning for Image Recognition: A Survey

By

[Are you this author?](#)

Shafiq, M (Shafiq, Muhammad) ^[1]; Gu, ZQ (Gu, Zhaoquan) ^[2], ^[3]

[View Web of Science ResearcherID and ORCID](#) (provided by Clarivate)

Source

APPLIED SCIENCES-BASEL ▾

Volume: 12 Issue: 18

DOI: 10.3390/app12188972

Article Number

8972

Published

SEP 2022

Indexed

2022-09-30

Document Type

Review

Abstract

Deep Residual Networks have recently been shown to significantly improve the performance of neural networks trained on ImageNet, with results beating all previous methods on this dataset by large margins in the image classification task. However, the meaning of these impressive numbers and their implications for future research are not fully understood yet. In this survey, we will try to explain what Deep Residual Networks are, how they achieve their excellent results, and why their successful implementation in practice represents a significant advance over existing techniques. We also discuss some open questions related to residual learning as well as possible applications of Deep Residual Networks beyond ImageNet. Finally, we discuss some issues that still need to be resolved before deep residual learning can be applied on more complex problems.

Keywords

Author Keywords: deep residual learning for image recognition; deep residual learning; image processing; image recognition

Keywords Plus: AUTOMATED-SYSTEM; IDENTIFICATION; NORMALIZATION; NETWORK; CNN

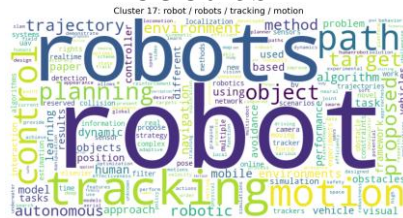
Web of Science Categories

Chemistry, Multidisciplinary; Engineering, Multidisciplinary; Materials Science, Multidisciplinary; Physics, Applied

