A Quantitative History of A.I. Research in the United States and China

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Abstract

Motivated by recent interest in the status and consequences of competition between the U.S. and China in A.I. research, we analyze 60 years of abstract data scraped from Scopus to explore and quantify trends in publications on A.I. topics from institutions affiliated with each country. We find the total volume of publications produced in both countries grows with a remarkable regularity over tens of years. While China initially experienced faster growth in publication volume than the U.S., growth slowed in China when it reached parity with the U.S. and the growth rates of both countries are now similar. We also see both countries undergo a seismic shift in topic choice around 1990, and connect this to an explosion of interest in neural network methods. Finally, we see evidence that between 2000 and 2010, China’s topic choice tended to lag that of the U.S. but that in recent decades the topic portfolios have come into closer alignment.
In July 2017, the State Council of the People’s Republic of China announced its goal to make China the world leader in A.I. technology by 2030.[1] Since then, a flurry of research has been conducted analyzing scientific publications in A.I. and machine learning in the U.S. and China, to probe the extent to which China has been able to follow through on this goal and overtake the U.S. as the “leader” in A.I. Some research, like Field Cady and Oren Etzioni’s work with the Allen Institute for Artificial Intelligence, explores total publication volume partitioned by citation counts to compare both the quantity and quality of Chinese and American papers.[2] Using its own Scopus database, Elsevier has also done extensive bibliometric work, largely focused on defining the terms and topics of the artificial intelligence field.[3] Complementary efforts have been undertaken to carefully characterize the extent and state of the A.I. research community internationally, such as the recent work of the China Academy of Information and Communications Technology Data Research Center, which combines bibliometrics with information on private sector AI companies.[4]

In this work, we intend to take a step back and widen the aperture of study on these questions, both in time and scope. Looking at longer term trends in A.I. publications in the U.S. and China, we will see that both countries have exhibited remarkably stable exponential growth in the volume of publications affiliated with their institutions. Notably, we are not the first to report an exponential growth in publication volume in a scientific discipline. As long ago as the middle of last century, researchers have noted exponential growth in the publication volume associated with various subfields of science.[5] The single exception we observe is a reduction in the rate of this exponential growth in institutions affiliated with China when their publication volume first began to match that of the U.S. between 2008 and 2009. We also report a metric for the overall similarity between the choice of topics in these two countries over time, and find evidence of a dramatic and persistent shift in the topic choices of both countries individually around 1990. Across this shift, we notice that China’s choice of research topics through the 1990s and 2000s generally lagged that of the U.S., with our metric suggesting that until 2010 the choice of topics in China’s research portfolio tended to more closely resemble that of the U.S. in previous years than that of the U.S. in the corresponding year. We offer a possible explanation for these phenomena, noting a dramatic increase of the proportion of publication on neural networks across both countries during the 1990s which then receded over time to be overtaken by a more diverse portfolio of topics. This shift was especially strong in China, where we note a marked overall reduction in the diversity of the topic portfolio during the 1990s. Both our similarity and diversity metrics, together with direct inspection of the popularity of selected topics, suggest that starting in 2010 these gaps closed and the modern topic portfolio of China bears close resemblance to that of the U.S.

These results suggest two considerations to keep in mind when analyzing trends in the A.I. research communities in the U.S. and China, particularly in the frame of nation state competition. The first and most critical of these is that our results suggest that the A.I. research communities in these two countries do not appear to evolve independently in time. The apparent shift of China’s publication growth when it first matched that of the U.S., the presence of the dramatic topic shift corresponding to an increase in focus on neural network methods in 1990 across both countries, and the evolution of China’s topic choice to more closely match that of the U.S. all suggest that the two research communities interact and affect each other’s development. This is perhaps to be expected, as publications are highly portable across national boundaries and it is not at all uncommon for researchers to move between the two communities.

The subject of our study is data scraped from the web interface of Scopus, an abstract and citation database run by Elsevier. We automatically queried Scopus for articles affiliated with China or the U.S. with certain A.I. related keywords in the title, abstract or keyword fields and recorded the number of results by year. Scopus defines article country affiliation as the country in which the author’s affiliated institution is located. Keywords were generated from the methodologies described in the scikit-learn
documentation as of January 2019 and topics listed in the tutorials and workshops at the 2018 Neurips, ICML, and AAAI conferences. We kept results starting in 1981 for papers affiliated with China, since 1980 was the latest year for which we did not find any publications associated with our keywords and affiliated with China on Scopus. For the U.S., we kept results starting in 1962, as this was the earliest year for which we found data. For both countries, we only analyzed data up to 2018, since that was the last full year of data as of time of writing.

