How much technical talent is there? A systematic estimate of the ML research pool among 3 million IT consultancy employees

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Abstract

Why was this study done?

To determine whether there is latent capacity of capable technical machine learning research talent in the IT Consultancy sector. This talent pool could advance AI risk mitigation and alignment research agendas.

How was the study conducted?

We systematically searched the internet, global business databases, and conference/paper affiliations for ML consulting firms. Employee LinkedIn resumes were then scored by keyword filters and large-language-model (LLM) classifiers; these signals were combined in a bootstrap probit model to estimate technical ML Research Talent per firm. A subset of companies also completed a 3-day ML research & engineering work trial.

Results

We screened 2 121 organizations and found 403 to offer broader ML related consulting services. 3 269 000 employees were associated with this sample. The distribution was 284 (70.5%) small (< 100 employees), 76 (18.9%) medium (100–999 employees), 23 (5.7%) large (1 000–9 999 employees), and 20 (5.0%) giant ($\geq$10 000 employees) companies. The 50th percentile aggregate estimate of highly technical ML Research Talent across these organizations was 1 121 (80% CI: 252–3 165).

For our work trial 97 companies were approached, 20 applied, 8 were invited to participate, and 5 of 8 (63%) received at least a conditional recommendation for technical AI safety work. No AI model was able to pass the work trial successfully.

Limitations and future research

Some companies, particularly in certain geographic regions, might be poorly represented on LinkedIn. More generally, resumes remain an inherently noisy signal of competence and our definition of technical ML research talent might have excluded some competent ML practitioners. For very large companies we often had fewer estimates due to data collection limitations. Future research could incorporate broader LinkedIn data sweeps and public outputs such as papers or code repositories to assess competence further.

Conclusion

We identify a substantial pool of technically competent ML Research Talent in the low thousands across companies offering ML consulting services. These organizations represent a viable path for expanding capacity for technical AI assurance work.

Conflicts of Interest

The authors report no conflict of interest.

Author Contributions

Conceptualization: MS, NZ, RB, GL, SH · Methodology: MS, NZ, OE, GL · Software: FA-Z, OE · Formal analysis: MS, FA-Z, OE · Investigation: RB, NZ · Data curation: RB, MS · Visualization: MS, OE · Writing, original draft: MS · Project administration: MS, RB · Supervision: MS, SH

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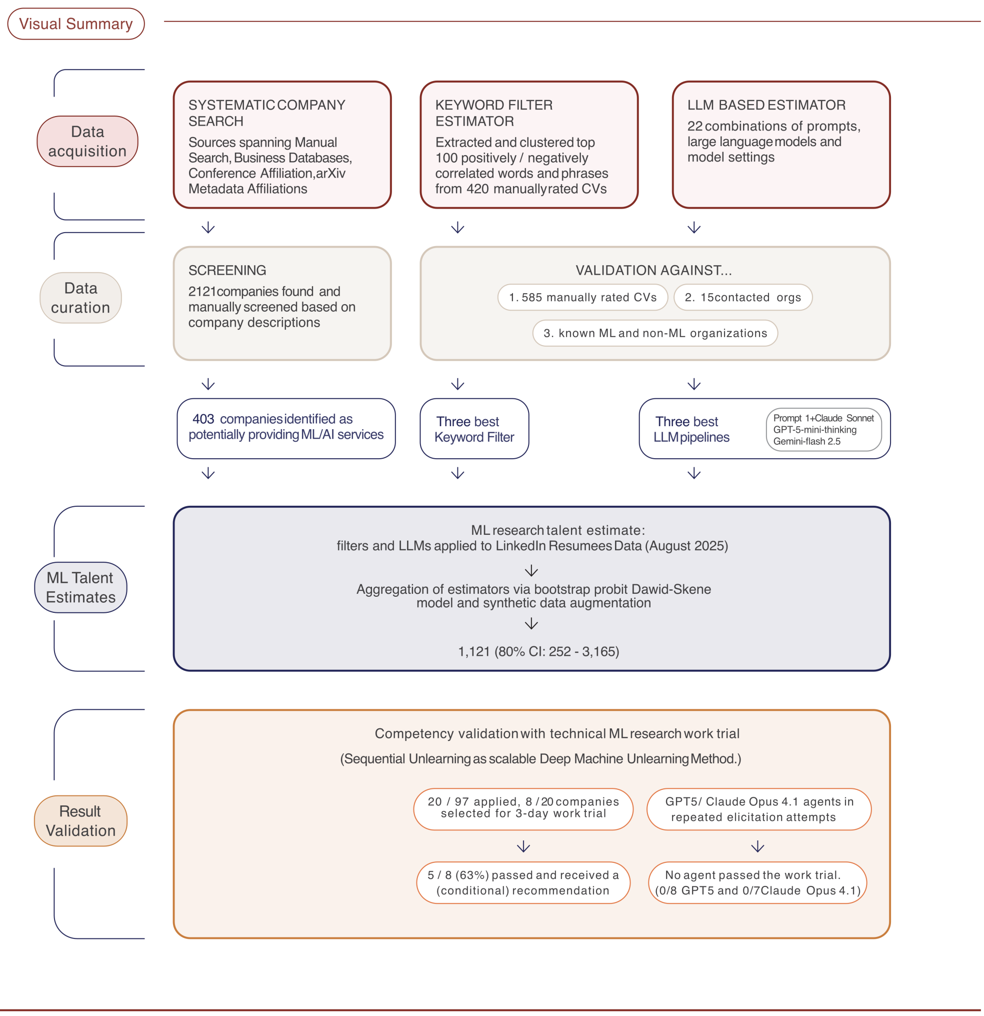
Statement on AI Use

We used large language models (OpenAI GPT-4/5, Google Gemini 2.5 Flash/Pro, and Anthropic Claude 3.7/4/4.5) as described in the method section. Beyond individual prompts, models were used for literature search and to generate early section drafts. Models were also used for data-analysis support. All AI-generated content was thoroughly reviewed, verified, and edited by the authors, who take full responsibility for the final content.



Visual summary of the study

Introduction

The bottleneck for AI safety and alignment work is access to technical talent. Capital expenditure for AI infrastructure is rising at an exceptional rate (see [1–4]), yet outside a handful of frontier labs and academic groups, few organizations can execute difficult alignment and evaluation work at production speed. Existing programs such as MATS (ML Alignment & Theory Scholars) have supported several hundred scholars since 2021—meaningful, but small relative to the scale of the challenge.

This paper tests whether IT consulting firms can supply a scalable pool of competent engineers and researchers for technical AI assurance. The sector is sizeable, with individual companies employing hundreds of thousands of workers and investing heavily in AI capabilities—for example Accenture's $3 billion plan and Capgemini's multi-year multibillion-euro initiative (Accenture Newsroom, Capgemini). If a fraction of this workforce can be identified and directed toward alignment tasks, funders and operators could expand capacity rapidly.

We contribute three things. First, we assemble a first-of-its-kind systematic sample of ML consultancies globally; second, we estimate their technical ML research headcount using LinkedIn resumes; and third, we validate capabilities through a multi-day work trial benchmarked against modern LLM agents and established AI/non-AI companies.

Results

Systematic Search

Figure 1 provides a flow chart of the inclusion and exclusion of companies at various stages of the project. In total 2 121 companies were identified and screened, eventually leaving 403 companies that promised to provide ML consultancy services. Consultancies were globally distributed, but leaned towards the US and Europe as shown in Figure 2.

The total headcount of current employees based on LinkedIn Sales Navigator was 3 269 000 with the top organizations having hundreds of thousands of employees. In 126/403 (31.3%) of companies we were not able to detect any talent as per our definition.

