Mapping the Movement of AI into the Marketplace with Patent Data

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The Problem: Existing Science and Technology Indicators Cannot Track the Movement of AI into the Marketplace

The National Academies of Science, Engineering, and Medicine recently released *Information Technology and the U.S. Workforce: Where Are We and Where Do We Go From Here?,* the formal report of an expert committee co-chaired by MIT economist Eric Brynjolfsson and Carnegie Mellon University computer scientist Tom Mitchell (hereafter, NASEM Report). This document highlighted the potential for emerging technologies to further reshape demand in the U.S. labor market, and outlined a research agenda for better understanding this impact and dealing effectively with its economic consequences. The NASEM Report and a related essay in *Nature*, published by the committee co-chairs Brynjolfsson and Mitchell, emphasized the central importance of better measures of the development and diffusion of potentially disruptive new technologies associated with artificial intelligence (AI) and machine learning. The expert panel that authored the NASEM report agreed that these technologies could have a disruptive impact on the U.S. labor market, even as they raise productivity and output. However, existing official science and technology indicators are far too crude to trace the development of these technologies and track their deployment in actual goods and services. This poses a fundamental challenge for public policies that might seek to ameliorate the disruptive impact these technologies are likely to have on the U.S. labor market – one cannot target what one cannot see.

The Solution: Use AI to Identify AI-related Patents

Fortunately, firms that succeed in using artificial intelligence to create new goods and services have a strong incentive to patent their inventions. If they fail to do so, other firms can copy their innovations without penalty or use patents to block the original innovator from applying their inventions in the marketplace. This means that firms throughout world are filing thousands of AI-related patents every year with the U.S. Patent and Trademark Office. By law, each patent document becomes public 18 months after filing, even if it is still being adjudicated by the patent office. Each patent application is supposed to provide sufficient detail such that the invention could be replicated by an independent expert in the technology.

Patents are classified according to the technology they contain, and the U.S. Patent and Trademark Office has created a detailed taxonomy containing several hundred patent classes (and thousands of subclasses). However, if we only count patents in the class and subclasses specifically and primarily associated with AI we vastly undercount the true scope and scale of the AI/machine learning revolution that is now transforming American invention. The reason a narrow focus is insufficient is precisely the reason that this emerging technology is so important — the applications, current and potential, of artificial intelligence, machine learning, "big data," and analytics are so broad as to encompass virtually the entire economy. Broadly similar machine learning algorithms can be used in combines, cars, aircraft, banks, insurance companies, and travel agencies, and the patents that apply them to these different domains could show up across a vast range of classes, including classes associated with the domain of application of the patent (i.e., aircraft or combines) rather than the patent class specifically set aside for artificial intelligence.

If AI-related inventions can show up virtually anywhere with the patent classification system, how might we find them? An efficient answer to this question requires the use of AI! By training machine learning algorithms to parse patent documents, we can identify which patented inventions contain a substantial amount of AI with a reasonably high degree of accuracy. Implementing this idea in practice requires a multidisciplinary research team with a broad range of skills. Fortunately, CMU has exactly the right mix of expertise and an academic culture that fosters interaction across disciplines. Lee Branstetter, Director of the Future of Work Initiative within Carnegie Mellon's new Block Center for Technology and Society, is an internationally recognized expert in the use of patent data to track the direction, pace, and economic impact of innovation. Social scientists, including Branstetter, have already begun using simple text mining algorithms to search for key words and phrases inside patent documents (Branstetter et al., 2013; Branstetter et al., 2018), that can provide more detailed information on the content of individual inventions than that conveyed by the classes to which they are assigned. However, recent developments in machine learning are vastly expanding the degree to which software can evaluate and draw sophisticated conclusions from complex streams of digital text. Eduard Hovy, Research Professor at Carnegie Mellon's Language Technologies Institute, is one of the world's leading experts in natural language processing. Together with graduate student Andrew Runge, Professor Hovy led the team's efforts to train a support vector machine (SVM) that could classify AI patents effectively and accurately. CMU doctoral student Dean Alderucci, a former patent attorney with prior expertise in patent data analytics, provided a training data set that included "hand-labeled" AI and non-AI patents, and evaluated the accuracy of the SVM's output. After several months of iterative work, our team has created a robust algorithm that achieves a high degree of classification accuracy.[1] An additional useful feature of our algorithm is that it tags each patent with an estimated likelihood of being AI-related, allowing us to compare and contrast the "core" AI patents the algorithm identifies with near certainty and the "borderline" patents to which the algorithm assigns a significantly lower likelihood of being AI-related.

