A Large-Scale, Automated Study of Language Surrounding Artificial Intelligence

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Abstract

This work presents a large-scale analysis of artificial intelligence (AI) and machine learning (ML) references within news articles and scientific publications between 2011 and 2019. We implement word association measurements that automatically identify shifts in language co-occurring with AI/ML and quantify the strength of these word associations. Our results highlight the evolution of perceptions and definitions around AI/ML and detect emerging application areas, models, and systems (e.g., blockchain and cybersecurity). Recent small-scale, manual studies have explored AI/ML discourse within the general public, the policymaker community, and researcher community, but are limited in their scalability and longevity. Our methods provide new views into public perceptions and subject-area expert discussions of AI/ML and greatly exceed the explanatory power of prior work.

1 Introduction

You shall know a word by the company it keeps.

J. R. Firth

Referenced in a wide-range of domains, from science fiction to autonomous vehicles, artificial intelligence (AI) has gained significant attention from societies and governments worldwide. Despite its emerging prominence in the public sphere, AI still lacks a consistent, universally-accepted definition, making it a challenging subject to analyze over time [Bryson, 2019; Cave et al., 2018; Chuan et al., 2019; Fast and Horvitz, 2017; Krafft et al., 2020; Legg and Hutter, 2007]. Recent studies conducted surveys and manual annotation tasks to understand how subject-area experts, the general population, and policy makers define and perceive AI [Fast and Horvitz, 2017; Krafft et al., 2020; Cave et al., 2018; Cave et al., 2019; Chuan et al., 2019; Russell and Norvig, 2002; Sweeney, 2003]. While these studies are a necessary preliminary step in uncovering historical and current perceptions of AI, these studies are limited in scalability and constrained to the period of time in which they were performed.

To improve on these limitations and gain new insights, we present a large-scale, automated approach to analyze the language surrounding AI in the public sphere during any time period. Using text corpora from news articles and scientific publication abstracts, we analyze AI references in two domains: one that represents public perceptions of AI and one that represents subject-area expert applications of AI. Our analysis includes more than 170,000 AI-related news articles and 77,000 AI-related scientific publication abstracts. To the best of our knowledge, our work is the largest-scale study on AI references in the public sphere, specifically in text corpora.

Our approach uses word association structures in text corpora and measures the strength of and the shifts in word associations over time. In psycholinguistics, word association structures are often identified through human studies where participants are presented with a word (e.g., coffee) and respond with a word that comes to mind (e.g., mug). Word association structures in text corpora can be automatically identified by analyzing words that frequently co-occur within a designated proximity of each other. Thus, word association structures can be automatically derived from a text corpus, indicating the different characteristics of a word by the “company it keeps.”

We use mutual information to measure the strength of association and a normalized co-occurrence frequency value to measure the shifts in frequently co-occurring words over time. Mutual information is an indicator of words that have a high probability of exclusively co-occurring with a target word. In this way, mutual information values identify words that have an exclusive co-occurrence with a target word, as opposed to words with a general co-occurrence. For example, in news articles, we find that robotics has a high co-occurrence frequency with artificial intelligence and machine learning and a high mutual information value, whereas big has a high co-occurrence frequency but a low mutual information value. Shifts in co-occurrence frequency ranks indicate words that are emerging, decreasing in frequency, or increasing in frequency. For example, in scientific publication abstracts, we find that convolutional is an emerging word co-occurring with artificial intelligence and machine learning.

In the following sections, we provide a background on word association structures (Section 2), summarize related work (Section 3), describe the datasets studied in our analysis (Section 4), define our methodology (Section 5), and present and discuss our experimental results (Sections 6 and 7).
2 Background

In psychology, the law of mental association defines the phenomena of learning by contiguity, a learning process that associates a stimulus and response based on their frequency and proximity (e.g., coffee being associated with mug) [James, 1890]. Applied to linguistic theory, the law of mental association relates to language acquisition; words associated to a particular concept are stored closely in a human’s “mental lexicon” [Dobel et al., 2010]. When words frequently co-occur, by some definition of proximity, their association in a mental lexicon is strengthened [Wettler and Rapp, 1993; Church and Hanks, 1990].