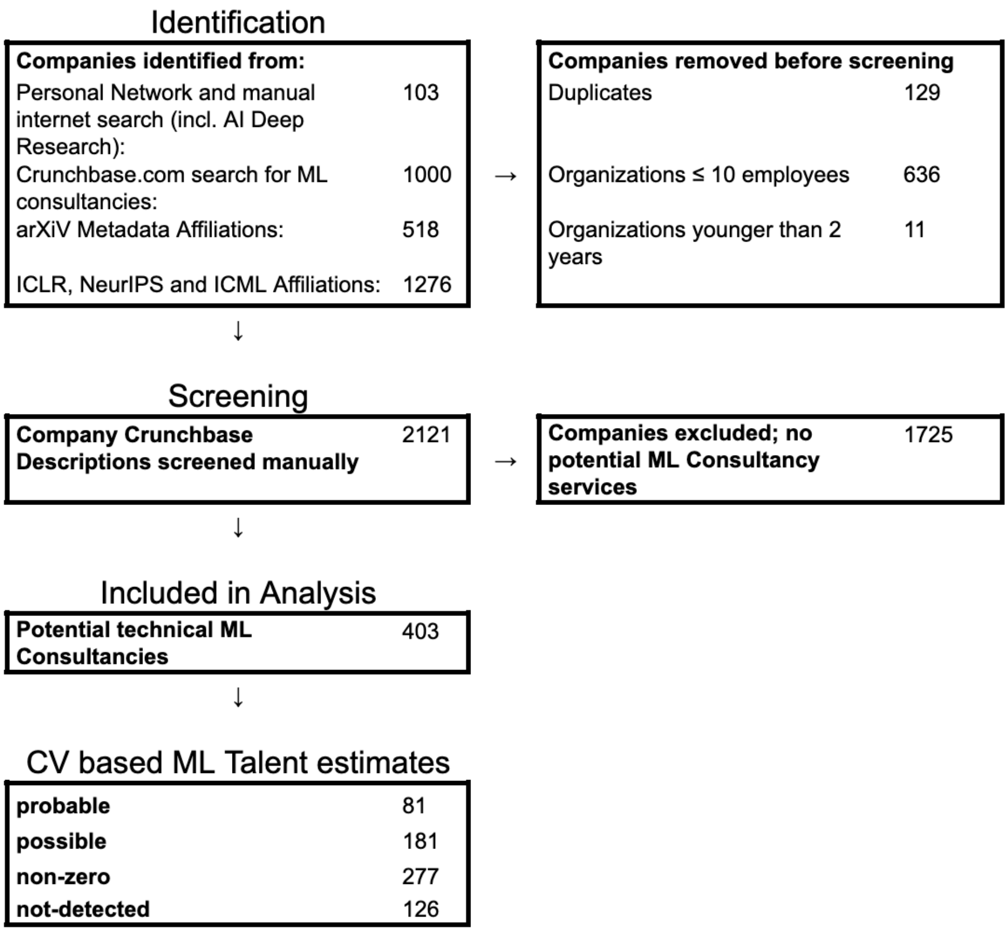


Figure 1. Flow chart of search process

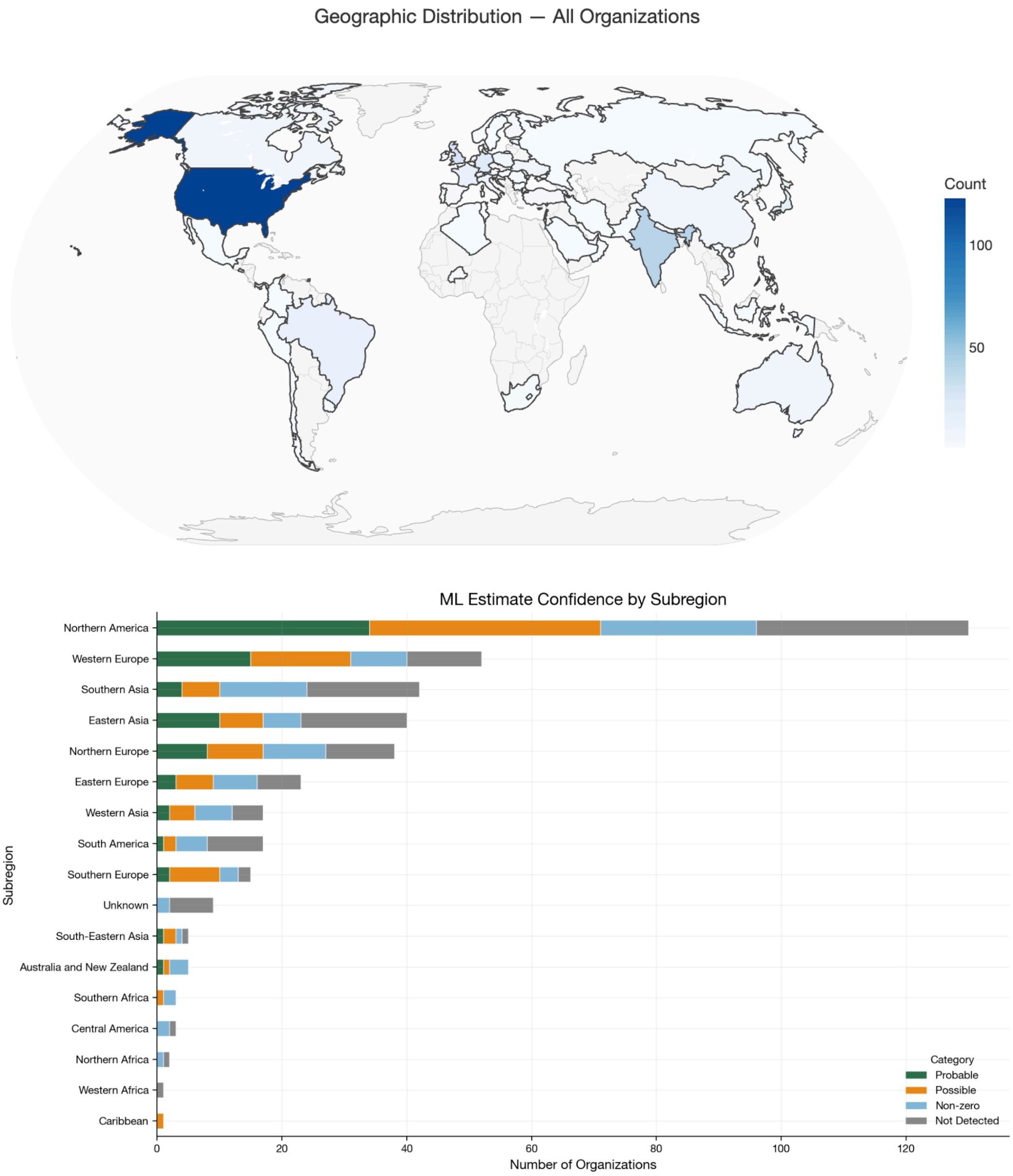


Figure 2. A) Map of 403 identified ML Consultancies B) Breakdown by Country and category. Organizations are classified into mutually exclusive confidence categories based on their ML research talent estimate distributions (q10, q50, q90 representing the 10th, 50th, and 90th percentiles).

Table 1. Descriptive Statistics on various cohorts of the analysis

Characteristic	**All**	**Probable**	**Possible**	**Non-zero**
Total				
Organization N	403 (100.0%)	81 (100.0%)	100 (100.0%)	96 (100.0%)
Total employees	3 269 000	2 931 516	280 284	3 365
Median founding year	2014	2014	2013	2016
Median total employees	28	442	90	22
ML research staff (q50)	1 121 (252 - 3 165)	890 (218 - 2 522)	205 (33 - 537)	24 (0 - 99)
ML % of total	0.0% (0.0% - 0.1%)	0.0% (0.0% - 0.1%)	0.1% (0.0% - 0.2%)	0.7% (0.0% - 2.9%)
Small (< 100 employees)				
Organization N	284 (70.5%)	19 (23.5%)	55 (55.0%)	87 (90.6%)
Median total employees	15	48	36	20
ML research staff (q50)	166 (28 - 420)	71 (20 - 140)	71 (8 - 179)	23 (0 - 94)
ML % of total	2.6% (0.4% - 6.5%)	6.9% (1.9% - 13.6%)	2.9% (0.4% - 7.4%)	1.0% (0.0% - 4.1%)
Medium (100-999 employees)				
Organization N	76 (18.9%)	37 (45.7%)	30 (30.0%)	9 (9.4%)
Median total employees	232	388	215	112
ML research staff (q50)	398 (134 - 823)	320 (117 - 638)	76 (16 - 180)	1 (0 - 4)
ML % of total	1.7% (0.6% - 3.5%)	2.1% (0.8% - 4.2%)	1.0% (0.2% - 2.5%)	0.1% (0.0% - 0.4%)
Large (1,000-9,999 employees)				
Organization N	23 (5.7%)	10 (12.3%)	11 (11.0%)	0 (0.0%)
Median total employees	2 900	4 600	2 300	
ML research staff (q50)	154 (32 - 446)	117 (25 - 337)	37 (6 - 108)	0 (0 - 0)
ML % of total	0.2% (0.0% - 0.5%)	0.2% (0.1% - 0.7%)	0.1% (0.0% - 0.4%)	n/a
Giant ($\geq$10 000 employees)				
Organization N	20 (5.0%)	15 (18.5%)	4 (4.0%)	0 (0.0%)
Median total employees	60 000	85 000	42 500	
ML research staff (q50)	401 (57 - 1 474)	381 (55 - 1 406)	20 (2 - 68)	0 (0 - 0)
ML % of total	0.0% (0.0% - 0.0%)	0.0% (0.0% - 0.0%)	0.0% (0.0% - 0.0%)	n/a
Regions (orgs)				
Northern America	130 (32.3%)	34 (42.0%)	37 (37.0%)	25 (26.0%)
Western Europe	52 (12.9%)	15 (18.5%)	16 (16.0%)	9 (9.4%)
Southern Asia	42 (10.4%)	4 (4.9%)	6 (6.0%)	14 (14.6%)
Eastern Asia	40 (9.9%)	10 (12.3%)	7 (7.0%)	6 (6.2%)
Northern Europe	38 (9.4%)	8 (9.9%)	9 (9.0%)	10 (10.4%)
Eastern Europe	23 (5.7%)	3 (3.7%)	6 (6.0%)	7 (7.3%)
Western Asia	17 (4.2%)	2 (2.5%)	4 (4.0%)	6 (6.2%)
South America	17 (4.2%)	1 (1.2%)	2 (2.0%)	5 (5.2%)
Southern Europe	15 (3.7%)	2 (2.5%)	8 (8.0%)	3 (3.1%)
Unknown	9 (2.2%)	0 (0.0%)	0 (0.0%)	2 (2.1%)
Australia and New Zealand	5 (1.2%)	1 (1.2%)	1 (1.0%)	3 (3.1%)
South-Eastern Asia	5 (1.2%)	1 (1.2%)	2 (2.0%)	1 (1.0%)
Central America	3 (0.7%)	0 (0.0%)	0 (0.0%)	2 (2.1%)
Southern Africa	3 (0.7%)	0 (0.0%)	1 (1.0%)	2 (2.1%)
Northern Africa	2 (0.5%)	0 (0.0%)	0 (0.0%)	1 (1.0%)
Western Africa	1 (0.2%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Caribbean	1 (0.2%)	0 (0.0%)	1 (1.0%)	0 (0.0%)

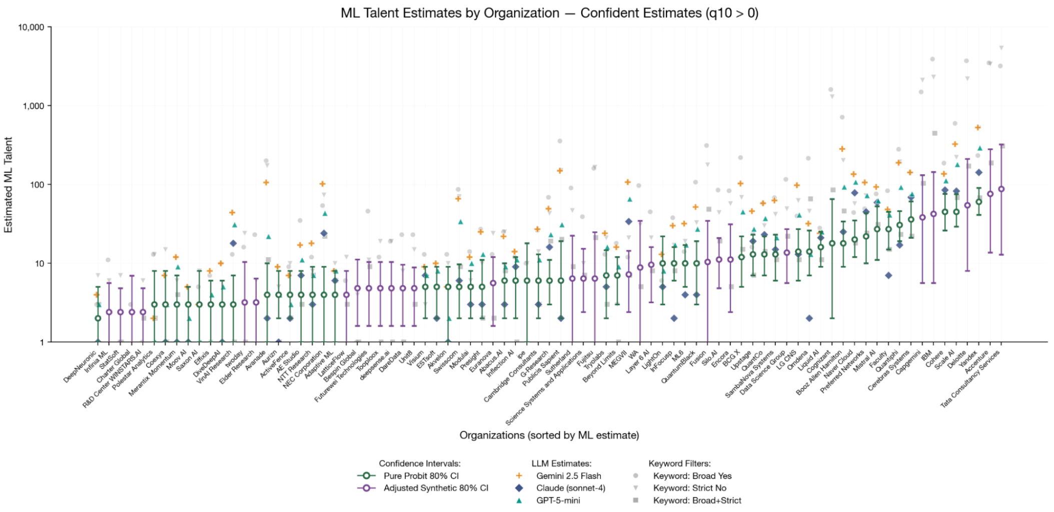


Figure 3. Individual and aggregated ML Research Talent estimates of 81 organizations among identified technical ML consultancies classified as probable—the 80% confidence interval excludes zero, indicating confident ML presence. When LLM estimates were not available, synthetic data approaches were used (purple).

ML Research Talent Estimates

Table 1 presents the aggregated ML Research Talent estimates. For 81/403 (20%) organizations the 80% confidence interval excludes zero, indicating relative confidence for ML Research Talent presence; these firms account for 890 (218–2 522), or 79.4% of all ML Research Talent in our sample (Figure 3). Figure 4 plots the ML staff count against the percentage of technical ML Research Talent. Individual company estimates and categorizations are available in the Supplements.

Our final estimator had a sensitivity of 0.79 and specificity of 0.926, yielding the best accuracy across estimators (0.89), a Positive Likelihood Ratio (LR+) of 10.67, and a Negative Likelihood Ratio (LR-) of 0.23.

As an additional validation step, we applied the selected estimation methods to companies we knew to have high technical ML Research Talent counts and to organizations who certainly don't. The results are presented in the Supplements. Our method arrived at high technical ML Research Talent counts for established AI organizations (e.g., OpenAI, Mistral AI, HuggingFace) and low to zero counts for non-AI companies (e.g., Patagonia, Crocs, Inc., The British Museum) when priors were chosen accordingly.

However, for several established ML organizations—particularly those where LLM-based estimates were unavailable and synthetic imputation was used instead—the pipeline produced estimates that appear implausibly low. For example, Anthropic (2 000 employees) received a median estimate of only 9 (1–26) ML research staff. Similarly, other large organizations relying on synthetic estimates (marked with * in the Supplements), such as Amazon, Meta, Microsoft, and NVIDIA, yielded lower estimates relative to their known ML research activity. This pattern was most pronounced for companies where the consultancy-calibrated priors (Table 4) were applied to organizations with fundamentally different talent compositions, and where

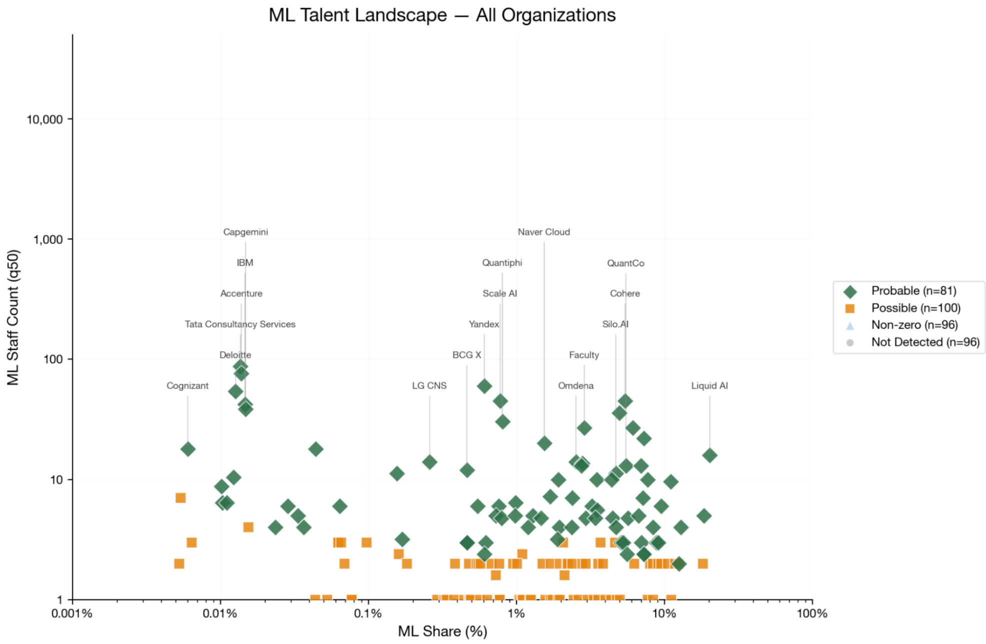


Figure 4. Visualization of ML staff count by share of ML Research Talent of total company employees. A) IT Consultancies B) 18 comparator ML Companies C) 18 non-ML companies

the absence of LLM-based individual CV assessments left the pipeline reliant solely on keyword-derived synthetic annotations.

