ACM/IEEE Joint Conference on Digital Libraries (JCDL 2020)
Wuhan, Hubei, P. R. China
August 1 - 5, 2020

Document Clustering and Labeling for Research Trend Extraction and Evolution Mapping

1st Workshop on Extraction and Evaluation of Knowledge Entities from Scientific Documents (EEKE2020)

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01/08/2020

Introduction

Understanding and predicting future discoveries and scientific achievements is an emerging field of research, which involves scientists, businesses, and even governments.

This topic falls under the emerging field of Science of Science (SciSci) which aims to understand, quantify and predict scientific research dynamics and the drivers of the dynamics in different forms such as the birth and death of scientific fields and their subfields; that can be identified by tracking the changes of research trends and dynamics.

Objective & Outline

The objective of this study is to **detect** and **map** scientific trends.

Revealing these trends requires us to exploit contextual features in the scientific research domain and understand its dynamics. In this study we propose a simple framework to facilitate the exploration of scientific trends and their evolution, utilizing contextual features and deep neural embeddings.

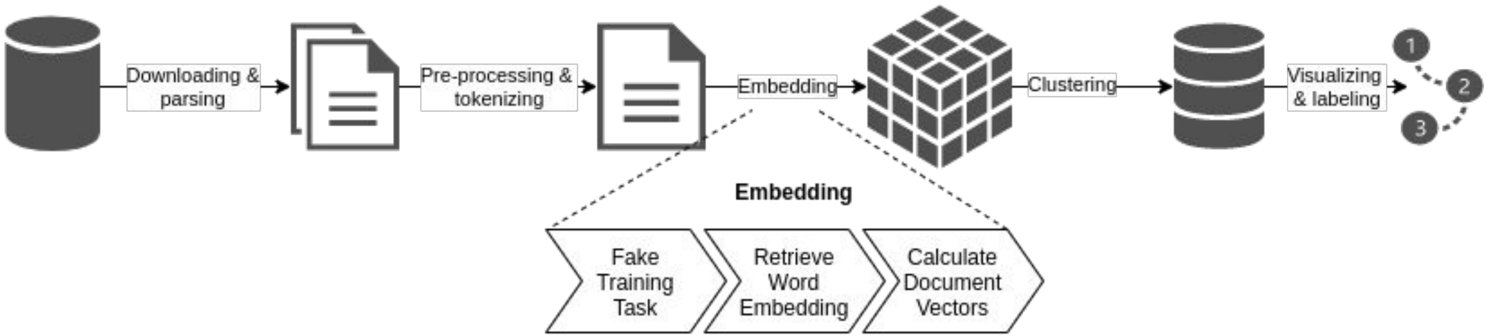
Our proposed framework is then applied in a case study to understand the path of scientific evolution in artificial intelligence. In this study, we show how the trends and topics in science can be extracted using document vectors and extraction of context.

The Literature

- Co-word analysis & topic modeling
  - [6],[7],[8],[9],[10],[11]
- Word and document embedding and clustering
  - [12],[13],[15],[16],[17],[18]

- Embedding methods are superior to traditional methods like TF-IDF for clustering tasks.
- A framework to detect, track and visualize the trends in alluvial like diagrams is out of focus

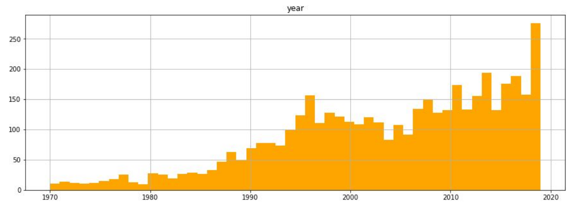
Methodology



Methodology

1) Data Collection

- Dataset A (Word embedding model training data):
  - Abstracts and titles
  - Scopus search in titles, abstracts, and keywords with ``artificial intelligence'' query
  - Yielding 310k records
- Dataset B (Case study and analysis data):
  - Abstracts and titles
  - 3 mainstream journals:
    - ``Artificial Intelligence'' (2575 records)
    - ``Artificial Intelligence Review'' (890 records)
    - ``Journal of Artificial Intelligence Research'' (1006 records)



Methodology

2) Preprocessing

- Common data pre-processing: Carried out on both datasets, including data cleaning, removal of common abbreviations and noun level lemmatization.
- Analysis data preprocessing: (Carried out on dataset B.)
  - Removal of stop words.
  - N-gram keyword tagging and creation of auxiliary labeling dataset.
  - Splitting data to temporal periods: [1970,1989] , [1990,1994], [1995,1999], [2000,2004], [2005,2007], [2008,2010], [2011,2013], [2014,2016], and [2017,2019].