Word associations are dynamic, as language evolves associations will change [Nelson et al., 2004]. Prior psycholinguistic studies identify word association norms across populations [Nelson et al., 2004; Wettler and Rapp, 1993; Church and Hanks, 1990; Buchanan et al., 2019]. These studies commonly use priming—showing a stimulus (an image or word)—and measure the speed of a response or the consistency of responses across the participants. For example, Nelson et al. conducted a free response survey where participants were asked to write the first word that came to mind after reading a cue word [Nelson et al., 2004]. This survey was designed to capture associative knowledge and characteristics of meaning; responses were shown to be affected by culture and trends. Consistent word associations across participants indicate a common experience with words, and inconsistent word associations across participants highlight experiences that vary from the norm [Nelson et al., 2004].

These human surveys are translated to automated procedures performed on text corpora, providing a scalable analysis of word associations, by defining word co-occurrences as two words appearing within a designated window size of each other [Günther et al., 2016]. Window size defines a proximity constraint for word co-occurrence; for example, a window size of two considers only two words to the left and two words to the right of the target word. Wettler and Rapp find that a window size of five is optimal for large text corpora, as it does not dilute the language surrounding a target word and maintains a close enough proximity to capture true association [Wettler and Rapp, 1993].

Word co-occurrences, measured by using a specified window size, have been used in natural language processing tasks, such as generating semantic spaces [Lund and Burgess, 1996]. In practice, applying word association methods on large-scale text corpora eliminates the sample bias of participants, as participant judgements are used to measure norms. However, word association methods do not eliminate other types of biases captured in linguistic norms, though they have also proven useful in this space [Caliskan et al., 2017; Bolukbasi et al., 2016].

3 Related Work

Previous studies have taken various manual approaches to define AI and present public perceptions of AI. Russell and Norvig analyzed AI definitions in eight textbooks published between 1978 and 1993, and then specified four main ways AI is defined: 1) think like humans, 2) act like humans, 3) think rationally, and 4) act rationally [Russell and Norvig, 2002]. Building on Russell and Norvig’s work, Sweeney manually categorized 996 AI-related publications cited by Russell and Norvig [Sweeney, 2003]. Sweeney found that 987 of these publications favor defining AI in terms of rational thinking and rational behavior [Sweeney, 2003].

Cave et al. surveyed 1,078 UK participants and collected responses from multiple choice and free response questions to learn about public perceptions of AI [Cave et al., 2019]. Notably, 85% of respondents stated that they had heard of AI before, with 25% of them defining AI in terms of robots. Krafft et al. conducted two surveys, one with 98 participants and one with 86 participants, where the authors asked AI researchers what they consider AI systems to be and how they define AI in practice [Krafft et al., 2020]. They compared the survey responses to policy definitions of AI, which they collected by manually annotating 83 policy documents from 2017 through 2019 [Krafft et al., 2020]. Krafft et al. found that policy documents typically use “human-like” definitions of AI, whereas AI researchers define AI through technical problems and functionality [Krafft et al., 2020].

Fast and Horvitz analyzed AI-related news articles from the New York Times between 1986 and 2016, approximately 3 million articles in total [Fast and Horvitz, 2017]. Any paragraph in an article that mentioned the terms artificial intelligence, AI, or robot was selected, reducing the data down to 8,000 paragraphs over the thirty years. The paragraphs were manually annotated by Amazon Mechanical Turkers, and the results describe trends in the public perception of AI over time. Specifically, mentions of AI have increased, the general population has become more optimistic about AI, and concerns over the loss of control of AI are increasing [Fast and Horvitz, 2017]. Chuan et al. sampled news articles from LexisNexis and ProQuest from five U.S. news sources (USA Today, The New York Times, Los Angeles Times, New York Post, and Washington Post) that contain the term artificial intelligence. Using stratified sampling, they reduced the 2,485 AI-related articles to 399 articles that are manually annotated by three graduate students. Chuan et al.’s study focused more on understanding the framing of AI in news articles and presented findings on the main topics, cited sources, and sentiment in their subset of AI-related news articles. They found that AI was mainly discussed in Business and Economy and Science and Technology article topics and that AI ethics is increasingly discussed [Chuan et al., 2019].