Work Trials

In parallel to the talent estimation work, we reached out to a total of 97/403 (24.1%) companies for a 2-month engagement, including a 3-day work trial. 57/97 (59.8%) were not part of the IT consultancies we identified as "ML consultancies" and functioned as additional validation. We were able to get in contact with 47/97 (48.5%) companies and eventually received 20/97 (20.6%) applications. 12 organizations were either rejected or pulled back during the application process, leaving 8 organizations who were offered a work trial. All organizations invited to a work trial performed it during a 4 week period in July to August 2025.

The work trial task was to implement a "Sequential Unlearning" method - a multi-stage wrapper around their existing RMU algorithm that progressively unlearns data in folds - and integrate it into their evaluation codebase, with daily progress updates and a final code/write-up deliverable. The full repository is available in the appendix.

The breakdown of the work trial evaluation is presented in Table 2. Three organizations received a recommendation, two a conditional recommendation, 3/8 (37.5%) no recommendation. Prices varied from \$45 to \$350 per hour, with two organizations providing the work trial free of charge. For confidentiality reasons, individual results, evaluations and company names related to the work trial are not shared with this publication.

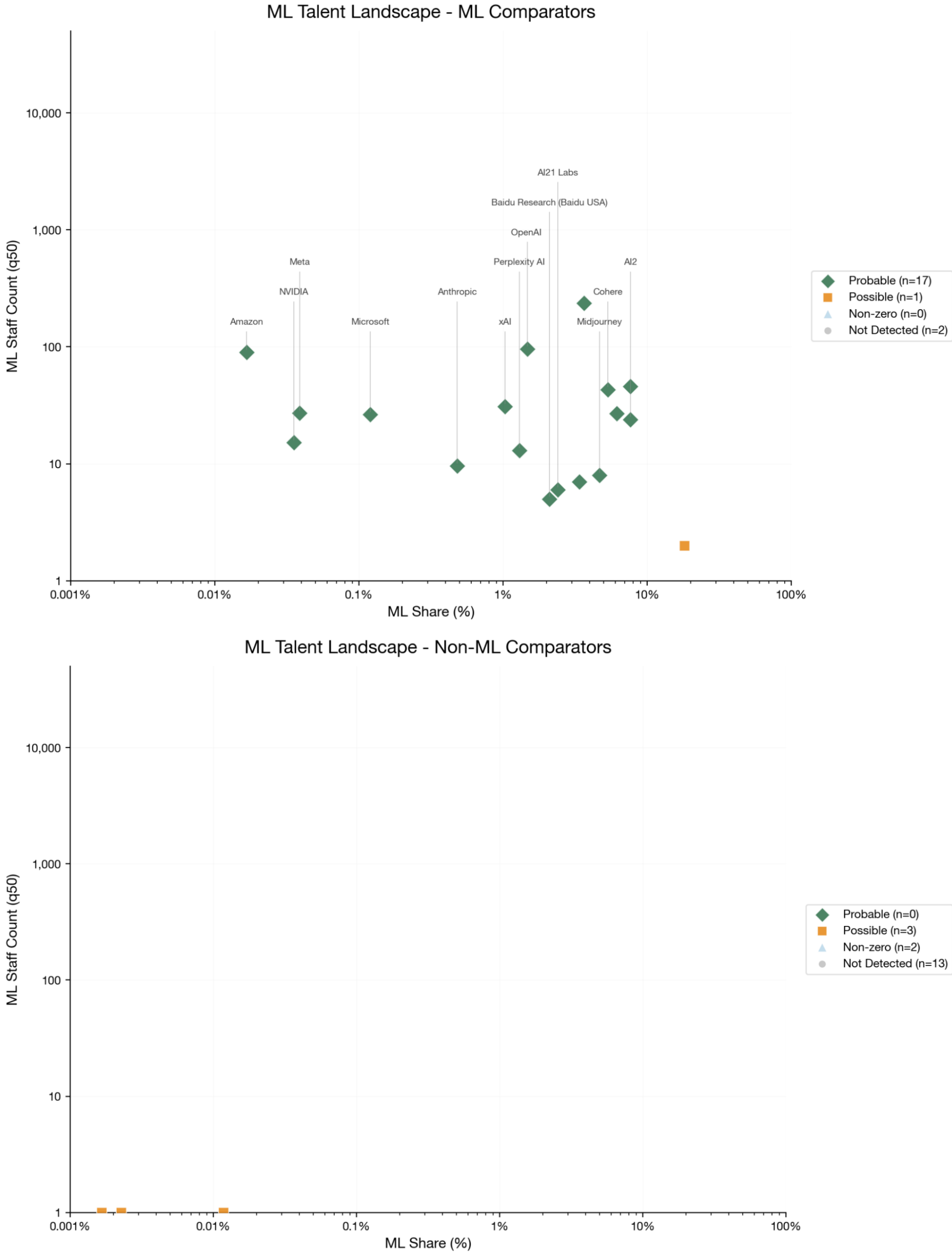


Figure 5. ML Research Talent estimates comparison

In collaboration with a member of the technical staff from METR we let GPT-5 and Claude Opus 4.1 Agents perform multiple runs at the work trial task as well. After some elicitation, agents were evaluated by the same criteria. All agents scored between 30 and 40% on our work trial, resulting in no recommendation.

Table 2. Overview of work trial results. Most agents implemented a somewhat well-documented Sequential Unlearning, integrated it into the pipeline, and provided usable configs with coherent write-ups. However, only a small subset executed any unlearning to completion, and none followed through with RTT evaluation.

	No Recommendation (<50%)	**Conditional Recommendation (50-70%)**	**Recommendation (>70%)**
ML Consultancies	3/8 (37.5%)	2/8 (25%)	3/8 (37.5%) Note: all three organizations scored >90%
AI Agents	ChatGPT-5: 8/8 (100%) Claude Opus 4.1: 8/8 (100%)	-	-

Discussion

To our knowledge, this is the first systematic assessment of the "dormant" pool of technical ML Research Talent inside IT consultancies. We introduce a transparent estimation pipeline for identifying high-quality ML practitioners, and we validate it via multiple modalities: validation datasets for screening and estimation, organization-level outreach, and targeted work trials. While our work was motivated by advancing AI assurance work, these methods offer a pragmatic general map of where skilled ML capacity might exist.

Our global sweep estimated roughly 1 100 individuals with robust AI/ML profiles across 403 consultancies. Final ML Research Talent estimates aligned with our work-trial experiences and conversations with various IT consultants. Organizations concentrated in the US and Europe. Diversified conglomerates whose services span far beyond ML/AI are one of the reasons why overall ML Research Talent density with ~0.01% is low. At the level of individual firms, however, the picture is heterogeneous, with skilled technical ML staff ranging up to 20%. Funders and program managers should therefore avoid treating "consultancies" as a homogeneous class and require careful targeting of the right sub-units.

AI agents are continuously advancing, but at least in our analysis they fell far behind consultancies, despite repeated expert elicitation. This suggests that the right consultancies can deliver useful ML R&D outputs we can't replace with AI today. Activation requires deliberate scoping, credible sponsorship, and (often) smaller, faster contracting paths.

Our findings should be interpreted with several caveats. First, we used a particular definition of ML Research Talent that could exclude competent practitioners in adjacent domains such as ML Ops. The systematic search was English-only and anchored to Crunchbase and LinkedIn, likely underrepresenting non-Western markets and firms with limited public footprints. Our final estimators, with a positive likelihood ratio of ~11 and a negative likelihood ratio of 0.23, remain an imperfect signal, particularly at the scale of over 3 million assessed individuals.

For several established ML organizations—where LLM-based estimates were unavailable and synthetic imputation was used instead—the pipeline produced implausibly low estimates (e.g., Anthropic: 9 of 2 000 employees). This reflects a mismatch between our consultancy-calibrated priors (Table 4) and the fundamentally higher talent density at frontier labs. Future applications to such organizations would benefit from domain-specific priors or full LLM-based CV evaluation.

Our work trial was an important validation step, but resumes remain an inherently noisy proxy for competence and we were not able to systematically connect individual CVs to public artifacts (e.g., publications, GitHub/GitLab) at scale. The work-trial component involved only 20 organizations, a single 3-day task, and no true control arm of lab/academic researchers. We instead leveraged state-of-the-art AI coding tools. Through conducting the work trials a consistent operational lesson also emerged: even highly competent consultancies prefer an external "vision holder" (e.g., a senior AI-alignment researcher) to specify outcomes and own the research direction. Smaller organizations we engaged tended to cite capacity challenges, larger organizations minimum contract sizes.

Within these limits, we find clear "proof of existence" for technical ML practitioners who can execute a challenging technical ML task to the highest levels of satisfaction. This should be an encouragement for funders and program managers in the AI assurance and general AI space to consider this accelerated path of increasing capacity for AI safety projects.

Methods

Systematic company search

Over the course of June to August 2025 we identified companies via

1. personal network recommendations,
2. unstructured web search with 2 independent research assistants (leveraging Deep Research functionalities of LLMs),
3. extracting arXiv affiliation metadata,
4. extracting ICLR / ICML / NeurIPS affiliations back to 2019, and
5. Crunchbase.com database keyword search.

The details for the search strategy are available in the supplements (see Search Strategies). All company names identified in steps 1 to 4 were searched for and exported from Crunchbase. We screened all company descriptions provided by Crunchbase for relevance to technical ML consultancy services, using Claude Sonnet 3.7 and a human validator. Organizations with fewer than 10 staff members on Crunchbase (and later LinkedIn exports), or younger than 2 years were excluded. The date of Crunchbase data extraction for final analysis was 8th of August 2025.

There is an emerging literature on the use of LinkedIn for labor measurement. LinkedIn has over 1.2 billion profiles and we expect it to be the most representative data source available (LinkedIn Statistics for Professionals [8]). Comparative studies show that LinkedIn-derived indicators can correlate well with official statistics while exhibiting selection effects by country, age, and sector (SpringerOpen, Oxford Academic, World Bank).

Access to staff LinkedIn Resumes for evaluation

To assess a company's staff technical ML capabilities we decided to evaluate respective LinkedIn resumes. We used two approaches: access via LinkedIn's own Sales Navigator Recruiter Lite and Brightdata's LinkedIn data. The former provided up-to-date information from LinkedIn, but did only allow for simple filtering and keyword search. The latter enabled us to screen CVs more comprehensively with LLMs, but did not always represent current LinkedIn data and had to exclude extremely large companies with more than 50,000 employees.

Methodology of Resume Evaluation Validation

According to our data constraints we designed and validated two complementary evaluation pipelines. One keyword based, another LLM prompt based.

First, we created a comprehensive validation dataset with a total of 585 CVs extracted from LinkedIn. Two independent human reviewers rated all CVs against our definition of technical ML Research Talent as either yes or no (see Supplements). The examples included randomly selected individuals from IT consulting firms and work trial consultancies. We also included random sets selected from small-scale technical AI Alignment organizations and AI labs like OpenAI, Anthropic and Google to ensure sufficient positive examples.