Methodology

3) Word Embedding

- Represent the data in vector space.
- FastText is used to extract word vectors.
- Dataset A is used to train the model.
- Embeddings are in 50 dimensions.
- No further dimensionality reduction is used.

Methodology

4) Document Embedding

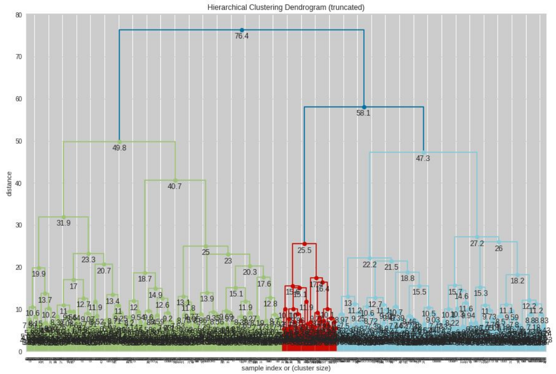
- Simple document averaging
- SIF [28]

$$w(t) = \frac{\alpha}{\alpha + p(t)}$$

$$wv(t) = w(t) * v(t)$$

5) Document Clustering

- Hierarchical agglomerative clustering.
- Assist in number of clusters by dendrogram.



Methodology

6) Cluster Labeling

- Document keywords

$$score(t,c) = tf(t,c) * icf(t)$$

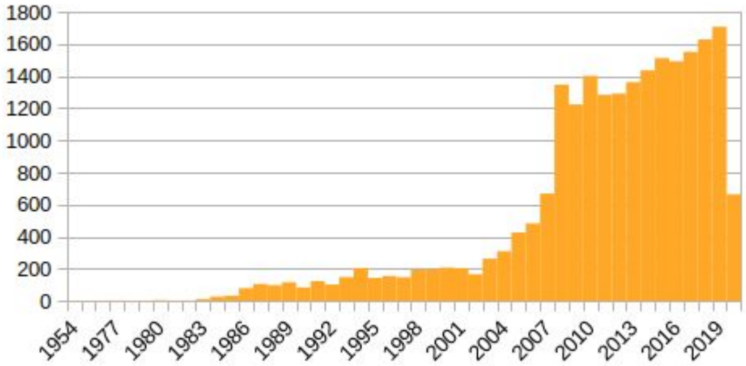
$$icf(t) = log\frac{(1+n)}{(1+cf(t))} + 1$$