4 Datasets

We study two large-scale datasets to generate subsets of AI/ML text data: 1) AI/ML NEWS, 170,858 news articles from the LexisNexis database [LexisNexis, 2020] and 2) AI/ML ABSTRACTS, 77,880 scientific publication abstracts from the Microsoft Academic Graph [Sinha et al., 2015]. We categorize an article or abstract as AI/ML if it contains the terms artificial intelligence or machine learning at least once, using Bryson’s description of important terms for understanding AI [Bryson, 2019]. For both news articles and scientific publication abstracts, we normalize the text by setting all words to lower case and removing symbols, digits, URLs,
email addresses, phone numbers, and punctuation except for apostrophes. Additionally, we remove all stop words using NLTK’s English set of stop words.1

LexisNexis Database: The LexisNexis database contains news article texts that were published between 2011 and 2020. We analyze English-language articles from 2011, 2015, and 2019 that were published by sources of good editorial quality. LexisNexis generates source editorial rankings for news articles on a rank scale from 1 to 5, with 1 being high quality (e.g., The New York Times) and 5 being low quality (e.g., message boards). We select news articles that have an editorial rank of 1, 2, or 3, which includes international, national, business, regional, industry, and government news sources. We use the duplicate ID assigned by LexisNexis to de-duplicate the articles. The 170,858 news articles in AI/ML NEWS is comprised of these filtered and de-duplicated documents.

Table 1 provides details for each year’s subset of AI/ML NEWS. Over time, the number of documents, tokens (unique vocabulary words), and sources significantly increase. Figure 1 displays the counts of artificial intelligence and machine learning mentions in AI/ML NEWS. Mentions of artificial intelligence are more frequent than mentions of machine learning over the entire period of study; there are 2,446 AI mentions and 554 ML mentions in 2011 and 187,066 AI mentions and 103,175 ML mentions in 2019.

5 Methodology

We use two word association measurements to provide a comprehensive understanding of how words co-occurring with artificial intelligence and machine learning change over time: mutual information and normalized co-occurrence rank. Both measurements rely on a definition of co-occurrence, thus we define co-occurrence as a word co-occurring within a window size of the terms artificial intelligence and machine learning. Since AI and ML are two-word terms, we consider words to the left of artificial/machine and words to the right of intelligence/learning within the defined window size. We account for edge cases in selecting co-occurring words, such as artificial intelligence or machine learning ending a document. Figure 3 demonstrates term co-occurrences within a five-word window under various text positions.

Microsoft Academic Graph: Microsoft Academic Graph (MAG) contains scientific research publication documents from eight categories: Book, Book Chapter, Conference, Dataset, Journal, Patent, Repository, and Thesis [Sinha et al., 2015]. We use a subset of MAG documents from 2011, 2015, and 2019 that contain an abstract in their publication record.

Table 2 provides details for each year’s subset of AI/ML ABSTRACTS. There are comparatively fewer words per text instance and fewer documents in AI/ML ABSTRACTS than in AI/ML NEWS. Figure 2 displays the counts of artificial intelligence and machine learning mentions in AI/ML ABSTRACTS. Mentions of machine learning are more frequent than mentions of artificial intelligence over the entire period of study, the opposite of AI/ML mentions in AI/ML NEWS. In 2011, there are 6,210 ML mentions and 3,012 AI mentions, and in 2019, there are 59,006 ML mentions and 22,414 AI mentions.