Based on 421 of the rated CVs we extracted the top 100 positively and negatively associated keywords (see supplements). Features were selected after a manual sanity pass to drop misleading tokens (e.g., organization names or cities) at a "strict" and "broad" level for both positive and negative terms. "Broad" selected terms with a discriminative_score >= 0.8 AND raw category specificity >= 0.7, "strict" selected at a discriminative_score >= 0.9 AND raw category specificity >= 0.8. The minimum frequency across all CVs for a keyword was five. In parallel we created two evaluation LLM prompts (see code repository) we tested with different models and temperature settings at 0 or default (usually 1.0 or 0.7; at the time of testing gpt-5 models did not support a temperature parameter)[1]. Models included:

- Google: gemini-2.5-pro, gemini-2.5-flash and gemini-2.5-flash-lite
- OpenAI: gpt-5-thinking-2025-08-07, gpt-5-mini-thinking-2025-08-07, gpt-5-nano-thinking-2025-08-07
- Anthropic: opus-4-1-20250805, sonnet-4-20250514

All permutations of keyword filters and all permutations of LLMs were validated against the full 585 CVs. The top three performing filters and top performing model per LLM provider were selected: broad_yes, strict_no, and broad_yes_strict_no for keywords. For LLMs, we selected prompt 1 and gemini-2.5-flash, sonnet-4-20250514, and gpt-5-mini-thinking-2025-08-07 as they provided robust results while being relatively fast and cheap (see Table 3 for keywords and prompt). Exploratory results for worktrial companies aligned with both company statements about their internal capacity as well as us reviewing CVs manually.

[1]Temperature controls the randomness of an LLM's text generation. Lower values (e.g., 0.1) make outputs more deterministic and focused, while higher values (e.g., 0.9) make them more creative and unpredictable.

Table 3. Selected Keywords and prompts

Highly Skilled technical ML Research Talent (Definition)	**Keyword Filter**	**LLM Prompt**
Professionals who can: • Train models from scratch: Comfortable implementing and training transformer architectures like GPT-2 end-to-end, including loss calculation, attention mechanisms, and training loops • Work from specs to code: Take a method specification and build a working implementation, handling data pipelines, model internals, and distributed training setups • Debug model behavior: Diagnose and isolate root causes when training goes wrong or models behave unexpectedly • Engage with research: Read papers, understand novel approaches, and translate ideas into concrete implementation plans • Communicate clearly: Report progress, challenges, and solutions in accessible terms • Evidence: Public GitHub repos, papers/blog posts, or other forms of demonstrated experience	ML Selection (”machine learning” OR ”machine-learning” OR ”ML” OR ”deep learning” OR ”deep-learning”, ”reinforcement learning” OR ”reinforcement-learning” OR ”RL”) AND Broad_yes (optional) (”augmented generation” OR ”agent reinforcement” OR ”mats scholar” OR ”mats” OR ”research scientist” OR ”evals” OR ”interpretability” OR ”feature engineering” OR ”research intern” OR ”candidate” OR ”graduate research assistant” OR ”science institute” OR ”staff research scientist” OR ”doctor”) Strict_no (optional) NOT (”certificate” OR ”programmer” OR ”council” OR ”companies” OR ”capital” OR ”proven track record” OR ”pilot” OR ”money” OR ”specialist” OR ”chief” OR ”udemy” OR ”track record” OR ”customer” OR ”management” OR ”today” OR ”cross functional” OR ”administrator” OR ”excellence” OR ”commerce” OR ”linkedin” OR ”leader” OR ”incident” OR ”tier” OR ”brand” OR ”investment” OR ”hr” OR ”sites” OR ”offerings” OR ”prior” OR ”centers” OR ”advising” OR ”certified information” OR ”key responsibilities” OR ”master data” OR ”anti” OR ”deadlines” OR ”physiology” OR ”carbon” OR ”impacts” OR ”certified machine” OR ”qualification”)	Question: Could this person design and implement complex ML architectures from scratch (e.g., transformers, VAEs, diffusion models) and is qualified for technical AI engineering or research? Quick Check: GOOD FIT - Look for: - Built neural networks or created novel architectures - Deep understanding demonstrated through: custom loss functions, attention mechanisms, or architecture modifications - Advanced degree in ML WITH thesis/research on model architecture (not just applications) - Implemented training algorithms or frameworks from scratch (not using existing libraries) - LLM/RLHF experience - distinguish between using vs. building these systems NOT A FIT - Reject if they’re primarily: - Using pre-built models (even advanced ones like fine-tuning LLMs) - Data Scientists (dashboards, analytics, A/B tests) - MLOps/DevOps without architecture design - Hardware optimization for ML (GPU programming) without model design - Applied ML without evidence of understanding underlying math/algorithms Output: [ACCEPT/REJECT]

Data was collected in the time from 1st – 15th of August. For the keyword analysis, we manually selected the company name on LinkedIn’s Sales Navigator Recruiter Lite and pasted the respective keyword combinations together with the shared search term (”machine learning” OR ”machine-learning” OR ”ML” OR ”deep learning” OR ”deep-learning”, ”reinforcement learning” OR ”reinforcement-learning” OR ”RL”). The number of total company and filter specific hits were manually transferred into our database. LinkedIn’s public interface rounds counts (e.g., >1,000 results rounded; >100k rounded to 10k) and offers limited public API access, constraining programmatic precision at large scales.

For the LLM evaluation, we sourced all company profiles via Bright Data (brightdata.com) for organizations with fewer than 25,000 LinkedIn profiles in the previous filter search. Data was processed by selected models with Prompt 1 and results cleaned from hallucinated profiles. We ran the evaluation of approximately 250 000 profiles using the batching APIs of the three models. LLM estimates were excluded if the headcount was off by a factor of more than 3 compared to the LinkedIn Sales Navigator Recruiter Lite data.

Aggregation of individual estimates

We estimated technical ML headcount using a bootstrap multivariate probit model that combines six imperfect annotators: three keyword filters (broad, strict, and combined) and three LLM classifiers (Gemini 2.5 Flash, GPT-5 Mini, Claude Sonnet 4) which each produce a binary label for each employee (ML expert / not an ML expert). Our approach is based on the Dawid-Skene model, but rather than assuming independent annotator errors, our approach models correlated mistakes through a multivariate normal latent structure, capturing, for instance, when multiple LLMs fail on the same edge cases. The model assumes each annotator's binary decision arises from thresholding a latent continuous score in probit space (inverse standard normal CDF), allowing us to model correlations in the underlying decision-making process rather than just in the binary outcomes. The full pipeline is illustrated in Figure 5 and code available in the repository.

From 585 manually-labeled validation CVs (153 ML experts, 432 non-ML), we estimated each annotator's sensitivity and specificity via confusion matrices, and their pairwise error correlations via tetrachoric correlation, which estimates the correlation between latent continuous variables underlying binary annotations, consistent with the probit model's assumption that binary labels arise from thresholding latent Gaussian scores. (see Figure 5). The combined probit model achieved the highest accuracy (0.89) with sensitivity of 0.79 and specificity of 0.93, outperforming any individual annotator.

For inference, we compute the posterior probability that each employee is a true ML expert given their pattern of annotations across all six methods. The likelihood of observing a particular annotation pattern under each true label class (ML expert vs. non-expert) is computed as a multivariate normal orthant probability—the probability mass in the region of latent space corresponding to that binary pattern. The posterior probability is then obtained via Bayes' theorem, combining these likelihoods with company-size-stratified Beta priors on ML Research Talent prevalence.

Table 4. Company-size-stratified Beta priors on ML Research Talent prevalence

Organization Type	**Company Size**	**Beta Prior**	**Mean**
Consulting & Comparator ML Organisations	< 100	Beta(2.4, 21.7)	10%
Consulting & Comparator ML Organisations	100–1,000	Beta(3.0, 57.0)	5%
Consulting & Comparator ML Organisations	1,000–10,000	Beta(1.6, 154.8)	1%
Consulting & Comparator ML Organisations	> 10,000	Beta(1.0, 999.0)	0.1%
Comparator Non-ML	All sizes	Beta(1.0, 9999.0)	0.01%
All (unknown size)	Unknown	Beta(1.6, 154.8)	1%

For organizations with only aggregate LinkedIn keyword counts (due to lack of access or substantial headcount discrepancies), we generate synthetic employee-level annotations using a Gaussian copula that preserves the estimated correlation structure between keyword filters while matching company-level prevalences (aggregate counts divided by total headcount). This approach assumes that the latent correlation structure estimated from validation data generalizes across companies, allowing us to create realistic synthetic annotation patterns that can be processed by the same probit model as real employee-level data. These synthetic annotations are used only when real employee-level data is unavailable, enabling unified estimation across all companies. Synthetic estimates were adjusted by a factor of 0.5 based on systematic comparison with real-data estimates for companies where both were available (see Figure 6).

The bootstrap procedure (1,000 iterations) captures five sources of uncertainty: (1) confusion matrix estimation from resampled validation data, (2) prior uncertainty via Beta sampling, (3) within-company sampling variation, (4) correlation structure uncertainty from resampled test data, and (5) realization uncertainty through Bernoulli draws of true labels. The bootstrap procedure works by running the full pipeline many times, and for each source of uncertainty, resampling (with replacement) the relevant population or re-drawing from the relevant distribution. The resulting distribution yields point estimates (means) and intervals (10th/90th percentiles) for company-level headcounts.

We defined subsets for technical ML Research Talent-dense organizations as follows: Organizations are classified into mutually exclusive confidence categories based on their ML research talent estimate distributions (q10, q50, q90 representing the 10th, 50th, and 90th percentiles):

- **Probable:** q10 $>$ 0 — The 80% confidence interval excludes zero, indicating confident ML presence
- **Possible:** q50 $>$ 0 and q10 = 0 — The central estimate is positive but the confidence interval includes zero

- **Non-zero:** q90 > 0 and q50 = 0 — Only the upper bound is positive; the central estimate is zero
- **Not Detected:** q90 = q50 = q10 = 0 — All estimates are zero, indicating no ML signal detected

Pure probit estimates are used when available; otherwise, adjusted synthetic estimates are used.

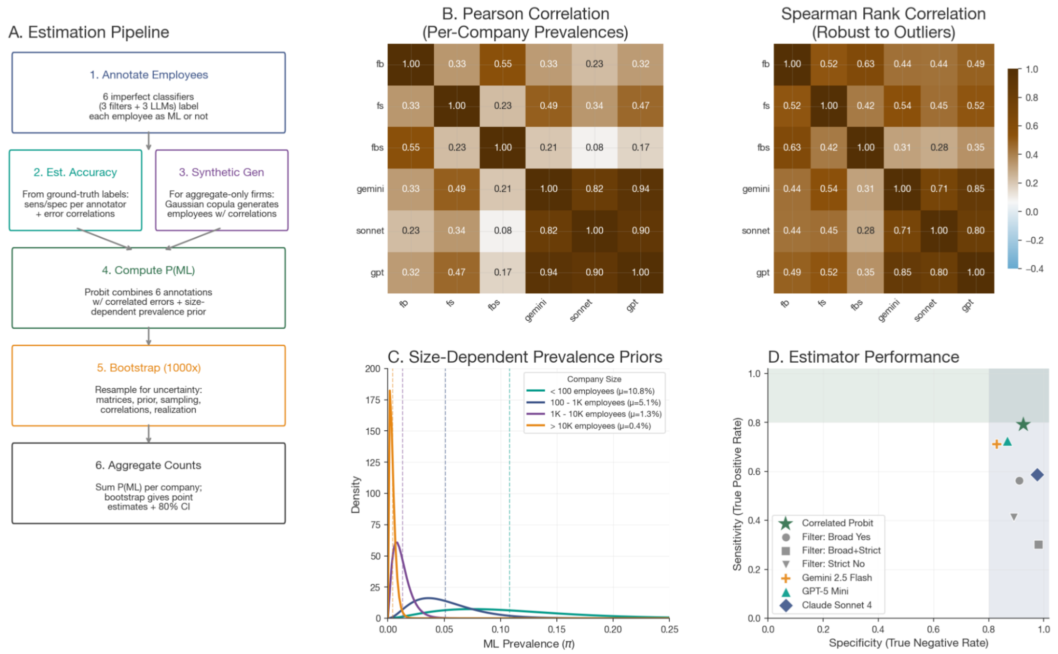


Figure 6. Comparison of Real and Synthetic estimates per company.