- Wikipedia labels
    - Applications
    - Approaches

7) Research Trend Mapping

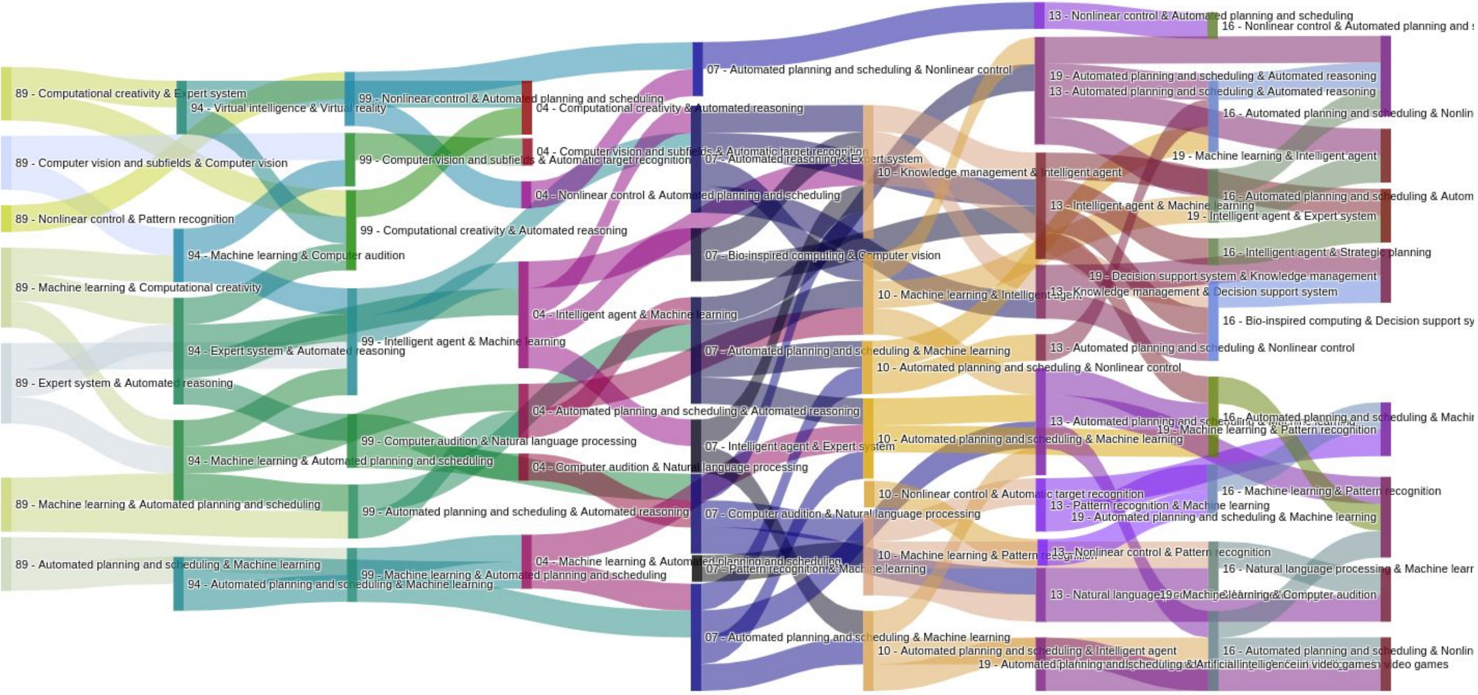
- The final stage of the proposed framework comprises the mapping of the evolution of scientific trends.

Results (1/4)



Wiki Application Est. 2011-2013	Wiki Application Est. 2014-2016
Intelligent agent & ML	Bio-inspired computing & Decision support system
auto. planning and scheduling & Nonlinear control	auto. planning and scheduling & Nonlinear control
KM & Decision support system	AI & PR
auto. planning and scheduling & auto. reasoning	CV and subfields & Automatic target recognition
auto. planning and scheduling & AI in video games	auto. planning and scheduling & Nonlinear control
NLP & ML	NLP & AI
auto. planning and scheduling & ML	auto. planning and scheduling & auto. reasoning
PR & Intelligent control	Intelligent agent & Strategic planning
Nonlinear control & auto. planning and scheduling	Nonlinear control & auto. planning and scheduling
PR & ML	PR & Nonlinear control
Nonlinear control & PR	auto. planning and scheduling & AI

Results (2/4)