Using Patent Data to Map the Movement of AI from Theory to Practice

With this algorithm in hand, we can identify all of the patents classified by the algorithm as being AI-related up to a chosen likelihood threshold. Once we have identified these patents, we know the date on which the patent application was filed, which is likely to be proximate in time to the date of invention, as well as the date the patent was granted.[2] We also know the corporate owners of the patents and the geographic location of the inventors who created the new technology. This allows us to create a dynamic statistical portrait of AI invention across time and geographic space that updates every week, as newly published patent applications provide new information on the latest AI inventions. We can compare and contrast the AI patent portfolios of different individual firms engaged in R&D in this domain. Patents often contain information describing the industry in which the invention is expected to be applied, and this can be different from the industry classification of the firm that created the patents. We are currently

[1] Technical details can be obtained from the authors.

[2] With some exceptions, U.S. patent law follows international rules in assigning ownership of an idea to the first party to file a successful patent application, whether or not that party is actually the first to invent the patent.

investigating how these data could be utilized to map our AI patents into their industries of use more accurately.[3]

Even as that research continues, we can already describe some important features of the statistical map of AI invention sketched out by our data. The figures found at the end of this short summary illustrated some of these important aspects of our data. In creating all of these figures, we have imposed a likelihood threshold of 85%. In other words, for a patent to be included in the data used to create these figures, our algorithm had to estimate a likelihood of 85% or greater that this particular patent was truly AI-related.

AI patenting extends well beyond the specialized patent class specifically designated for AI inventions. Figure 1 underscores the idea that originally motivated our research project. Because patents that apply AI concepts are likely to classified in the domains of application, officially designated "AI" patents will vastly undercount the number and range of real AI inventions.

AI-related inventive activity is growing rapidly, and has already reached high levels. Figure 2 provides a simple count of the number of AI-related inventions by grant year of the patent. For 2018, only data from the first few weeks of the year are available — by year's end, we expect total 2018 patent counts to exceed those of previous years. We should emphasize that these counts only include patents granted by the U.S. Patent and Trademark Office (USPTO). However, the U.S. is the world's largest economy and, arguably, the most important market for AI-related invention, so tens of thousands of AI-related inventions originally created by inventors outside the United States have been patented in the U.S. as well as in their home countries and other major markets. Nevertheless, there may be some AI-related inventions for which no U.S. patent is ever granted. Such inventions would not be reflected in this graph or the ones that follow. As of early 2018, our algorithm classifies 71,871 patents granted since 1990 as being AI-related at the 85% confidence level. Numbers of grants have grown sharply over the past decade, and annual flows of new patented inventions now exceed 8,000 per year.

An extremely diverse group of firms are investing in AI-related inventions. U.S. patent data identify the "assignee" (owner) of a patent document, so we can rank assignees by their cumulative number of AI patent grants. This breakdown is provided for the largest AI patentees in Figure 3. While the identities of the firms at the far left, which hold the largest numbers of AI patents, are not surprising, our team members were surprised to see how many traditional manufacturing firms are in the set of large AI patentees, and also how collectively important these enterprises are in terms of generating AI patents over time. Because of space constraints, we are only able to identify the very largest AI patentees. Recent grant recipients include a large number of young, start-up enterprises that are actively patenting in this space. This is not a domain that is utterly dominated by a small number of digital giants.

The U.S. is the overwhelmingly dominant source of AI invention; China barely registers on our statistical map. Figure 4 breaks down cumulative AI patent counts by country of residence of the inventors. We need to acknowledge that these data, taken from the U.S. Patent and Trademark Office, will tend to exaggerate the importance of American inventors, because inventors around the world tend to file patent applications at home for a large fraction of their inventions, while they are more selective in terms of seeking patent protection abroad. Nevertheless, as we noted above, the size of the U.S. market and the advanced development of AI technology in the U.S. makes it arguably one the most strategically important AI market in the world. This should induce inventors outside the United States to obtain American patents for their valuable ideas. Given that reality, it is interesting to note that U.S.-based

[3] This component of the project is being undertaken in collaboration with Dr. Nikolas Zolas of the U.S. Census Bureau.

inventors account for an overwhelming majority of granted AI patents. The next largest inventor country is Japan. Despite the flood of recent articles pointing nervously to the prowess of China in this domain, China remains a relatively unimportant source country. In fact, our data identify more AI patents invented in Taiwan than on the Chinese mainland. As our research project moves forward, we can contend with the "home market bias" of American inventors in USPTO data more directly by applying our techniques to patent data from other major patent jurisdictions, including Western Europe, Japan, and China.