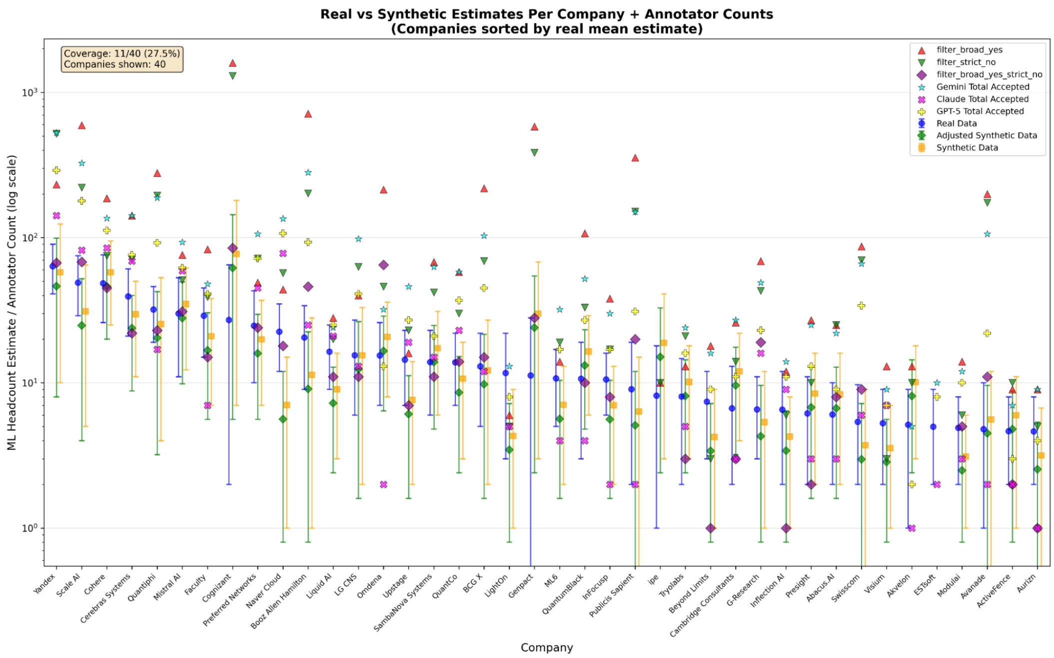


Figure 7. Methodology overview diagram. A) Pipeline overview B) Visualization of the distribution prior of the bootstrap probit Dawid-Skene model C) Sensitivity vs Specificity across all estimators, including final correlated probit.

Interviews and Work Trials

In parallel to the systematic search and ML Research Talent estimates, we reached out to organizations for a work trial and consecutive two-month technical AI alignment project to be funded by Coefficient Giving.

Companies were approached with a comprehensive project description. Applications were scored by at least two reviewers for competence, scale and maturity (see supplements). We followed up at least two times using various channels such as contact emails / forms, LinkedIn outreach, and personal connections. Strong applications were invited to interviews and eventually to participate in a paid 3-day work trial. Compensation happened according to the respective rates of the consultancy.

The work trial consisted of a three day 2 FTE implementation of an adapted unlearning method[2] (research code repository in the Supplements). Each team was provided with a Slack channel to discuss progress on the task and point out any upcoming questions / issues. The final submission, including git repository, end-of-work-trial report, and group chat history was then scored on a 0 to 3 scale by two independent ML research staff on a weighted metric, including Technical Correctness (40 %), Experimental Rigor & Reproducibility (25 %), Code Quality & Maintainability (15 %), Communication & Insight (15 %), and Bonus Innovation / Extras (up to 10%) (see Supplements for the evaluation metrics). Final scores were averaged. As a control we asked a technical staff member from METR to let modern AI coding agents (Claude Code, GPT-5) execute the task as well.

[2]In short, we asked consultancies to implement Qian et al. [12] in the RTT codebase by Deeb et al. [13].

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Supplements

Repository

The following repository includes all analysis and work trial code. It only includes partial information on the exported profiles.

https://github.com/MxSchons-GmbH/consultancy-ml-research-talent-estimates

Extended Flow Chart

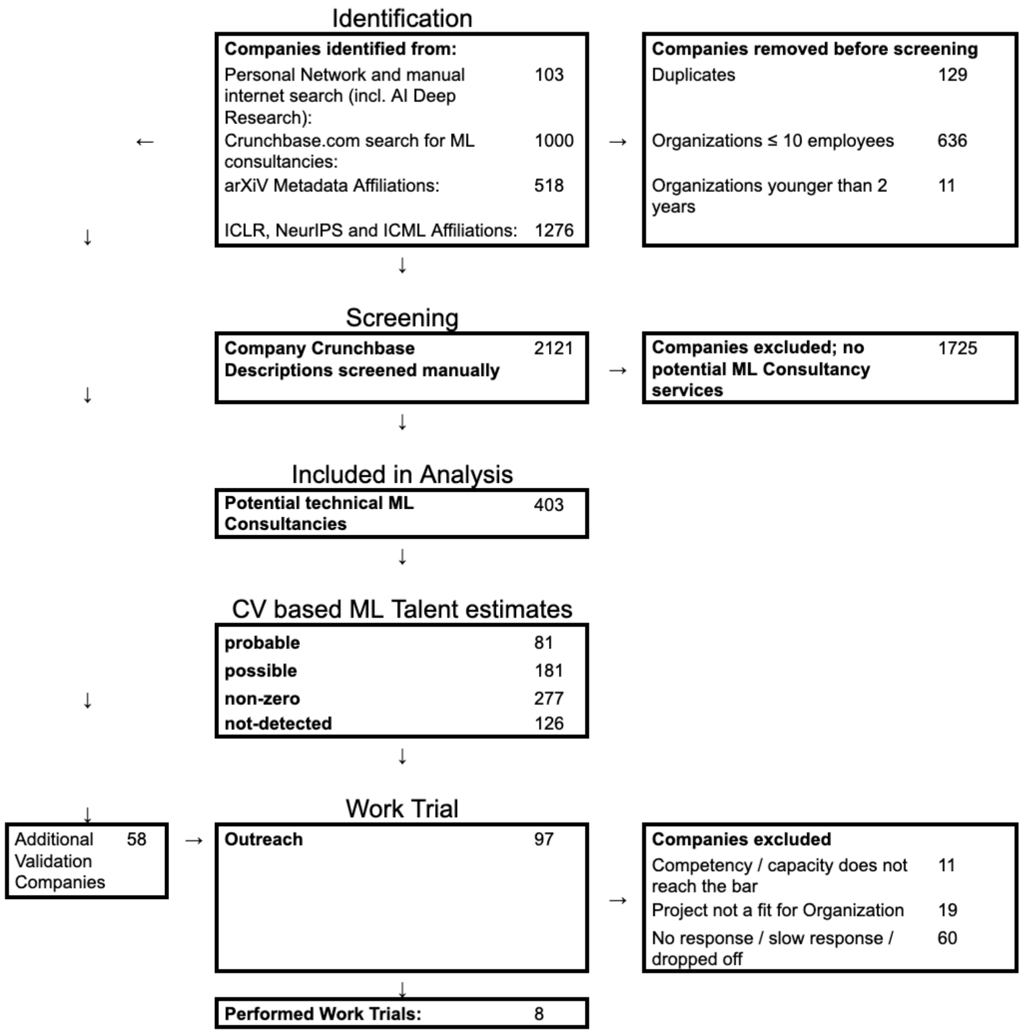

Figure S1. Extended flow chart of the systematic search and estimation pipeline

Search strategies

1. Team's contacts and its networks recommendations
2. LLM deep research based
3. Unstructured Web Search with two independent RAs
4. Research & publication venues: arXiv Metadata (see code repository for details)

5. Conferences & sponsor/exhibitor lists: ICLR, ICML and NeurIPS 2019 onwards (see code repository for details)
6. Crunchbase Pro + keyword filters

Crunchbase Pro Query Filters

INDUSTRY: Includes (Outsourcing, Consulting)

FOUNDED DATE: Before (01/01/2022)

FULL DESCRIPTION: Includes (artificial intelligence, machine learning, deep learning, ai, ml, LLM, large language model, reinforcement learning)

DESCRIPTION: Includes (artificial intelligence, machine learning, deep learning, ai, ml, LLM, large language model, reinforcement learning)

OPERATING STATUS: Does not include (Closed)

FULL DESCRIPTION: Does not include (SaaS, Cloud-based analytics, Cloud infrastructure, Biodegradability testing, Enterprise software, Data center, Data capture, Document management, Semiconductor, Venture studio, Credit bureau reporting, Data labeling, Training data curation, Business growth consulting, Blockchain, Geospatial database, Incubator, Acquiring target audiences, Pyrotechnic products, Proprietary, self-service, Quantum software, software framework, Business development and communications, Leadership development, Sales enablement, Graphic Design Studio, Cloud Provider, GenAI Platform, PaaS, IaaS, Low-code application, Exoplanet discovery, ARM industry, Credit risk, Commercialization, subsurface environments, Brand intelligence, Customer relationship, Content creation, Podcast, Quantitative finance, Mobile app, Conference, Video analytics, Servicetitan, Call center, ACMI, Electric fan, Investment advisory, Market intelligence, Low code, web mobile, real estate, web development, financial services, cyber security, digital marketing, robotic process automation, robotic process, ui ux, mobile application, mobile development, ar vr, ux design, ux ui, mobile application development, development mobile, virtual reality, ios android, search engine, mobile apps, ui design, ui ux design, neo technologies, maktoum neo technologies, ux ui design, web development mobile, ai blockchain, website development, web mobile development, web mobile application development, web mobile application, blockchain development, blockchain ai, phone calls, sales service, web application, web scraping, web services, telefonica open, intelligence blockchain, iot artificial, iot data, consulting web, content marketing, marketing services, marketing solutions, search engine optimization, retail commerce, marketing sales, web applications, web design, web app, supply chain, management consulting, internet things, design development, social media, strategic consulting, market research, iot, cloud, strategy consulting, sales marketing, data security, legal services, media scope, oil gas, law firms, injury illness, analytics big data, E-commerce, Subscription, Data labelling, Ai-powered platform, Virtual assistant, Global brands, Intellectual property solutions, Industrial engineering, Intellectual property solutions, Intellectual property, Geochemical, Lead conversion, Workforce management, Personal learning products, Design-led, Translation agency, Online robot lawyer, Business process architecture, Contact center, Salesforce, Ophthalmology, Cultural tourism, Emotion analytics, EEG, Jobs marketplace, MIPS services, Product storytelling, Smart Signals, Revenue-raising, Licensing, online learning, Moodle-based, staffing and recruitment, AI-powered growth partner, AI-powered language technology, AI engine, Wellbeing support, Ambient intelligence, Marketing Mix, Transaction flows, Human resources technology, Marketplace, asset health, Smart recruitment, CRO, Annotation services, Safety solution strategy, Asset of value, Innovation intelligence, Competitive intelligence, High quality courses)

We did not explicitly search through startup & accelerator programs, nor make any big public announcements in mailing lists or run ads. Other data streams we either did not explore or were not satisfied with for getting data on companies: GitHub, Kaggle teams leaderboard, Gartner Market Guide, Forrester Wave, PitchBook, CapitalIQ, CB Insights, G2, Clutch, GoodFirms. The search was only in the English language. We investigated government repositories, but it wasn't helpful as keywords like machine learning weren't available.

Specs for identification

Keyword extraction was carried out in Google Colab with KeyBERT, which ranks candidate 1- to 4-gram phrases by computing cosine similarity between their TF-IDF-weighted representations and sentence-level embeddings generated by the

Salesforce/SFR-Embedding-Mistral model from SentenceTransformers running on an NVIDIA A100 GPU via PyTorch.