89 - Computational creativity & Expert system
89 - Computer vision and subfields & Computer vision
89 - Nonlinear control & Pattern recognition
89 - Machine learning & Computational creativity
89 - Expert system & Automated reasoning
89 - Machine learning & Automated planning and scheduling
89 - Automated planning and scheduling & Machine learning
94 - Virtual intelligence & Virtual reality
94 - Machine learning & Computer audition
94 - Expert system & Automated reasoning
94 - Machine learning & Automated planning and scheduling
94 - Automated planning and scheduling & Machine learning
99 - Nonlinear control & Automated planning and scheduling
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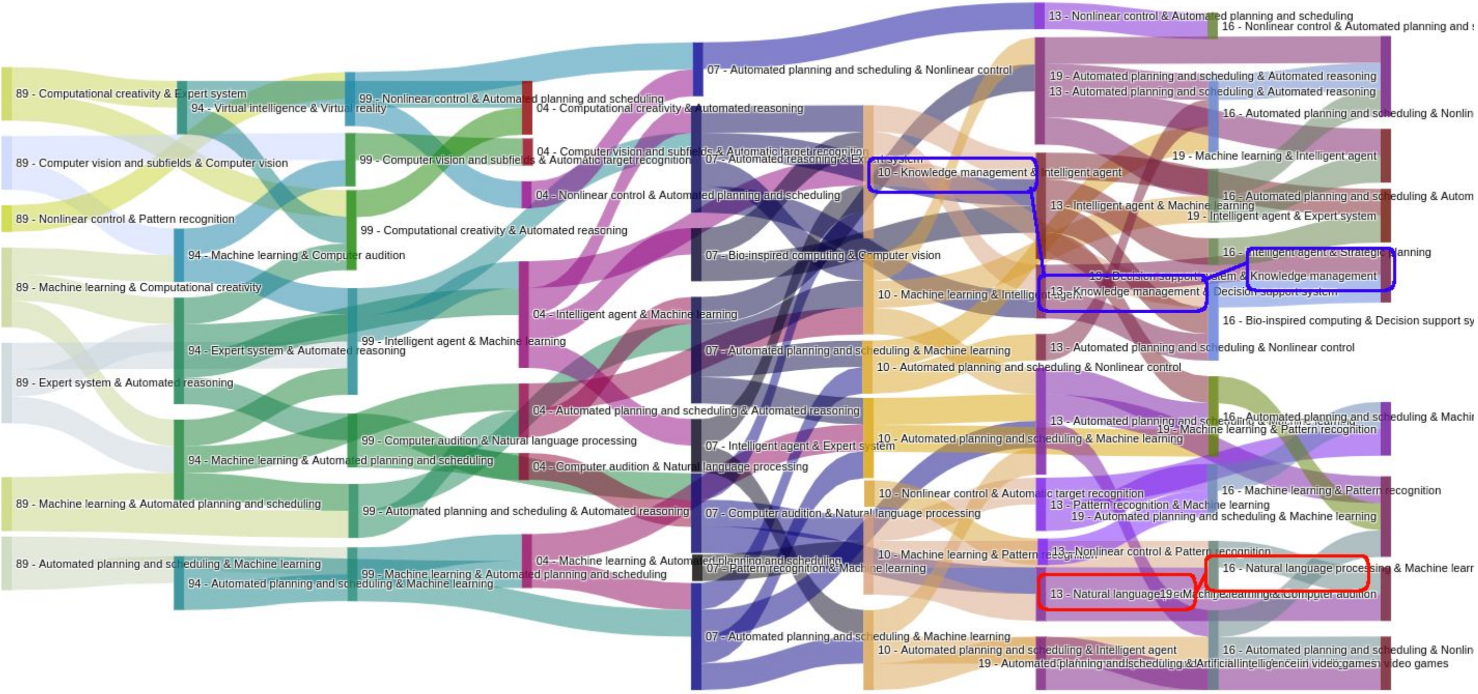
Results (2/4)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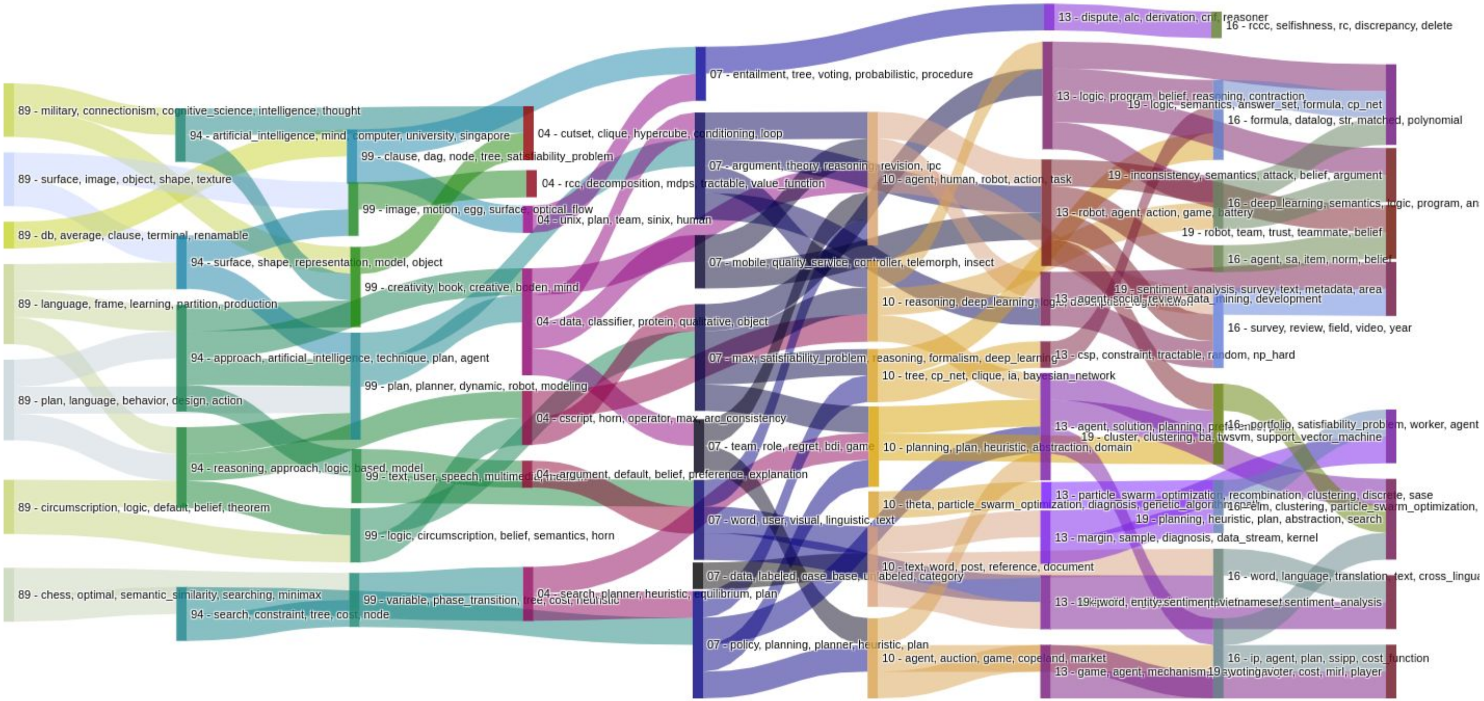
Results (3/4)