Even within the United States, AI invention is fairly concentrated. U.S. patent data identify not only the country of residence, but also the address of each listed inventor.[4] Assigning our AI inventors to cities, as in Figure 5, we see that AI-related invention is highly clustered on the coasts and in a relatively small number of inland cities. The West Coast looms especially large, with significant clusters in Seattle, the Bay Area, and Southern California.

How is AI Affecting Demand for Labor?

Having identified AI patents and linked them to the firms, countries, cities, and years in which they were invented, can we also make any quantitative statements about the impact of this rising tide of AI invention on labor demand? This question can be probed empirically by linking the data on AI patents to the firms that invent them and the industries that use them. Annual surveys undertaken by national statistical agencies in the United States and other advanced industrial nations generate detailed data on the employment of various kinds of labor by AI-intensive firms and their industry peers who are lagging in the development of these technology. We can thus measure how increasing development of AI by a given firm impacts the quantity and quality of labor it hires. We can track these changes across firm size categories, industries, and time, within the United States and other major industrial economies, providing important early evidence on the ways in which this emerging technology may be reshaping labor demand.

In the United States, the Census Bureau maintains a comprehensive database linking patents to firms, including private held firms not listed on any equity exchange, and economists working for the Bureau have access to the confidential data records that track these firms' employment of various categories of workers. Access to these data is restricted to Census employees and researchers who have been cleared to use these data for specific projects, so the ability of our team to link data on AI invention to data on labor demand at the enterprise level would be contingent on the approval and cooperation of the U.S. Census Bureau. Provided such cooperation could be established and maintained, it would be possible to get direct estimates of the impact of AI on labor demand and wages using exactly the kind of disaggregated, enterprise-level data one would need to estimate this effect most credibly.

The existence of similar datasets outside the United States raises the interesting possibility that this study could examine labor market impacts in other advanced Western countries. The Office of National Statistics in the U.K. maintains databases quite similar to those of the U.S. Census Bureau, and could conduct a parallel study of foreign-owned and domestically owned enterprises in the United Kingdom. Despite similarities of language and culture, and a close trading and investment relationship between the two countries, labor markets in the two countries operate under different rules and institutional arrangements. It may therefore be instructive to observe how the labor market changes resulting from the deployment of AI-related technologies are affected by these different rules and institutions. Study of the

[4] These data have issues of completeness and accuracy that are already well documented by other studies. While the data on individual inventors may be problematic, we nevertheless believe the data are of sufficiently high quality on average that with tens of thousands of AI-linked patents, the figure provides a reasonable representation of the allocation of AI-linked inventive activity across U.S. cities.

changing labor practices of the U.K. affiliates of U.S.-based multinationals may be particularly helpful; these affiliates are likely to possess access to the same technology as the U.S. parent, but still have to comply with U.K. labor law and practice. In principle, similar comparative studies could be undertaken with the cooperation of the statistical agencies of other advanced industrial nations.

Given the high and growing degree of concern about the potential impact of AI-related technologies on future wages and employment, such analysis is badly needed. At the moment, the debate over the economic impact of AI is highly polarized, with pessimists contending that the technology will bring an apocalypse of mass unemployment and optimists arguing that, instead, AI and its many applications will bring prosperity for all. Neither position is yet supported by sufficient empirical analysis. The research strategy sketched out here can help us better understand what the future impact of AI will be by combining data on thousands of AI-inventing and AI-using firms with data on tens of thousands of AI patents to show what the impact on employment has been so far.