Sensitivity / Specificity across models

True / False Positives and Negatives, Sensitivity / Specificity and F1 value of various LinkedIn Search methods

filter	TP	FP	FN	TN	sensitivity	specificity	F1
strict_yes_strict_no	36	5	117	427	0.235	0.988	0.371
strict_yes_broad_no	13	1	140	431	0.085	0.998	0.156
broad_yes_broad_no	18	2	135	430	0.118	0.995	0.208
broad_yes_strict_no	46	8	107	424	0.301	0.981	0.444
strict_yes_only	0	0	153	432	0.000	1.000	NaN
broad_yes_only	0	0	153	432	0.000	1.000	NaN
strict_no_only	63	45	90	387	0.412	0.896	0.483
broad_no_only	25	14	128	418	0.163	0.968	0.260
prompt-1-claude-sonnet-4-20250514	90	11	63	421	0.588	0.975	0.709
prompt-1-claude-sonnet-4-20250514-t-at-1.0	75	25	78	407	0.490	0.942	0.593
prompt-1-claude-opus-4-1-20250805	75	24	78	408	0.490	0.944	0.595
prompt-2-claude-sonnet-4-20250514	68	12	85	420	0.444	0.972	0.584
prompt-2-claude-sonnet-4-20250514-t-at-1.0	73	16	80	416	0.477	0.963	0.603
prompt-2-claude-opus-4-1-20250805	43	13	110	419	0.281	0.970	0.411
prompt-1-gemini-2.5-flash-lite	102	36	51	396	0.667	0.917	0.701
prompt-1-gemini-2.5-flash	109	74	44	358	0.712	0.829	0.649
prompt-1-gemini-2.5-flash t=1.0	106	56	47	376	0.693	0.870	0.673
prompt-1-gemini-2.5-pro	111	61	42	371	0.725	0.859	0.683
prompt-2-gemini-2.5-flash-lite	26	28	127	404	0.170	0.935	0.251
prompt-2-gemini-2.5-flash	88	20	65	412	0.575	0.954	0.674
prompt-2-gemini-2.5-flash t=1.0	12	13	141	419	0.078	0.970	0.135
prompt-2-gemini-2.5-pro	99	37	54	395	0.647	0.914	0.685
prompt-1-gpt-5-nano-2025-08-07	68	38	85	394	0.444	0.912	0.525
prompt-1-gpt-5-mini-2025-08-07	111	57	42	375	0.725	0.868	0.692
prompt-1-gpt-5-mini-2025-08-07-v2	116	51	37	381	0.758	0.882	0.725
prompt-1-gpt-5-2025-08-07	71	27	82	405	0.464	0.938	0.566
prompt-2-gpt-5-nano-2025-08-07	38	9	115	423	0.248	0.979	0.380
prompt-2-gpt-5-mini-2025-08-07	75	15	78	417	0.490	0.965	0.617
prompt-2-gpt-5-mini-2025-08-07-v2	11	12	142	420	0.072	0.972	0.125
prompt-2-gpt-5-2025-08-07	40	11	113	421	0.261	0.975	0.392

Annotator	Sensitivity	Specificity	Accuracy
correlated_probit	0.791	0.926	0.891

Validation Dataset

Available in code repository.

Profiles included the following companies:

Small-scale technical AI Alignment: Palisade Research, CHAI, FAR.AI, Apollo Research, Goodfire and Transluce. Large-scale technical AI Alignment: Google DeepMind, OpenAI, and Anthropic

IT Consultancies: Accenture, HCL Technologies, Ernst & Young (EY), Infosys, Wipro, PricewaterhouseCoopers (PwC), Cognizant, Tata Consultancy Services, Deloitte, Capgemini, Bain, BCG X

Validation: AI and non-AI companies

As an additional validation step, we applied the selected estimation methods to companies we knew to have high technical ML Research Talent counts and to organizations who certainly don't. The results are presented in the Supplements. Note that some companies were not evaluated with LLMs due to their size and associated costs.

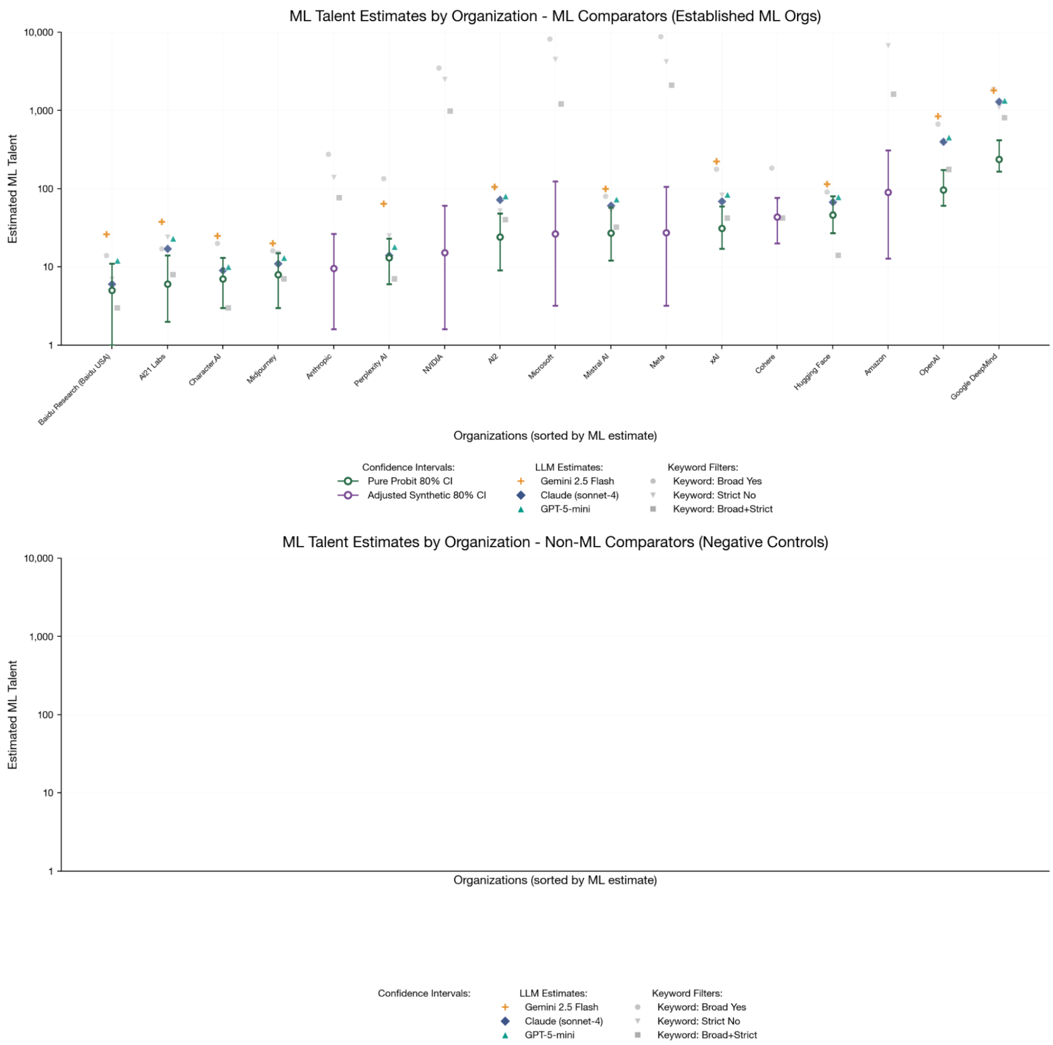

Figure S2. Validation: AI and non-AI company estimates

Company Name	Founded	Country	Total Staff (LinkedIn)	Individual Estimates [broad+strict, strict, broad, claude, gpt5, gemini]	ML Research Talent q50 (q10 – q90)	ML % of Total	Category
Google DeepMind	1970	Unknown	6 500	[801, 1100, 1900, 1285, 1330, 1803]	237 (166 - 414)	3.65% (2.55% - 6.38%)	Probable
OpenAI	1970	Unknown	6 500	[175, 391, 671, 397, 454, 845]	96 (61 - 173)	1.48% (0.94% - 2.66%)	Probable
Amazon	1970	Unknown	540 000	[1600, 6700, 11000, -, -, -]	89 (12 - 308) *	0.02% (0.00% - 0.06%)	Probable
Hugging Face	1970	Unknown	603	[14, 48, 91, 67, 78, 114]	46 (27 - 80)	7.63% (4.48% - 13.27%)	Probable
Cohere	1970	Unknown	810	[42, 73, 183, -, -, -]	43 (20 - 76) *	5.33% (2.47% - 9.38%)	Probable
xAI	1970	Unknown	3 000	[42, 83, 177, 69, 84, 223]	31 (17 - 59)	1.03% (0.57% - 1.97%)	Probable
Mistral AI	1970	Unknown	440	[32, 52, 80, 61, 73, 100]	27 (12 - 57)	6.14% (2.73% - 12.95%)	Probable
Meta	1970	Unknown	70 000	[2100, 4200, 8800, -, -, -]	27 (3 - 105) *	0.04% (0.00% - 0.15%)	Probable
Microsoft	1970	Unknown	22 000	[1200, 4500, 8200, -, -, -]	26 (3 - 123) *	0.12% (0.01% - 0.56%)	Probable
AI2	1970	Unknown	313	[40, 52, 103, 72, 80, 106]	24 (9 - 48)	7.67% (2.88% - 15.34%)	Probable
NVIDIA	1970	Unknown	43 000	[974, 2500, 3500, -, -, -]	15 (1 - 60) *	0.04% (0.00% - 0.14%)	Probable
Perplexity AI	1970	Unknown	1 000	[7, 25, 135, 14, 18, 64]	13 (6 - 23)	1.30% (0.60% - 2.30%)	Probable
Anthropic	1970	Unknown	2 000	[76, 140, 276, -, -, -]	9 (1 - 26) *	0.48% (0.08% - 1.32%)	Probable
Midjourney	1970	Unknown	171	[7, 15, 16, 11, 13, 20]	8 (3 - 15)	4.68% (1.75% - 8.77%)	Probable
Character.AI	1970	Unknown	207	[3, 9, 20, 9, 10, 25]	7 (3 - 13)	3.38% (1.45% - 6.28%)	Probable
AI21 Labs	1970	Unknown	250	[8, 24, 17, 17, 23, 38]	6 (2 - 14)	2.40% (0.80% - 5.60%)	Probable
Baidu Research (Baidu USA)	1970	Unknown	238	[3, 7, 14, 6, 12, 26]	5 (1 - 11)	2.10% (0.42% - 4.62%)	Probable
LawZero	1970	Unknown	11	[1, 2, 4, 4, 5, 5]	2 (0 - 5)	18.18% (0.00% - 45.45%)	Possible

Thinking Machines Lab	1970	Unknown	67	[12, 15, 22, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Mila-Quebec Artificial Intelligence Institute	1970	Unknown	872	[130, 163, 424, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected

Company Name	Founded	Country	Total Staff (LinkedIn)	Individual Estimates [broad+strict, strict, broad, claude, gpt5, gemini]	ML Research Talent q50 (q10 – q90)	ML % of Total	Category
Burberry	1970	Unknown	8 500	[0, 2, 5, 1, 1, 2]	1 (0 - 3)	0.01% (0.00% - 0.04%)	Possible
Sherwin-Williams	1970	Unknown	44 000	[2, 29, 28, 1, 2, 6]	1 (0 - 3)	0.00% (0.00% - 0.01%)	Possible
The Coca-Cola Company	1970	Unknown	60 000	[2, 31, 68, 3, 9, 30]	1 (0 - 5)	0.00% (0.00% - 0.01%)	Possible
The North Face	1970	Unknown	4 500	[0, 0, 2, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Desigual	1970	Unknown	2 500	[0, 0, 0, 0, 0, 1]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Jotun	1970	Unknown	6 000	[0, 1, 5, 0, 0, 2]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Sierra Nevada Brewing Co.	1970	Unknown	769	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Penguin Random House	1970	Unknown	8 000	[1, 9, 18, 2, 2, 7]	0 (0 - 2)	0.00% (0.00% - 0.03%)	Non-zero
HarperCollins Publishers	1970	Unknown	4 000	[0, 8, 7, 0, 0, 1]	0 (0 - 2)	0.00% (0.00% - 0.05%)	Non-zero
Patagonia	1970	Unknown	3 500	[0, 1, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Crocs, Inc.	1970	Unknown	5 500	[0, 1, 3, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
The British Museum	1970	Unknown	1 000	[0, 1, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Museo Nacional del Prado	1970	Unknown	296	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
London Symphony Orchestra	1970	Unknown	232	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
New York Philharmonic	1970	Unknown	288	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Hydro Flask	1970	Unknown	135	[0, 1, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
YETI	1970	Unknown	2 000	[0, 0, 5, 1, 0, 1]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
LVMH	1970	Unknown	7 000	[0, 2, 17, 1, 5, 12]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected

Work Trial Repository and Evaluation Metric

https://github.com/MxSchons-GmbH/consultancy-ml-research-talent-estimates

1. Technical Correctness (Weight = 40 %)

Score	Description
3 – Excellent	All required artefacts present; metrics reported for Forget T, Validation V, Retain R before and after RTT; Recovery-Rate stated and ≤ 1.05 (i.e. ≤ 105 % of original performance); code implements correct data splits and loss functions described in RTT (§4.3) .
2 – Minor flaws	Runs finish and metrics exist, but one of: (i) wrong split sizes, (ii) Recovery-Rate omitted, (iii) retain-drop exceeds stated 5 / 10 / 30 % boundary without explanation .
1 – Major flaws	Pipeline executes but results conflict with spec (e.g., forget accuracy increases after unlearning); or RTT fine-tunes the original not the unlearned model
0 – Invalid	Script crashes, wrong target task, or any hand-edited prediction/metric file detected (MLE-Bench red-flag).