Algorithmic Optimization



Robotics



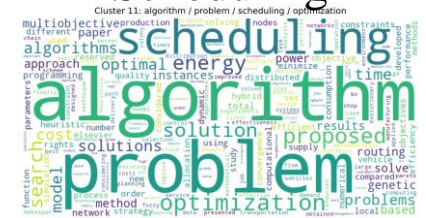
Feature Selecion



Recommendation System



Scheduling



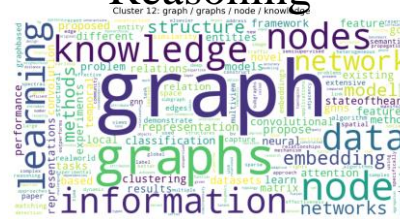
Medical Analytics



Image Recognition



Reasoning



Clustering



Diagnosis



Sentiment Analysis



NLP



Classification



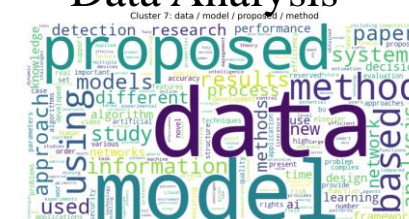
Prediction



Face Recognition



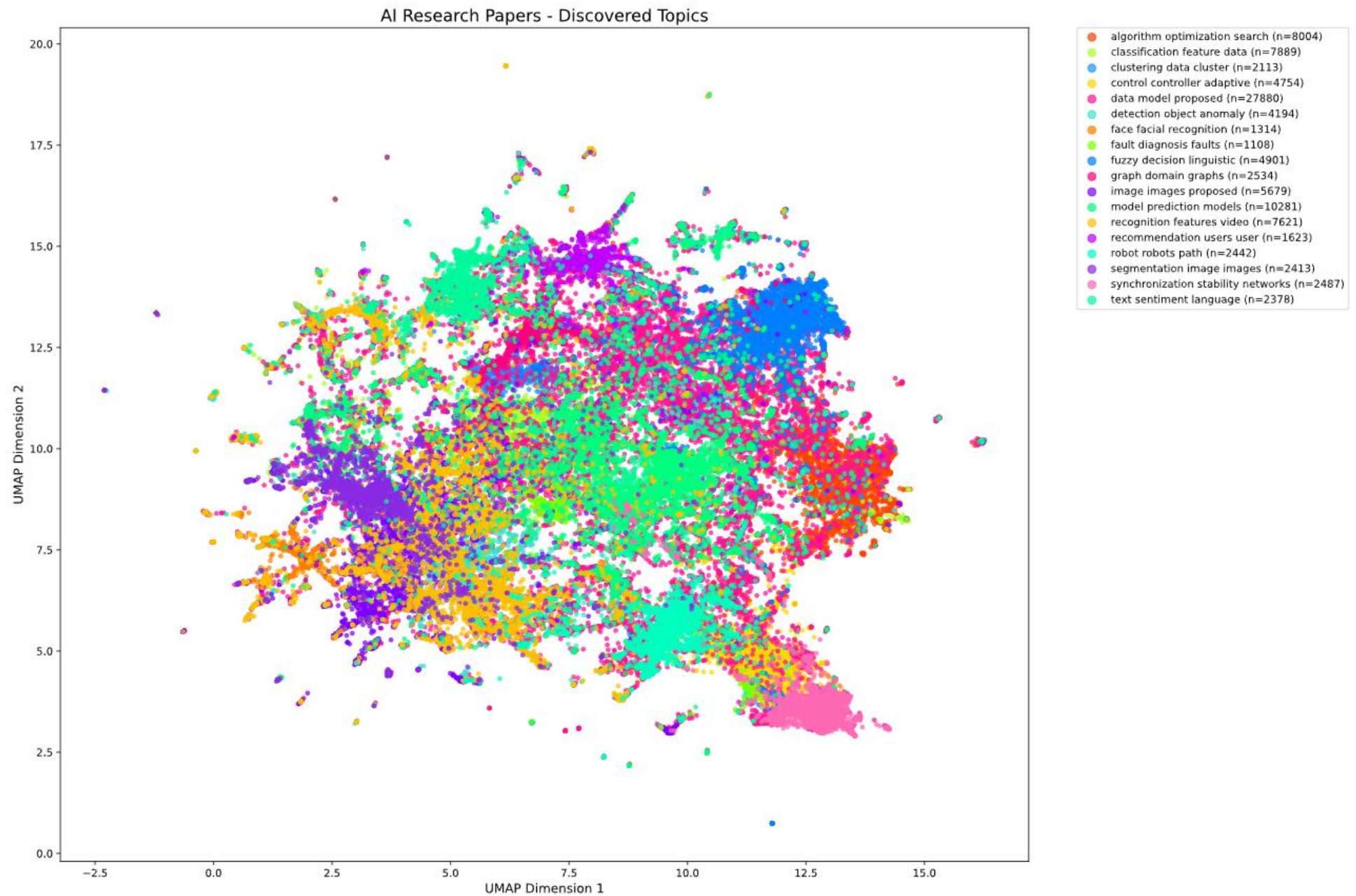
Data Analysis

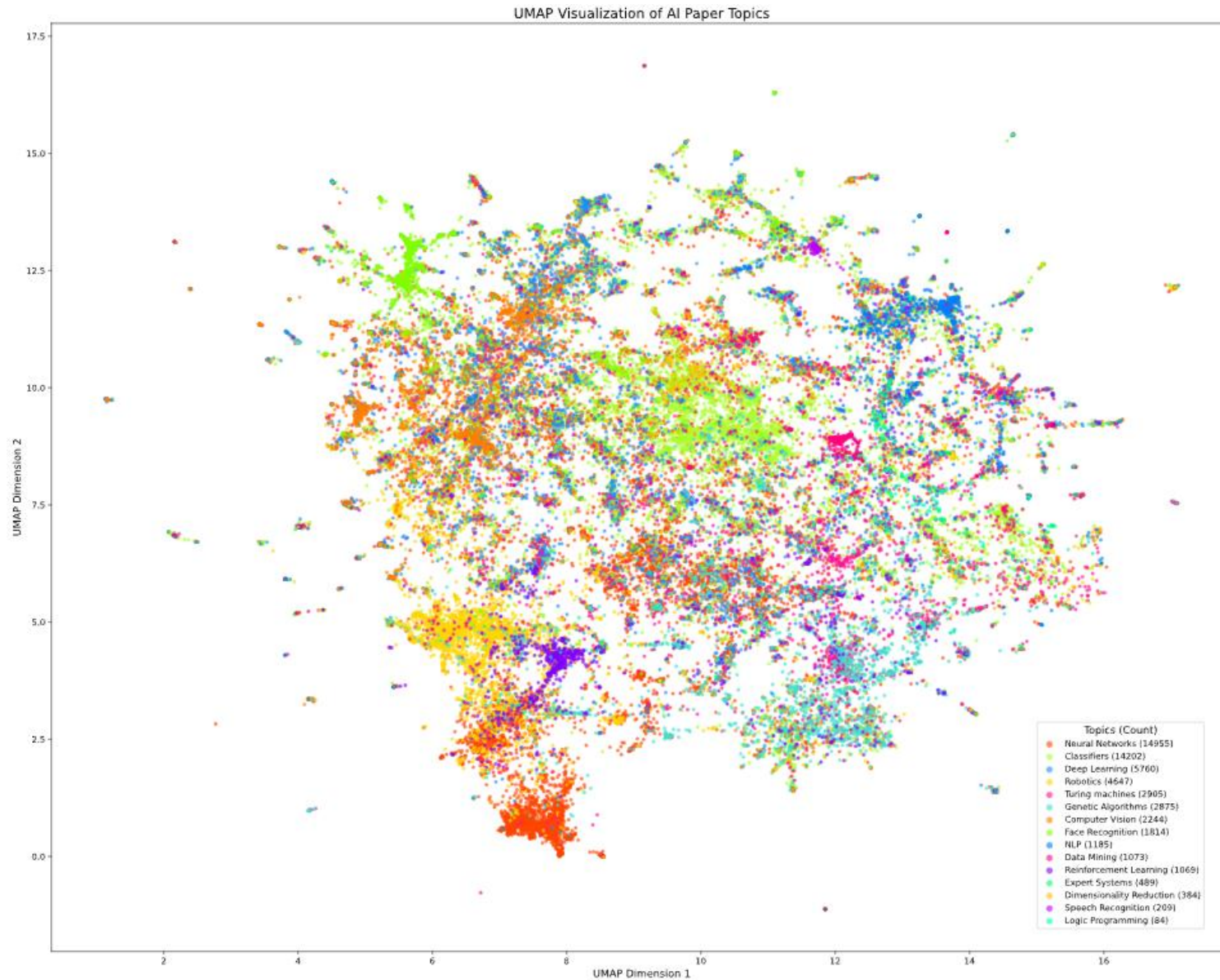


Control Systems



Method: typical text preprocessing; removal of most and least used words; TfidfVectorization; Silhouette Score for optimal Cluster size (arbitrary between 12 and 20); K-Means





research goal

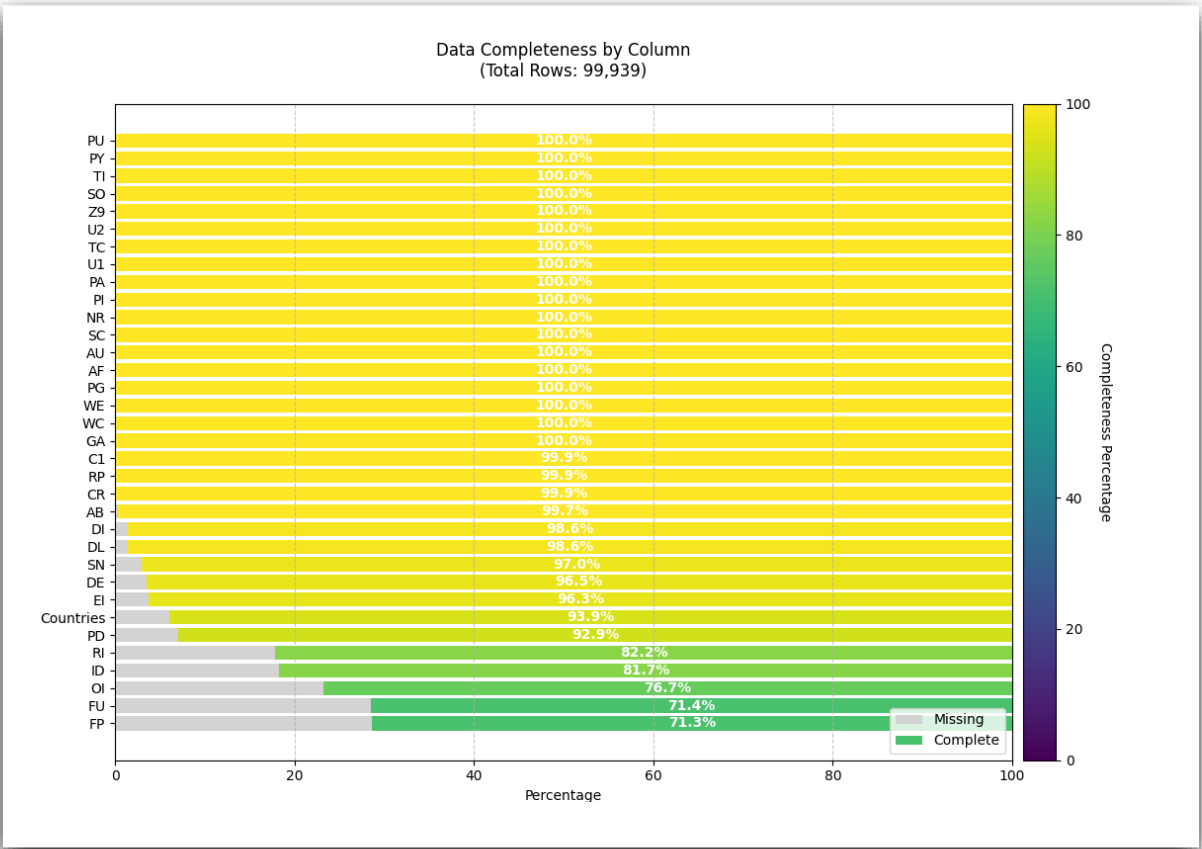
locate countries and institutional types within this projection