5.1 Mutual Information

We define mutual information between two words according to Church and Hanks [Church and Hanks, 1990]. Given two words, \( w_1 \) and \( w_2 \), their mutual information \( I(w_1, w_2) \) is defined as:

\[
I(w_1, w_2) = \log_2 \frac{Pr[W_1 = w_1, W_2 = w_2]}{Pr[W_1 = w_1]Pr[W_2 = w_2]} \tag{1}
\]

\( Pr[W = w] \) is the probability that a word drawn at random from a document in the text corpus is equal to \( w \). Specifically, \( Pr[W = w] = \frac{w_{count}}{total_{count}} \), where \( w_{count} \) is the number of times that \( w \) appears in the document and \( total_{count} \) is the number of words in the document. \( Pr[W_1 = w_1, W_2 = w_2] \) is the joint probability that the two words co-occur (within a window size) in a text corpus, indicating association. If two words frequently co-occur in text, \( Pr[W_1 = w_1, W_2 = w_2] \) is...
1. The term has at least five words preceding it and five words following it:

\[ ... w_1 w_2 w_3 w_4 w_5 \ \text{artificial intelligence} \ \hat{w}_1 \ \hat{w}_2 \ \hat{w}_3 \ \hat{w}_4 \ \hat{w}_5 \ ... \]

2. The term has less than five words preceding it, following it, or both:

\[ w_1 \ \text{artificial intelligence} \ \hat{w}_1 \ \hat{w}_2 \ \hat{w}_3 \ \hat{w}_4 \ \hat{w}_5 \]

\[ ... w_1 w_2 w_3 w_4 w_5 \ \text{artificial intelligence} \ \hat{w}_1 \ \hat{w}_2 \ \hat{w}_3 \ \hat{w}_4 \ \hat{w}_5 \ ... \]

\[ w_1 \ \text{artificial intelligence} \ \hat{w}_1 \ \hat{w}_2 \]

3. The term either starts or ends the article:

\[ \text{Artificial intelligence} \ \hat{w}_1 \ \hat{w}_2 \ \hat{w}_3 \ \hat{w}_4 \ \hat{w}_5 \]
datasets for machine learning. None of the words that appear in Table 3b consistently over time appear in the Table 4 consistently over time. While algorithms appear in 2019 in Table 4, the rest of the words that have the highest co-occurrence frequency with artificial intelligence and machine learning are not distinctly unique to AI/ML. In general, words with high mutual information to artificial intelligence and machine learning remain consistent over time; however, few words have increasing mutual information, like deep and big.

### 6.2 Normalized Co-occurrence Rank: Language Shifts Over Time

We measure the shift of words co-occurring with AI/ML by computing the standard deviation of the normalized co-occurrence ranks for words with frequencies in the top 1% of AI/ML NEWS and AI/ML ABSTRACTS for at least one year. This measurement produces 921 results for AI/MLS NEWS and 457 results for AI/ML ABSTRACTS. Standard deviation values fall between 0 (no variation) and 0.47 (maximum variation) using this 1% frequency threshold. Table 5 displays results for the standard deviation values of 0, 0.05-0.1, 0.1-0.4, and 0.4-0.47 (limited to 20 words per bin) to showcase words with the least and the most variance over time (see Supplementary Materials for full results). For the words with fluctuating co-occurrence ranks, we examine the direction of their shift (decreasing in rank or increasing in rank), and if a word is not observed in 2011 but is observed in 2015 and 2019, we consider the word to be emerging.

**AI/ML NEWS:** Of the 921 resulting words from AI/ML NEWS, 17% of words have σ values in (0, 0.1], such as robotics and software, indicating a consistent co-occurrence frequency with AI/ML. Only two words (siri and laboratory) have downward trending co-occurrence ranks. Both words lose popularity from 2011 to 2015, but stay consistent from 2015 to 2019. The remaining words, such as ethical and quantum, have an upward trend in co-occurrence ranks. Emerging words, such as blockchain and cybersecurity, signal new application areas, systems, and products that are integrating AI/ML. Words with minimal increasing ranks not displayed in Table 5 include company names and systems(e.g., ibm, watson, google, siri, and mit) and application areas (e.g., biotechnology, military, and manufacturing).