As that agenda moves forward, it will be increasingly important to accurately identify the "industries of use" of our AI patents. It will be reasonably straightforward to estimate the impact of AI created for the firm's own use on the employment of the inventing firms. In many cases, however, the patented AI inventions documented in our data are created by firms in one industry in order to be used by different firms in different industries, and we would expect the first-order impact of these inventions on employment to be found in the firms and industries that use them. Building on the work of Lybbert and Zolas (2014), and using additional machine learning techniques, we seek to create a high-quality mapping of our patents to their industries of use.[5]

As this research project moves forward, paper drafts and progress reports will be posted to this website. Questions can be directed to Lee Branstetter at branstet@cmu.edu.

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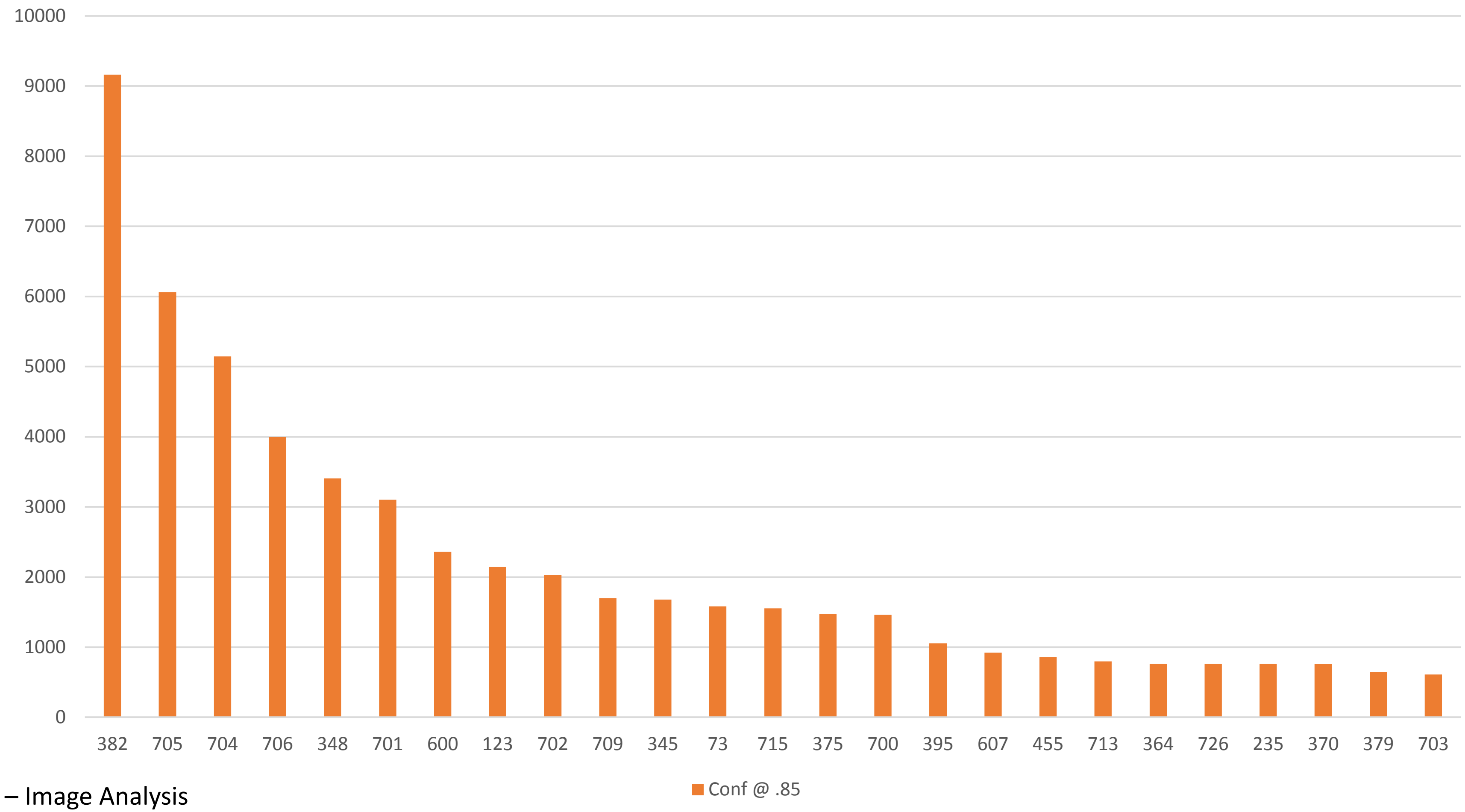
[5] See "Travis J. Lybbert & Nikolas J. Zolas" ("2014"). "Getting patents and economic data to speak to each other: An 'Algorithmic Links with Probabilities' approach for joint analyses of patenting and economic activity". *"Research Policy", "43"*, "530 - 542".