add timeline to analyse research trends

combine research impact and semantic position

problems

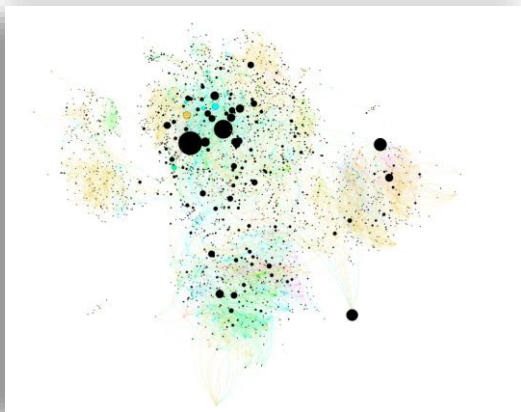
Missing Values (DOI; Country; Funding; ORCID)



Author disambiguation (missing ORCID)

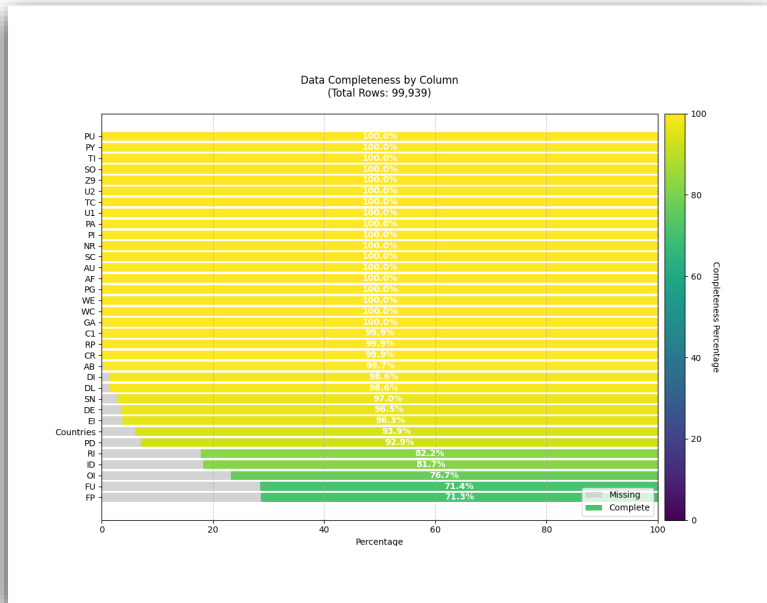
Lee, DK
Lee, E; Park, Y; Shin, JG
Lee, JK; Lee, KJ; Park, HK; Hong, JS; Lee, JS
Lee, KJ; Lee, JK; Choi, SY
Lee, KR
Lee, SJ; Woo, JH; Shin, JG
Lee, YG; Ju, S; Woo, JH

WoS Categories



possible solutions?

Missing Values (DOI; Country; Funding; ORCID)



→ Create dictionary with institutions, that contains information about, country of origin, type (corporate; university, etc.)

Matching with institution or field of research



Author disambiguation (missing ORCID)

Lee, DK
 Lee, E; Park, Y; Shin, JG
 Lee, JK; Lee, KJ; Park, HK; Hong, JS; Lee, JS
 Lee, KJ; Lee, JK; Choi, SY
 Lee, KR
 Lee, SJ; Woo, JH; Shin, JG
 Lee, YG; Ju, S; Woo, JH

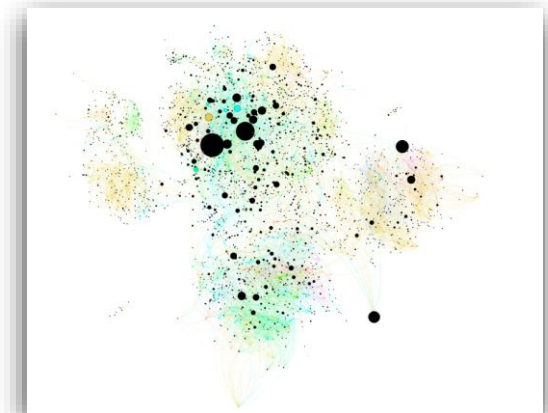
Use Keyword Search instead of categories; take everything and then filter according to abstract



```
(((((ALL=(neural network)) OR ALL=(classifier)) OR ALL=(deep learning)) OR ALL=(robotics)) OR ALL=(turing machine)) OR ALL=(genetic algorithms)) OR ALL=(computer vision)) OR ALL=(face recognition)) OR ALL=(natural language processing)) OR ALL=(data mining)) OR ALL=(reinforcement learning)) OR ALL=(expert system)) OR ALL=(dimensionality reduction)) OR ALL=(speech recognition))
```

→ 1,189,379 results

WoS Categories



thanks!