Before proceeding with our analysis, we offer a few caveats about the quality of the data we obtained this way. The first and most glaring issue is that our data collection methodology does not capture any information about publications that are not written in English. As such, our estimate of publication volume affiliated with China are probably a significant underestimate and it is possible that the overall topic portfolio of research affiliated with China is different from what we see in our data. Indeed, while our search for “machine learning” returned 4,365 articles affiliated with China on Scopus, a search for the Mandarin equivalent (“机器学习”) on CNKI, a repository of scholarly publications Chinese scholarly publications, returned 10,733 results, suggesting rough parity between the size of the English and Mandarin literatures. In their recent work tracking China’s overall scientific output, Qingnan Xie and Richard Freeman found this to be true of scientific articles in general.[7] We did not collect information on citations for each paper, so we have no proxy for the quality or impact of a particular paper. Our analysis also relies on assigning national affiliation by institution, which elides the tricky question of how to assign the research production of, for example, a Chinese national affiliated with a U.S. university or a U.S. national affiliated with a Chinese A.I. research firm. While this omission seems especially acute in our dataset, it is emblematic of the difficulty inherent in analyzing entangled international institutions like research communities in the frame of competition between nation states.

We should also point out that the way we assembled our dataset and chose our keywords is somewhat ad hoc and biased towards the modern conception of the field in the U.S. technology sector. One might reasonably be concerned about missing research on substantially similar topics, particularly the farther into the past one looks, possibly even connected to the citation network of some of the papers we do assemble. Based on some checks performed by hand, it is also likely that some number of publications which the authors would not consider artificial intelligence or machine learning papers made it into the dataset. For example, we observed psychology papers among the results for our search of “transfer learning.” We are somewhat concerned about the implications for our results on the keyword “logistic regression” in particular, since a large number of other fields of science use logistic regression as method for statistical inference. Ultimately, this presents a definitional problem like that tackled in the Elsevier study[3] and we proceed under the theory that further manual tweaks to our dataset to try to address these deficiencies are as likely to introduce additional bias as remove any. For this work, we leave it to the reader to decide how substantively they believe these considerations affect the results presented and look forward to future work which explores this topic with a more robust data collection process.

As a simplifying assumption to enable our analysis, we take each of these keywords to be mutually exclusive. That is, we assume that the papers returned in the search for each keyword do not appear in the searches for any other keyword. Put another way, we ignore any double counting that has occurred in the process of assembling our data. This is certainly not true in reality (e.g. machine vision papers are likely to utilize neural networks), but is hopefully close enough to true as a first approximation to provide some insight. To address the question of trends in Chinese and U.S. publication volume relative to one another, we develop two metrics. The first of these is simply the total number of publications we observed under the assumption of mutual exclusivity. That is, if $n_C(y,k)$ (resp. $n_U(y,k)$) is the total

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1 On 8/21/2019
number of publications observed with keyword \( k \) in year \( y \) from China (resp. the U.S.), we track

\[
n_I(y) = \sum_k n_I(y, k)
\]

as our proxy for the total number of papers produced, where \( I = C \) or \( U \). A visual inspection of the data suggests that the total volume for the U.S. is exponential over the whole period of study, so we fit it to the model

\[
\ln(n_U(y)) = m_U y + b_U + \epsilon_U(y)
\]

For China, the data also appears to follow an exponential growth pattern, though there is some suggestion that the rate of growth of the exponential changes when the publication volume of China first matches that of the U.S. between 2008 and 2009. So, we fit the total volume data for China to the model

\[
\ln(n_C(y)) = m_C y + \mu_C (y - y_0)_+ + b_C + \epsilon_C(y)
\]

where

\[
(x)_+ = \begin{cases} x & x \geq 0 \\ 0 & x < 0 \end{cases}
\]

and \( y_0 \) is chosen to be the point in time where we estimate that Chinese total publication volume first met that of the U.S. by linear interpolation between the data points in 2008 and 2009. \( \mu_C \) is the magnitude of the change in slope of the log-linear relationship, i.e. the putative change in the rate of growth of the exponential.

The second metric is somewhat more circuitous, but does not depend on our assumption of mutual exclusivity. We define the “lag” of the keyword \( k \) at year \( y \), \( \delta_k(y) \), to be the smallest integer such that

\[
n_C(y + \delta_k(y), k) \geq n_U(y, k)
\]

if such an integer exists. That is, the lag is the number of years by which Chinese publication volume is behind the U.S. publication volume in keyword \( k \). For example, in 1987, the U.S. volume of papers with the keyword “neural network” was 75, and China did not meet or exceed that volume of papers with the keyword “neural network” until

\[
\begin{array}{|c|c|c|c|}
\hline
\text{Fit Value} & \text{Std. Err.} & \text{t-statistic} \\
\hline
m_U & 0.1047 & 0.001 & 47.568 \\
\hline
m_C & 0.2935 & 0.004 & 66.718 \\
\hline
\mu_C & -0.2210 & 0.015 & -14.756 \\
\hline
m_\delta & -0.5964 & 0.008 & -76.245 \\
\hline
\end{array}
\]