LLM actions: parse main.py AST for data-loader arguments; diff reported numbers against wandb_run-*.json; compute Recovery-Rate automatically.

---

2. Experimental Rigor & Reproducibility (25 %)

Score	Description
3	Clear baseline run, ≥ 1 hyper-parameter sweep for both baseline & method; fixed seeds (torch.manual_seed or Hydra seed=); compute budgets (epochs, GPU type) stated; W&B run IDs and Git commit SHA logged.
2	Baseline exists or seeds fixed, but hyper-sweep partial (<3 values) or compute not recorded.
1	Only a single run; no baseline; ad-hoc HP search ("time constraints") .
0	No experimental details or logs recoverable.

---

3. Code Quality & Maintainability (15 %)

LLM parses the lone entry-point plus config.

Score	Description
3	PEP8-clean; functions/classes > 70 % documented; typing used; cyclomatic complexity < 15; configs externalised (Hydra / YAML).
2	Modular but sparse docs or missing types; minor duplication; lint passes with ≤ 10 warnings.
1	Monolithic script, hard-coded paths/HPs, > 30 warnings, acknowledged need for refactor.
0	Won't import, mixed tabs/spaces, or contains credentials.

---

4. Communication & Insight (15 %)

Score	Report Attributes
3	Executive summary, method diagram/figure, interprets failure modes, lists next-steps; cites RTT correctly; ≤ 10 pages; professional tone.

2	Complete narrative but thin reflection (e.g., "time constraints" repeated).
1	Mostly raw W&B screenshots; prose < 1 page; vague claims ("results look good").
0	Missing or incomprehensible.

---

5. Bonus Innovation / Extras (+0-10 ppt)

Award in 2-point increments for: ablation studies, alternative unlearning algorithms, automated sweep scripts, CI tests, dashboards, compute-matched comparisons, etc. (Cap bonus at +10 ppt so core metrics dominate.)

---

6. Aggregation

Final % = 0.40·A1 + 0.25·A2 + 0.15·A3 + 0.15·A4 + Bonus

Recommendation: $> 70\%$
Conditional Recommendation: $\geq 50\%$

No Recommendation: $< 50\%$

Specification of company profiles and talent

Applicants who passed a minimum bar of subject matter expertise (e.g. at least one strong ML researcher or past projects that demonstrated substantive research abilities) were invited to an interview. If applicants didn't meet the bar they were offered the opportunity to provide different team members. Interviews served for further validation of subject matter expertise ("share the two to three most complex machine learning projects you worked on in the past 6-12 months"), internal scale ("How many employees do you have who could tackle tasks such as training GPT-2 from scratch"), research approach ("Would you want to drive the research internally or do you need external guidance"), and providing additional context for the IT consultancies.

Ideal Company Profile

Here are some ideal attributes of organizations we are looking for (but not necessarily dealbreakers if a vendor does not satisfy 1 of these criteria).

Our goal is to test if potential consultancies in industry can contribute meaningfully to research in AI safety. As such, we have focused on the following attributes:

1. Consultancies that have existed or operated actively with client work for more than 2 years as an indicator of organizational execution
2. Organizations that have upwards of 15 staff (long-term contracts or permanent staff), or at least have demonstrated ability to manage increasing staff overhead successfully over time
3. Organizations that have enough liquidity to complete the project, ideally demonstrating they have the necessary resources to complete the 2-month project and manage their financial risks
4. Consultancies that can demonstrate that their project portfolio has a good amount of diversity (or at least that the ML work is not only related to AI safety research)

Unfortunately, we have decided to not prioritize contractor network groups (where team members are usually on a project-basis and are not long-term or permanent staff members) as our aim is to test consultancies that have some longer-term cohesion.

Staff Roles Required

Researcher (at least 1)

Focuses on conceptual understanding, creative problem-solving, and theoretical knowledge.

Responsibilities

- Attempt to understand the research problem deeply.
- Explore and articulate ideas and the approaches for creating the DMUM.
- Create detailed method specifications for the DMUM.
- Provide reports on progress, challenges, solutions, and assumptions.
- Shows excitement about potentially publishing research findings.

Desired traits

- Expertise in relevant academic fields, potentially evidenced by papers written with company affiliation or authorship. PhD is ideal but not required.
- Experience with public outputs (e.g., blogs, GitHub repos). Some engagement with relevant online communities on the research problem ideal but not required
- Tenacity in tackling challenges and asking pertinent clarifying questions.
- Comfortable working with Large Language Models (LLMs).
- Adept at identifying and isolating root causes of unexpected research outcomes or model behaviors.

ML Researcher (at least 1)

Focuses on the practical implementation, code integration, and ensuring functional output.

Responsibilities

- Understand the existing codebase(s), modify or add method logic, and create necessary configurations
- Implement methods according to specifications (ensure robust loss calculation and handling of the model's internal mechanisms)
- Ensures code runs without crashing and produces expected results, even if preliminary
- Provide clear and timely progress reports (e.g., Loom/text reports) detailing activities, challenges, and solutions.

Desired Background/Traits:

- Comfortable building implementations directly from specifications
- Comfortable with manipulating various data formats and handling their integration into the codebase
- Comfortable with distributed runs and RE-Bench type stuff
- Skills evidenced by public outputs like GitHub repositories
- Ability to communicate technical progress effectively

Complete Company Evaluation

Table S9. Complete Company Evaluation: ML Research Talent estimates for all 403 identified organizations

Company	Year	Country	Staff	Individual Estimates	ML q50 (CI)	ML %	Category
Tata Consultancy Services	1968	India	640 000	[305, 5400, 3200, 0, 0, 0]	87 (12 - 322) *	0.01% (0.00% - 0.05%)	Probable
Accenture	1989	Ireland	550 000	[186, 3400, 3500, 0, 0, 0]	76 (13 - 280) *	0.01% (0.00% - 0.05%)	Probable
Yandex	1997	Russia	9 900	[67, 521, 232, 142, 291, 528]	60 (41 - 90)	0.61% (0.41% - 0.91%)	Probable
Deloitte	1845	United Kingdom	430 000	[171, 2200, 3700, 0, 0, 0]	54 (8 - 211) *	0.01% (0.00% - 0.05%)	Probable
Cohere	2019	Canada	831	[45, 75, 187, 85, 112, 136]	45 (26 - 76)	5.42% (3.13% - 9.15%)	Probable
Scale AI	2016	United States	5 800	[68, 221, 594, 82, 179, 326]	45 (29 - 75)	0.78% (0.50% - 1.29%)	Probable
IBM	1911	United States	290 000	[443, 2300, 3900, -, -, -]	42 (5 - 143) *	0.01% (0.00% - 0.05%)	Probable
Capgemini	1967	France	260 000	[103, 2100, 1500, -, -, -]	38 (5 - 131) *	0.01% (0.00% - 0.05%)	Probable
Cerebras Systems	2016	United States	726	[22, 71, 142, 69, 76, 142]	36 (21 - 61)	4.96% (2.89% - 8.40%)	Probable
Quantiphi	2013	United States	3 800	[23, 195, 279, 17, 92, 188]	30 (19 - 46)	0.80% (0.50% - 1.21%)	Probable
Mistral AI	2023	France	442	[31, 51, 76, 59, 62, 93]	27 (11 - 53)	6.11% (2.49% - 11.99%)	Probable
Faculty	2014	United Kingdom	939	[15, 39, 83, 7, 41, 48]	27 (15 - 45)	2.88% (1.60% - 4.79%)	Probable
Preferred Networks	2014	Japan	303	[24, 72, 49, 45, 72, 106]	22 (10 - 43)	7.26% (3.30% - 14.19%)	Probable
Naver Cloud	2009	South Korea	1 300	[18, 57, 44, 78, 107, 135]	20 (12 - 35)	1.54% (0.92% - 2.69%)	Probable
Cognizant	1994	United States	300 000	[85, 1300, 1600, 0, 0, 0]	18 (2 - 65)	0.01% (0.00% - 0.02%)	Probable
Booz Allen Hamilton	1914	United States	41 000	[46, 202, 715, 25, 93, 281]	18 (9 - 34)	0.04% (0.02% - 0.08%)	Probable
Liquid AI	2023	United States	79	[11, 20, 28, 21, 25, 24]	16 (9 - 25)	20.25% (11.39% - 31.65%)	Probable
LG CNS	1987	South Korea	5 400	[11, 63, 40, 13, 41, 98]	14 (6 - 27)	0.26% (0.11% - 0.50%)	Probable
Omdena	2019	United States	556	[65, 46, 214, 2, 13, 32]	14 (7 - 26)	2.52% (1.26% - 4.68%)	Probable
SambaNova Systems	2017	United States	474	[11, 42, 68, 15, 21, 63]	13 (6 - 23)	2.74% (1.27% - 4.85%)	Probable

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Company	Year	Country	Staff	Individual Estimates	ML q50 (CI)	ML %	Category
Upstage	2020	South Korea	187	[7, 23, 16, 19, 27, 46]	13 (7 - 23)	6.95% (3.74% - 12.30%)	Probable
Data Science Group	2015	Israel	490	[22, 49, 116, -, -, -]	13 (5 - 27) *	2.78% (1.14% - 5.55%)	Probable
QuantCo	2017	United States	237	[14, 30, 58, 23, 37, 58]	13 (7 - 22)	5.49% (2.95% - 9.28%)	Probable
BCG X	1963	United States	2 600	[15, 69, 219, 12, 45, 103]	12 (5 - 22)	0.46% (0.19% - 0.85%)	Probable
Silo.AI	2017	Finland	239	[19, 44, 85, -, -, -]	11 (4 - 20) *	4.69% (2.01% - 8.70%)	Probable
Encora	2003	United States	7 200	[5, 57, 83, -, -, -]	11 (2 - 31) *	0.16% (0.03% - 0.43%)	Probable
LightOn	2016	France	287	[0, 5, 6, 5, 8, 13]	10 (3 - 22)	3.48% (1.05% - 7.67%)	Probable
Fusion	2004	United States	85 000	[48, 178, 312, -, -, -]	10 (0 - 34) *	0.01% (0.00% - 0.04%)	Probable
InFocusp	2009	India	228	[8, 17, 38, 2, 17, 30]	10 (6 - 16)	4.39% (2.63% - 7.02%)	Probable
QuantumBlack	2009	United Kingdom	523	[10, 33, 107, 4, 27, 52]	10 (3 - 19)	1.91% (0.57% - 3.63%)	Probable
ML6	2013	Belgium	130	[0, 19, 14, 4, 17, 32]	10 (5 - 17)	7.69% (3.85% - 13.08%)	Probable
Layer 6 AI	2016	Canada	87	[8, 21, 45, -, -, -]	9 (3 - 16) *	11.04% (3.68% - 18.39%)	Probable
WA	2009	Japan	87 000	[5, 31, 97, -, -, -]	8 (0 - 34) *	0.01% (0.00% - 0.04%)	Probable
Tryolabs	2010	Uruguay	98	[3, 21, 13, 5, 16, 24]	7 (2 - 14)	7.14% (2.04% - 15.00%)	Probable
Beyond Limits	2014	United States	295	[1, 3, 18, 0, 9, 16]	7 (3 - 12)	2.37% (1.02% - 4.07%)	Probable
MEGVII	2011	China	428	[7, 21, 12, 34, 65, 107]	7 (2 - 14) *	1.68% (0.56% - 3.36%)	Probable
Genpact	1997	United States	130 000	[28, 384, 582, -, -, -]	7 (0 - 28)	0.01% (0.00% - 0.02%)	Possible
G-Research	2001	United Kingdom	1 100	[19, 43, 69, 16, 23, 49]	6 (3 - 11)	0.55% (0.27% - 1.00%)	Probable
Cambridge Consultants	1960	United States	794	[3, 14, 26, 3, 11, 27]	6 (2 - 13)	0.76% (0.25% - 1.64%)	Probable
Inflection AI	2022	United States	63	[1, 6, 12, 9, 11, 14]	6 (2 - 12)	9.52% (3.17% - 19.05%)	Probable
ipe	2004	France	9 400	[0, 10, 10, 0, 0, 0]	6 (1 - 18)	0.06% (0.01% - 0.19%)	Probable