Figure 1 AI Patents by Patent Class



382 – Image Analysis
705 – Data processing: financial, business practice, management, or cost/price determination
704 – Data processing: Speech, Linguistics, Language Translation, Audio (de)compression
706 - Data processing: Artificial Intelligence
348 –Television
702 – Data processing: Vehicles, Navigation, and Relative Location
600 – Surgery
123 – Internal Combustion Engines

Figure 2 AI Patents by Patent Application Date

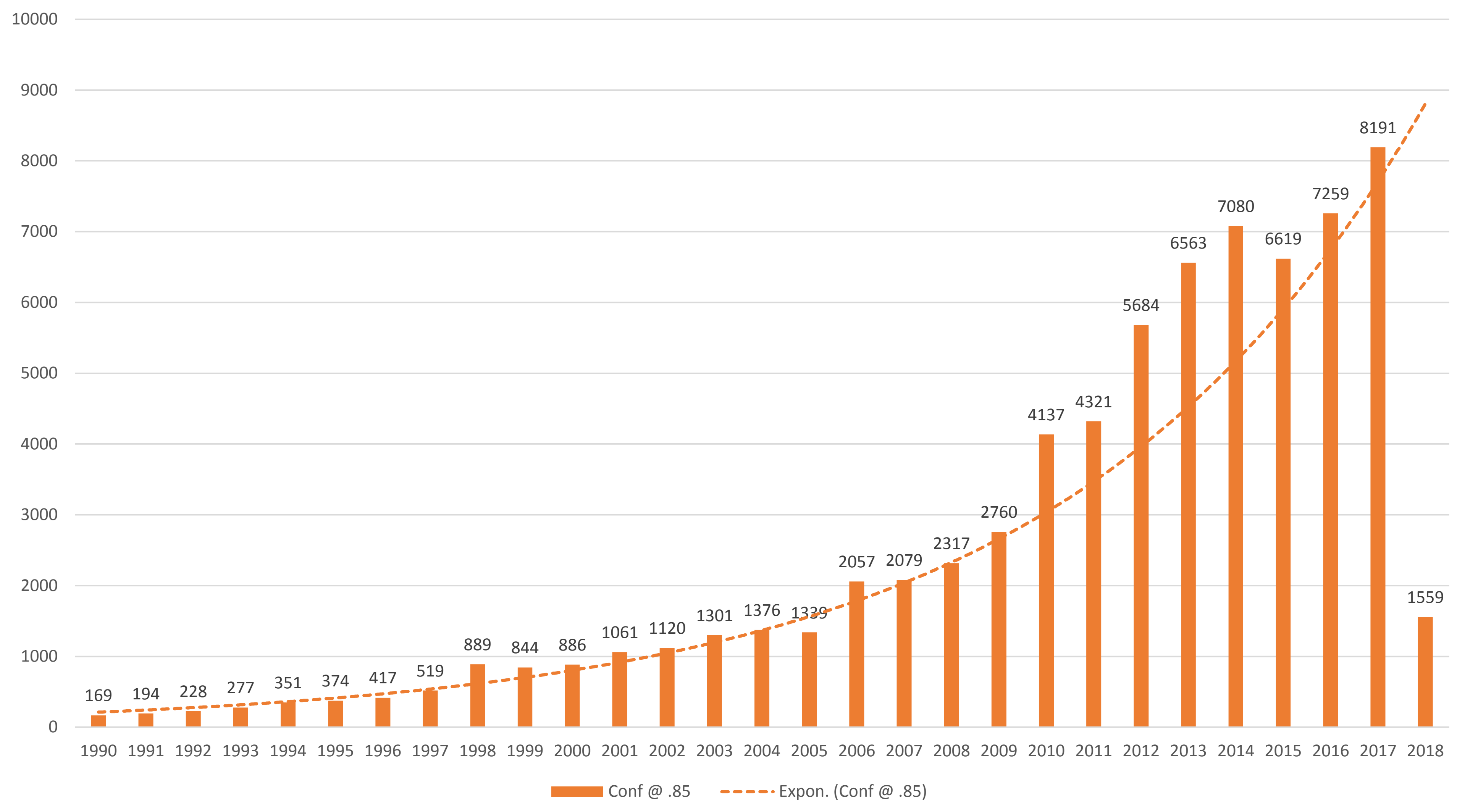


Figure 3 AI Patents by Assignee (Patent Owner)