Figure 1: Plots and linear fits of keyword-averaged lag and total volume. Note the logarithmic scale on the plots of total volume.
1993 when we observed 220 such papers. Thus the lag for the year 1987 and keyword “neural network” was 6 years. We then calculate the lag averaged over keywords

\[ \bar{\delta}(y) = \frac{1}{m(y)} \sum_k \delta_k(y) \]  

(6)

where \( m(y) \) is the number of keywords in year \( y \) for which \( \delta_k(y) \) exists, and fit it to the model

\[ \bar{\delta}(y) = m_\delta y + b_\delta + \varepsilon(y) \]  

(7)

The relationship between total volume and lag is somewhat complicated. If every keyword were individually exponential in time with the same rate of growth and \( \mu_C = 0 \) (which is not the case in our data), we would expect that

\[ m_\delta = \frac{m_U - m_C}{m_C} \]  

(8)

That is, if all the keywords grew at the same rate the slope of the lag would be related to the rates of growth of the total volumes by Equation 8. However, this relationship is no longer guaranteed under weaker assumptions. To see this, note that the lag weights each keyword individually while the total volume fit weights them by their observed volume. That is, this relationship could be violated if our data had a large number of low-volume keywords and a few high volume keywords with radically different time dependences. Put another way, the lag incorporates some information about how the keyword distributions compare and some information about the volume over time within each keyword and, generally speaking, rewards diverse research portfolios. The lag would remain large, for example, if China’s growth to match the U.S. in total publication volume occurred only within a few keywords with the U.S. continuing to lead by large numbers of years in many other keywords. Furthermore, it is mathematically possible for the lag to not assume a linear dependence on time despite the total volumes from each country remaining exponential in time.

We obtain the fit parameters for all these models with the ordinary least squares estimator, as this estimator remains consistent under any structure for the covariance matrix of the errors. The Durbin-Watson statistic of each of these fits suggest positive autocorrelation, however, so to quantify the extent to which these fit parameters differ from zero we use a Bartlett kernel HAC estimator with bandwidth \( \sqrt{N} \), where \( N \) is the number of data points, to calculate the standard error of each of the fit parameters. Thus, the “t-statistic" reported does not have a \( t \) distribution in finite samples, though it remains asymptotically normally distributed.

In general, these fits are quite convincing. The \( t \) statistics for the parameters of interest listed in the table in Figure 1 are all quite large, assuaging any anxiety we might have about the finite sample distributions of these quantities. This analysis suggests that publication volume on these topics in both countries grew exponentially in time, and that the time constant of China’s growth shifted to come into more close alignment with that of the U.S. when the two countries began to have similar publication volumes. This could be due, for example, to the growth of both countries’ publications being limited by a third independent process, e.g. the growth in the number of academic journals accepting publications on these topics. The right-hand quantity in Equation 8 is more negative than \( m_\delta \) by more than 5 times the standard error in \( m_\delta \). This is easily explained by our subsequent explorations of the keyword distribution, as China’s heavy focus on neural networks relative to the U.S. during its period of initial growth likely resulted in a larger lag value than simply observing the volume would suggest. This results in the lag suggesting that the moment China “caught up" to the U.S. was around mid-2011, later than the date suggested by the total volume, in mid-2008. It is remarkable that the dynamics of the diversity of each country’s portfolio interact with those of the total volume to produce a linear dependence of the lag on time, despite the complicated structure of topic choice over time we will see below.
We turn now to attempting to quantify and explore the similarities of topic choice both between countries and over time. We interpret the quantity
\[ \hat{p}_I(y, k) = \frac{n_I(y, k)}{n_I(y)} \]  
(9)
as being an estimate of the underlying probability for a paper produced by country \( I \) in year \( y \) to possess keyword \( k \). We then investigate the total variation distance
\[ \Delta_{I, I'}(y, y') = \frac{1}{2} \sum_k |\hat{p}_I(y, k) - \hat{p}_{I'}(y', k)| \]  
(10)
as our measure of the difference between the distribution of keywords of country \( I \) in year \( y \) and that in country \( I' \) in year \( y' \). Under the mutual exclusivity assumption, this quantity is the maximum difference in probability the two distributions would assign to an event.

Even absent this assumption, however, we can still regard \( \hat{p}_I(y, k) \) for fixed \( I \) and \( y \) as a random vector of unit \( \ell_1 \) norm which captures some information about the distribution of topics. \( \Delta \) is then simply half the \( \ell_1 \) distance between these vectors, which still captures some idea of the distance between the topic distribution in different years and countries. In either interpretation, smaller values of \( \Delta \) indicate that the topic portfolios being compared bear a closer relationship to one another.