89 - military, connectionism, cognitive_science, intelligence, thought
89 - surface, image, object, shape, texture
89 - db, average, clause, terminal, renamable
89 - language, frame, learning, partition, production
89 - plan, language, behavior, design, action
89 - circumscription, logic, default, belief, theorem
89 - chess, optimal, semantic_similarity, searching, minimax
94 - artificial_intelligence, mind, computer, university, singapore
94 - surface, shape, representation, model, object
94 - approach, artificial_intelligence, technique, plan, agent
94 - reasoning, approach, logic, based, model
94 - search, constraint, tree, cost, node
99 - clause, dag, node, tree, satisfiability_problem
99 - image, motion, egg, surface, optical_flow
99 - creativity, book, creative, boden, mind
99 - plan, planner, dynamic, robot, modeling
99 - logic, circumscription, belief, semantics, horn
99 - variable, phase_transition, tree, cost, heuristic
04 - cutset, clique, hypercube, conditioning, loop
04 - rcc, decomposition, mdps, tractable, value_function
04 - unix, plan, team, sinix, human
04 - data, classifier, protein, qualitative, object
04 - cscript, horn, operator, max, arc_consistency
04 - argument, default, belief, preference, explanation
04 - search, planner, heuristic, equilibrium, plan
07 - entailment, tree, voting, probabilistic, procedure
07 - argument, theory, reasoning, revision, ipc
07 - mobile, quality_service, controller, telemorph, insect
07 - max, satisfiability_problem, reasoning, formalism, deep_learning
07 - team, role, regret, bdi, game
07 - word, user, visual, linguistic, text
07 - data, labeled, case_base, unlabeled, category
07 - policy, planning, planner, heuristic, plan
10 - agent, human, robot, action, task
10 - reasoning, deep_learning, logic, description_logic, notion
10 - tree, cp_net, clique, ia, bayesian_network
10 - planning, plan, heuristic, abstraction, domain
10 - theta, particle_swarm_optimization, diagnosis, genetic_algorithm, elm
10 - text, word, post, reference, document
10 - agent, auction, game, copeland, market
13 - dispute, alc, derivation, cnf, reasoner
13 - logic, program, belief, reasoning, contraction
13 - robot, agent, action, game, battery
13 - agent, social, review, data_mining, development
13 - csp, constraint, tractable, random, np_hard
13 - agent, solution, planning, preference, plan
13 - particle_swarm_optimization, recombination, clustering, discrete, sase
13 - margin, sample, diagnosis, data_stream, kernel
13 - game, agent, mechanism
16 - rccc, selfishness, rc, discrepancy, delete
16 - formula, datalog, str, matched, polynomial
16 - deep_learning, semantics, logic, program, an
16 - agent, sa, item, norm, belief
16 - survey, review, field, video, year
16 - portfolio, satisfiability_problem, worker, agent
16 - elm, clustering, particle_swarm_optimization,
16 - word, language, translation, text, cross_lingua
16 - ip, agent, plan, ssipp, cost_function
19 - logic, semantics, answer_set, formula, cp_net
19 - inconsistency, semantics, attack, belief, argument
19 - robot, team, trust, teammate, belief
19 - sentiment_analysis, survey, text, metadata, area
19 - cluster, clustering, ba, twsvm, support_vector_machine
19 - planning, heuristic, plan, abstraction, search
vietnamese, sentiment_analysis
voter, cost, mirl, player