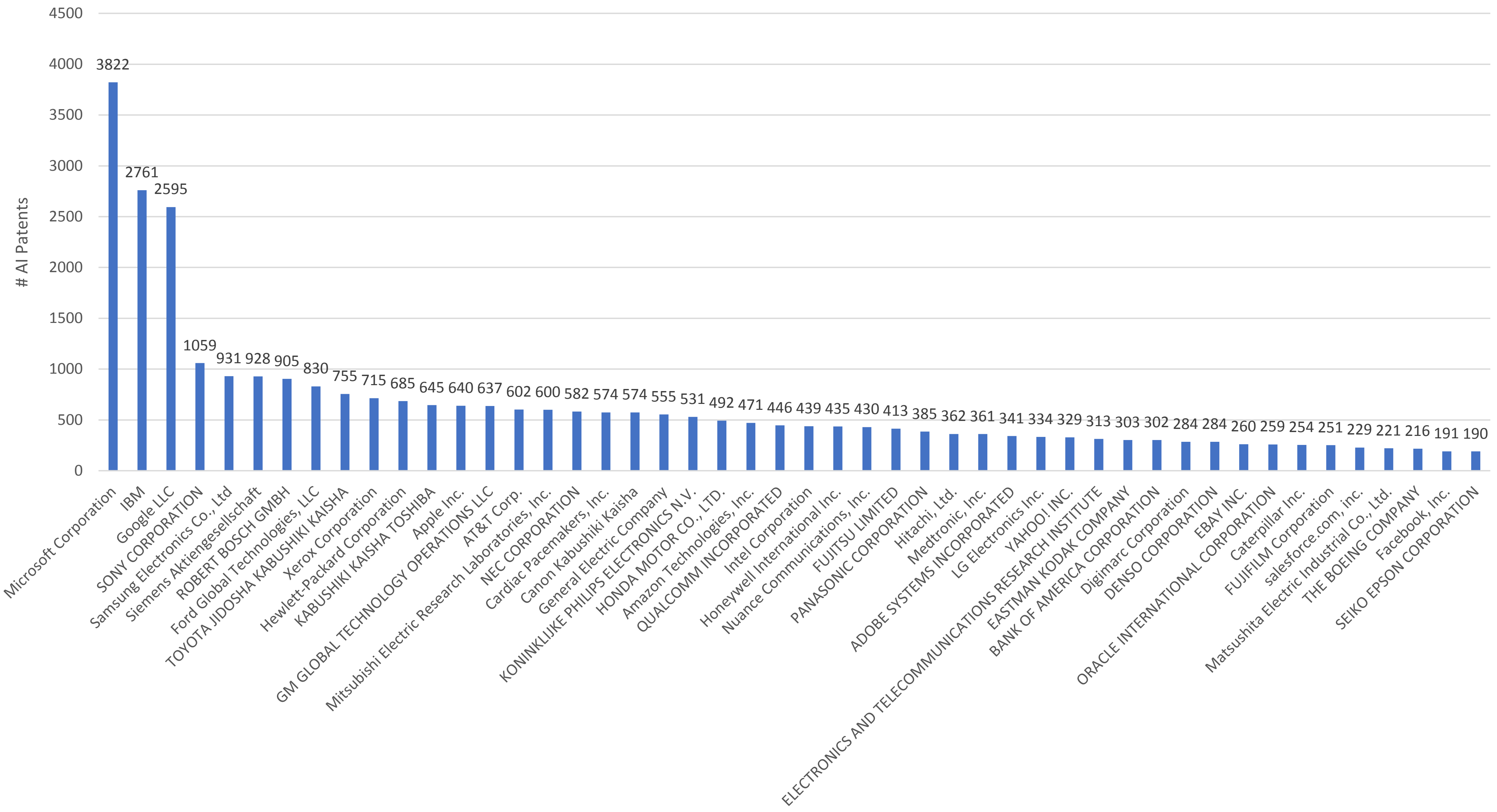


Figure 4 AI Patents by Inventor Country