Looking to Figure 2 we find a remarkable amount of structure. Both counties show a marked transformation of their research portfolio around 1990 that persists to the present day. This is perhaps most striking in the case of the U.S., which has significant autocorrelation both before and after this sudden shift. We see smaller shifts take place both before and after this realignment in the U.S. portfolio, suggesting a balance of topics slowly shifting over time. China does not show the same clear, marked autocorrelation before about 1990, but this is easily understood by returning to Figure 1 and noticing that before about 1990 China was producing less than 100 English language publications on these topics per year. The quantity in Equation 9 will be more noisy for smaller sample sizes, and so too will our estimate of the total variation distance between the underlying probabilities.
Considering the third plot in Figure 2 which depicts the total variation distance between the keyword prevalence in the U.S. and China across all available years, we see some evidence of similarity between the research programs of the two countries which carries across the large shift around 1990. Before 1990, this relationship is more noisy, likely due to the low volume of English language publications out of China during that time period. The two countries had similar research programs during the 1990s, during which time both exhibited visible autocorrelation. During the 2000s, however, China’s research
program bore more resemblance to the research program of the U.S. in the 1990s than that of the 2000s. In the past decade, however, China’s research program has become more closely aligned with the U.S. program from a broad base of years between 2000 and the present, mirroring the autocorrelation of the current U.S. research program.

While the total variation distance provides an attractive measure of the similarity between the research programs of different countries and years which captures the contributions of all keywords, it does not easily expose which keywords actually participated in these shifts in research nor admit a clear intuition for how similar two research programs actually are given their total variation difference. Figure 3 addresses the first question, allowing us in particular to assign the seismic shift that occurred in research focus around 1990 as due at least in part to the rise of neural networks. Similarly, we can see one possible explanation for the phenomenon observed in the third plot of Figure 2 in that the proportion of U.S. publication volume devoted to neural networks waned much more quickly at the turn of the millennium than that of Chinese publication volume.

Though the less popular topics which still met the criterion for inclusion in Figure 3 are different between the two countries, we can look to Figure 4 to see that the leading topics in both countries tend to appear in similar though distinct proportions, at least in 2018. The two research programs are

Figure 4: Fraction of total publication volume in 2018 by country for keywords which make up at least 1% of total volume of at least one country in that year.

Figure 5: The entropy of the two publication distributions (as estimated by Equation 11) over time.
different in emphasis rather than wholly different, at least by this analysis. This presents us with a bit more context on why the waning of popularity of neural networks in China began to bring China back into closer alignment with the U.S.: the next most popular topics are, broadly speaking, shared between both countries.

Looking at Figure 3, we see some evidence that though the U.S. shifted some focus onto neural networks, China shifted its focus much more aggressively. Some of that focus remains even today, as we can see in Figure 4, which still shows neural networks making up a greater fraction of China’s publication than any single topic makes up of the U.S. publications. In order to probe the extent to which this focus impacts the overall diversity of the research portfolio in China, we study the entropy

\[
S_I(y) = -\sum_k \hat{p}_I(y,k) \ln \hat{p}_I(y,k)
\]

of the publication distribution as a probe of the overall diversity of the research portfolio. If a country were to publish all of its on a single topic in a year, we would have \(S_I(y) = 0\). With our 64 keywords, the maximum value \(S_I(y)\) can take is \(\ln(64) \approx 4.16\), which would indicate a country that publishes equally on all topics.

Figure 5 confirms quantitatively one of our suspicions from looking at Figure 3. During the 1990s, the overall topic diversity of China’s English language publication output declined precipitously due to their focus on neural networks. Conversely, though the U.S. entropy shows a slight decline in the 1990s, the rise of neural networks did not affect the overall diversity of U.S. publication nearly as strongly. Notably, as neural networks waned in popularity in China we see the overall diversity of publication topics rise to eventually exceed that of the U.S.

Though the U.S. and China reacted to different degrees to the recent interest in neural network methods, the data shows a dramatic consonance between the research programs in both time and topic choice. China was and remains more focused on neural network methods than the U.S., at least by this data, but both countries clearly explore the same areas and react to the same trends in research topics. Notably, most of the regions of lower total variation distance between the two countries shown in Figure 2 occur above the diagonal. That is, from about 1990 through to the present, the portfolio of topics that institutions in China produced publications on in any given year bore more resemblance to the U.S. in previous years than it did to the U.S. in that year or future years. This is consistent with a picture wherein China lagged the U.S. not just in volume but also in topic choice. Without further study, however, it’s difficult to say whether this indicated that China’s research program was actually any less effective during that time.

Rather than a definitive accounting of the research capacities of the two countries in question, we hope this work serves to highlight the richness of the problem of determining the research capacities of countries or research communities. More study is needed to understand the extent to which national boundaries do, or do not, affect the evolution of research communities and how these effects manifest. At present, it is not even clear how best to pose the question of who is winning any putative AI race.

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