**AI/ML ABSTRACTS:** Of the 457 resulting words from AI/ML ABSTRACTS, 70% of words have σ values in (0, 0.1], such as theory and statistical, indicating a consistent co-occurrence frequency with AI/ML. Three words are labeled as emerging (convolutional, discloses, and iot) and seven words (retrieval, reasoning, genetic, web, fuzzy, cognitive, and logic) have minimally decreasing co-occurrence ranks. Words with increasing co-occurrence ranks signal new models, systems, and techniques (e.g., adversarial, quantum, and unmanned).

| 2011 | computer, technology, ai, science, software, research, data, techniques, using, uses, use, algorithms, robotics, said | 2015 | data, technology, ai, analytics, big, new, using, computer, technologies, science, research, said, algorithms, robotics, also, human | 2019 | ai, data, technology, technologies, intelligence, analytics, artificial, using, new, use, big, digital, learning, company, internet |
|------|-----------------------------------------------------------------------------------------------------------------|------|-----------------------------------------------------------------------------------------------------------------|------|-----------------------------------------------------------------------------------------------------------------|

(a) AI/ML NEWS

(b) AI/ML ABSTRACTS

Table 3: Timelines of top 15 most frequently co-occurring words with “artificial intelligence” or “machine learning” within a window size of 5 in AI/ML NEWS and AI/ML ABSTRACTS. Words bolded in blue appear in all three years for each dataset respectively.

| Word | MI | Freq |
|------|----|------|
| mit's | 13.6 | 0.001 |
| robotics | 12.9 | 0.004 |
| algorithms | 12.5 | 0.004 |
| siri | 12.1 | 0.002 |
| ai | 11.9 | 0.006 |

AI/ML NEWS

| Word | MI | Freq |
|------|----|------|
| ai | 11.7 | 0.007 |
| algorithms | 11.6 | 0.004 |
| robotics | 11.5 | 0.004 |
| azure | 10.8 | 0.001 |
| predict | 10.6 | 0.002 |

AI/ML ABSTRACTS

| Word | MI | Freq |
|------|----|------|
| uci | 12.6 | 0.002 |
| supervised | 10.8 | 0.002 |
| ai | 10.7 | 0.005 |
| repository | 10.3 | 0.002 |
| classifiers | 9.8 | 0.001 |

| Word | MI | Freq |
|------|----|------|
| ai | 10.9 | 0.02 |
| algorithms | 10.6 | 0.003 |
| robotics | 10.5 | 0.004 |
| artificial | 9.8 | 0.007 |
| augmented | 9.8 | 0.001 |

| Word | MI | Freq |
|------|----|------|
| uci | 12.5 | 0.002 |
| supervised | 10.9 | 0.003 |
| repository | 10.7 | 0.002 |
| ai | 10.4 | 0.003 |
| classifiers | 9.9 | 0.002 |

Table 4: Top five words with the highest mutual information to AI/ML over three years for AI/ML NEWS and AI/ML ABSTRACTS.

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3https://archive.ics.uci.edu/ml/index.php
### 7 Discussion

Generally, we find that the language surrounding AI/ML in news articles changes much more than in scientific publication abstracts. By measuring the strength of word associations and shifts in language over time, we find more consistent language use in AI/ML abstracts than in AI/ML news (displayed in Table 4 and 5). While frequently co-occurring words in AI/ML abstracts change minimally, frequently co-occurring words in AI/ML news shift from words such as software and research to words like analytics and digital.

Our word association measurements provide insight into words that have a consistent, strong association to artificial intelligence and machine learning, as well words that have a shifting strength of association. Comparing mutual information values over time, we highlight words with strong associations to AI/ML over all three years. For example, in AI/ML news, robotics and robots have consistently high mutual information values, aligning with Cave et al.’s finding that many adults define AI in relation to robots. Words with consistently high mutual information values in AI/ML abstracts identify commonly used models and fundamental components of AI/ML, such as supervised repository, and mining. Mutual information results from AI/ML abstracts align with Krafft et al.’s finding that most AI researchers define AI in terms of its capabilities and applications in technical problems [Krafft et al., 2020].