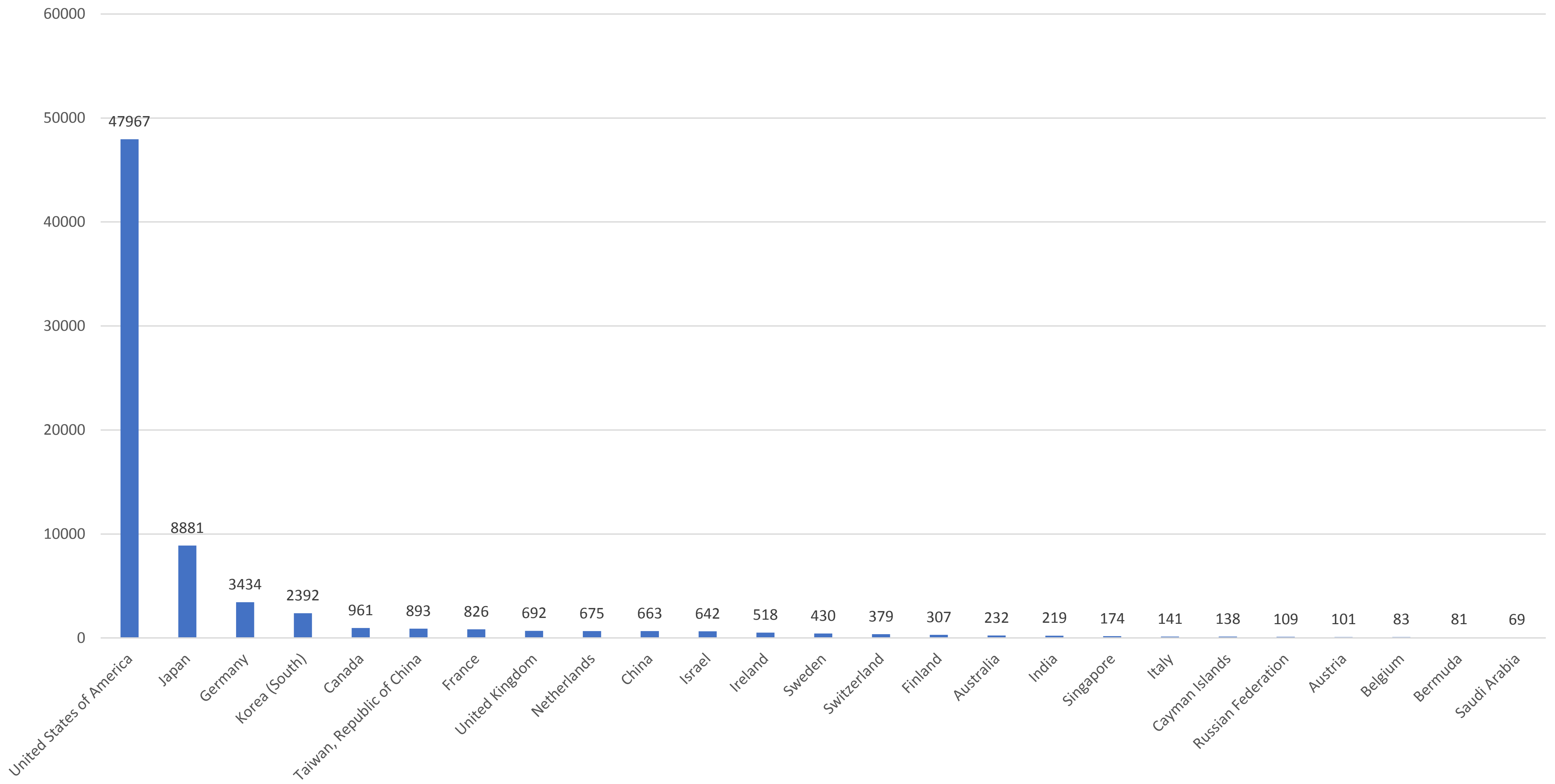


Figure 5 U.S. AI Patents by Inventor City