Results (4/4)

	Tag (TF-IDF score) - 2017-2019
1	* cluster (0.226), clustering (0.194), ba (0.156), twsvm (0.148), support vector machine (0.147), neural network (0.119), si (0.117)
2	* queen (0.537), kemeny (0.224), top (0.173), bound (0.158), borda (0.153), mining (0.15), item (0.148)
3	* logic (0.369), semantics (0.218), answer set (0.203), formula (0.179), cp net (0.177), revision (0.152), asp (0.151)
4	* market (0.257), sale (0.226), firm (0.226), car (0.164), customer (0.157), kidney (0.157), bike (0.157)
5	* knee (0.319), face recognition (0.253), acl (0.209), gait (0.198), gait pattern (0.176), facial (0.176), survey (0.172)
6	* planning (0.272), heuristic (0.237), plan (0.201), abstraction (0.181), search (0.177), planner (0.16), monte carlo tree search (0.13)
7	* sentiment analysis (0.268), survey (0.245), text (0.179), metadata (0.154), area (0.14), indian language (0.133), citation (0.124)
8	* word (0.271), entity (0.211), sentiment (0.176), vietnamese (0.135), sentiment analysis (0.13), semantic (0.124), target (0.122)
9	* voting (0.233), voter (0.218), cost (0.16), mirl (0.15), player (0.142), good (0.141), preference (0.139)
10	* inconsistency (0.231), semantics (0.156), attack (0.153), belief (0.153), argument (0.143), graph (0.139), argumentation framework (0.136)
11	* robot (0.401), team (0.217), trust (0.17), teammate (0.139), belief (0.121), revision (0.12), norm (0.112)

Conclusion

- This framework and labeling method facilitates the identification of trends and assist us in understanding the way fields of research are evolving.
- This became possible through the top term and Wikipedia application labeling methods.
- Wikipedia documents can be used to have an estimated embedding location of a field of research or an application in vector space.
- Wikipedia approaches are not as useful as Wikipedia application for this case study and purpose.

➢ In future works, more advanced clustering methods are planned to be used as an extension to this work, benefiting from deep neural networks in clustering and dynamic embedding and clustering techniques. Additionally, labeling can benefit from the vector space similarities to enhance TF-IDF weights.

Q&A

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