Computing the standard deviation of normalized co-occurrence ranks, we highlight words that are consistent, shifting (including the shift’s direction), and emerging in text. In AI/ML news, emerging words signal new application areas (e.g., blockchain and bitcoin) and words increasing in rank signal booming application areas or improved products (e.g., smartphones and chatbots). Notably, in AI/ML news, ethical emerges in 2015, an appearance consistent with reports on increasing concerns in policy and society surrounding the ethical implications of AI models [Fast and Horvitz, 2017; Cave et al., 2019; Chuan et al., 2019]. In AI/ML abstracts, emerging words (e.g., convolutional) highlight emerging models in AI/ML, while words increasing in rank (e.g., quantum) highlight growing AI/ML application areas.

These comprehensive results indicate how culture and trends affect how AI/ML are perceived, applied, and defined in the context of news articles and scientific publication abstracts. We are able to identify words that are consistent over time (e.g., algorithms, computers and data), thereby demonstrating word association norms. We can also identify emerging words—specifically companies, products, systems, models, and technologies that have strong associations to AI/ML (e.g., Facebook, quantum, and semiconductor)—providing insight into the evolution of AI.

### 8 Conclusion

Artificial intelligence is challenging to study, as it is an emerging and rapidly evolving technology that is actively integrated into various domains. Our work implements an automated analytical approach to study the language surrounding AI/ML over time in order to highlight consistent, shifting, and emerging language. We use two large-scale datasets from news articles and scientific research publications, applying our approach in a domain reflecting public perception and a domain reflecting subject-area applications. Capturing word association norms with AI/ML (e.g., robotics and algorithms), as well as emerging word associations (e.g., ethical and cybersecurity), our results not only align with prior manual research and surveys but also provide new insights into public perceptions and subject-area discussions of AI.

Interesting extensions of our analysis would be to use text corpora from different domains, such as social media text and policy documents as well as text in non-English languages, to provide a global perspective of AI.

| Rate of Change | AI/ML NEWS | AI/ML ABSTRACTS |
|----------------|------------|------------------|
| No shift $\sigma = 0$ | advanced, algorithms, computer, data, human, information, institute, language, mining, processing, research, researchers, robotics, science, software, system, techniques, technologies, university, use | analysis, classification, computational, data, engineering, information, methods, mining, model, network, neural, processing, recognition, repository, researchers, statistical, svm, technique, theory, used |
| Minimal increase $\sigma \in [0.05, 0.1]$ | apps, capability, chips, competitive, cutting-edge, economic, education, government, investment, marketing, modern, monitoring, navigation, operational, quantum, revolution, risk, state-of-the-art, sensing, surveillance | adversarial, analytics, apparatus, deep, equipment, obtaining, operation, quantum, rapid, relates, storage, things, utility, vehicle, voice |
| Significant increase $\sigma \in [0.1, 0.4]$ | cloud-based, defense, demand, drone, ethical, facebook, forecast, microsoft, nlp, novel, patent, policy, privacy, processors, rapid, saas, smartphones, stock, tesla, transforming | big, medium, terminal, unmanned |
| Maximum increase $\sigma \in [0.4, 0.47]$ | apis, amazon, azure, bitcoin, blockchain, chatbots, commerce, cybersecurity, data-enabled, disruptive, ethereum, facial, flashstack, fintech, genomic, ic,iot, newswire, selfdriving, semiconductor, startups | convolutional, discloses, iot |

Table 5: Words (listed alphabetically) from AI/ML news and AI/ML abstracts within binned normalized rank standard deviations. All words with $\sigma \in [0.4, 0.47]$ emerge in the 2015 subset of AI/ML news/AI/ML abstracts (flashstack emerges in the 2019 subset).
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