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Company	Year	Country	Staff	Individual Estimates	ML q50 (CI)	ML %	Category
Publicis Sapient	1990	United States	21 000	[20, 151, 356, 2, 31, 150]	6 (2 - 19)	0.03% (0.01% - 0.09%)	Probable
Abacus.AI	2019	United States	185	[8, 25, 25, 3, 9, 22]	6 (2 - 10)	3.24% (1.08% - 5.41%)	Probable
Sutherland	1986	United States	58 000	[9, 47, 90, -, -, -]	6 (0 - 22) *	0.01% (0.00% - 0.04%)	Probable
Fujitsu	1935	Japan	62 000	[21, 166, 161, -, -, -]	6 (0 - 24) *	0.01% (0.00% - 0.04%)	Probable
Science Systems and Applications	1977	United States	652	[7, 10, 39, -, -, -]	6 (2 - 15) *	0.98% (0.37% - 2.33%)	Probable
ESTsoft	1993	South Korea	388	[0, 0, 0, 2, 8, 10]	5 (2 - 9)	1.29% (0.52% - 2.32%)	Probable
Visium	2018	Switzerland	75	[0, 3, 13, 7, 7, 9]	5 (2 - 9)	6.67% (2.67% - 12.00%)	Probable
Euranova	2008	Belgium	159	[2, 24, 13, -, -, -]	5 (1 - 12) *	3.52% (1.01% - 7.55%)	Probable
Presight	2020	United Arab Emirates	510	[2, 10, 27, 3, 13, 25]	5 (2 - 11)	0.98% (0.39% - 2.16%)	Probable
Akvelon	2000	United States	688	[0, 10, 13, 1, 2, 5]	5 (1 - 9)	0.73% (0.15% - 1.31%)	Probable
Modulai	2018	Sweden	27	[5, 6, 14, 3, 10, 12]	5 (2 - 8)	18.52% (7.41% - 29.63%)	Probable
Swisscom	1998	Switzerland	15 000	[9, 70, 87, 6, 34, 66]	5 (2 - 9)	0.03% (0.01% - 0.06%)	Probable
Avanade	2000	United States	17 000	[11, 174, 200, 2, 22, 106]	4 (1 - 10)	0.02% (0.01% - 0.06%)	Probable
DareData	2019	Portugal	85	[1, 8, 23, -, -, -]	4 (1 - 9) *	5.65% (1.88% - 11.29%)	Probable
LatticeFlow	2020	Switzerland	48	[3, 12, 6, -, -, -]	4 (0 - 8) *	8.33% (1.67% - 16.67%)	Probable
NEC Corporation	1899	Japan	11 000	[22, 74, 54, 24, 43, 102]	4 (1 - 9)	0.04% (0.01% - 0.08%)	Probable
Futurewei Technologies	2001	United States	327	[9, 11, 46, -, -, -]	4 (1 - 10) *	1.47% (0.49% - 3.18%)	Probable
ActiveFence	2018	United States	334	[2, 10, 9, 2, 3, 7]	4 (2 - 8)	1.20% (0.60% - 2.40%)	Probable
AE Studio	2016	United States	205	[3, 4, 35, 7, 11, 17]	4 (1 - 8)	1.95% (0.49% - 3.90%)	Probable
NTT Research	1998	United States	85	[7, 8, 12, 3, 7, 18]	4 (1 - 9)	4.71% (1.18% - 10.59%)	Probable
FPT Software	1988	United States	26 000	[9, 199, 92, -, -, -]	4 (0 - 13) *	0.02% (0.00% - 0.05%)	Possible

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Company	Year	Country	Staff	Individual Estimates	ML q50 (CI)	ML %	Category
Bespin Global	2015	South Korea	605	[1, 4, 1, -, -, -]	4 (1 - 11) *	0.79% (0.26% - 1.85%)	Probable
Adaptive ML	2023	France	31	[6, 10, 8, 6, 8, 8]	4 (1 - 8)	12.90% (3.23% - 25.81%)	Probable
Aurizn	2022	Australia	169	[1, 5, 9, 1, 4, 9]	4 (2 - 8)	2.37% (1.18% - 4.73%)	Probable
Tooploox	2012	Poland	163	[1, 19, 12, -, -, -]	4 (1 - 10) *	2.94% (0.98% - 6.38%)	Probable
Unit8	2017	Switzerland	141	[3, 15, 23, -, -, -]	4 (1 - 8) *	3.40% (1.13% - 6.24%)	Probable
deepsense.ai	2014	United States	108	[1, 19, 19, -, -, -]	4 (1 - 10) *	4.44% (1.48% - 9.63%)	Probable
Moov AI	2018	Canada	57	[0, 1, 5, 1, 2, 5]	3 (1 - 5)	5.26% (1.75% - 8.77%)	Probable
Elder Research	1995	United States	170	[0, 6, 23, -, -, -]	3 (0 - 6) *	1.88% (0.47% - 3.76%)	Probable
Halfspace	2015	United States	81	[0, 12, 12, 0, 6, 10]	3 (0 - 7)	3.70% (0.00% - 8.64%)	Possible
Supply Solutions	2002	Brazil	47 000	[0, 0, 0, 0, 0, 0]	3 (0 - 10)	0.01% (0.00% - 0.02%)	Possible
MP DATA	2015	France	145	[4, 33, 14, 0, 12, 18]	3 (0 - 6)	2.07% (0.00% - 4.14%)	Possible
Orcawise	2011	Ireland	65	[0, 0, 10, 0, 3, 10]	3 (0 - 6)	4.62% (0.00% - 9.23%)	Possible
Merantix Momentum	2019	Germany	59	[4, 6, 12, 1, 9, 12]	3 (1 - 7)	5.08% (1.69% - 11.86%)	Probable
IFG	2008	United States	4 800	[0, 6, 13, 0, 0, 0]	3 (0 - 10)	0.06% (0.00% - 0.21%)	Possible
SAIT	1997	Italy	4 800	[0, 3, 37, 0, 0, 0]	3 (0 - 10)	0.06% (0.00% - 0.21%)	Possible
Polestar Analytics	2012	India	647	[2, 13, 13, 0, 1, 2]	3 (1 - 8)	0.46% (0.15% - 1.24%)	Probable
CAS	1988	Germany	4 600	[2, 9, 30, 0, 0, 0]	3 (0 - 9)	0.07% (0.00% - 0.20%)	Possible
DiveDeepAI	2021	Pakistan	43	[0, 3, 10, 1, 5, 10]	3 (1 - 6)	6.98% (2.33% - 13.95%)	Probable
Effixis	2017	Switzerland	34	[0, 1, 7, 0, 4, 8]	3 (1 - 6)	8.82% (2.94% - 17.65%)	Probable
BairesDev	2009	United States	3 100	[0, 20, 60, 2, 12, 28]	3 (0 - 8)	0.10% (0.00% - 0.26%)	Possible
VinAI Research	2019	Vietnam	33	[1, 18, 13, 18, 31, 44]	3 (1 - 7)	9.09% (3.03% - 21.21%)	Probable

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Company	Year	Country	Staff	Individual Estimates	ML q50 (CI)	ML %	Category
Saxon AI	2004	United States	484	[0, 8, 5, 0, 1, 3]	3 (1 - 8)	0.62% (0.21% - 1.65%)	Probable
twoday		Denmark	1 900	[1, 24, 16, -, -, -]	3 (0 - 10) *	0.17% (0.04% - 0.55%)	Probable
Coexya	2020	France	648	[1, 15, 3, 1, 3, 7]	3 (1 - 8)	0.46% (0.15% - 1.23%)	Probable
ML cube		Italy	25	[3, 11, 11, 2, 3, 8]	2 (0 - 4)	8.00% (0.00% - 18.80%)	Possible
Brainpool AI	2016	United Kingdom	24	[0, 0, 3, 1, 2, 3]	2 (0 - 4)	8.33% (0.00% - 16.67%)	Possible
ThinkCol	2016	Hong Kong	22	[0, 0, 0, 0, 2, 2]	2 (0 - 4)	9.09% (0.00% - 18.18%)	Possible
Xomnia	2013	Netherlands	91	[1, 10, 11, 0, 4, 5]	2 (0 - 5)	2.20% (0.00% - 5.49%)	Possible
Cogent Labs	2014	Japan	90	[0, 1, 4, 0, 0, 1]	2 (0 - 5)	2.22% (0.00% - 5.56%)	Possible
Boltzbit	2020	United Kingdom	11	[1, 2, 4, 1, 1, 1]	2 (0 - 3)	18.18% (0.00% - 27.27%)	Possible
Fiddler AI	2018	United States	102	[2, 5, 13, 1, 1, 5]	2 (0 - 4)	1.96% (0.00% - 3.92%)	Possible
Imandra	2014	United States	22	[2, 0, 5, 3, 3, 9]	2 (0 - 5)	9.09% (0.00% - 22.73%)	Possible
DeepNeuronic	2020	Portugal	16	[3, 7, 3, 1, 3, 4]	2 (1 - 5)	12.50% (6.25% - 31.25%)	Probable
Info Strategic	2016	United Arab Emirates	56	[0, 1, 4, 0, 1, 2]	2 (0 - 4)	3.57% (0.00% - 7.14%)	Possible
InferLink	2010	United States	21	[0, 2, 6, 2, 4, 6]	2 (0 - 4)	9.52% (0.00% - 19.05%)	Possible
Numlabs	2019	Poland	32	[0, 6, 2, 1, 4, 5]	2 (0 - 5)	6.25% (0.00% - 15.62%)	Possible
Infinia ML	2017	United States	33	[0, 6, 11, -, -, -]	2 (0 - 5) *	7.27% (2.42% - 16.97%)	Probable
Creatica	2014	Germany	84	[0, 0, 0, 0, 0, 1]	2 (0 - 5)	2.38% (0.00% - 5.95%)	Possible
StatSoft	1986	Germany	33	[1, 7, 1, -, -, -]	2 (0 - 4) *	7.27% (2.42% - 14.55%)	Probable
AMAI	2018	Germany	19	[0, 3, 4, 2, 3, 6]	2 (0 - 4)	10.53% (0.00% - 21.05%)	Possible
Enthought	2001	United States	72	[5, 6, 17, 1, 4, 11]	2 (0 - 5)	2.78% (0.00% - 6.94%)	Possible
R&D Center WINSTARS.AI	2016	Ukraine	43	[2, 6, 1, -, -, -]	2 (0 - 4) *	5.58% (1.86% - 11.16%)	Probable

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Company	Year	Country	Staff	Individual Estimates	ML q50 (CI)	ML %	Category
NNAISENSE	2014	Switzerland	16	[2, 4, 3, 4, 5, 5]	2 (0 - 5)	12.50% (0.00% - 31.25%)	Possible
EnliteAI	2017	Austria	17	[0, 1, 2, 1, 1, 1]	2 (0 - 4)	11.76% (0.00% - 23.53%)	Possible
Recursive	2020	Japan	52	[1, 3, 7, 3, 4, 5]	2 (0 - 5)	3.85% (0.00% - 9.62%)	Possible
HI Iberia	1989	Spain	118	[2, 9, 4, 0, 7, 10]	2 (0 - 4)	1.69% (0.00% - 3.39%)	Possible
Addepto	2018	Poland	68	[1, 7, 10, 0, 2, 2]	2 (0 - 4)	2.94% (0.00% - 5.88%)	Possible
XITASO	2011	Germany	198	[2, 12, 5, 2, 5, 10]	2 (0 - 5)	1.01% (0.00% - 2.53%)	Possible
Kyanon Digital	2012	Vietnam	294	[1, 5, 2, 0, 1, 4]	2 (0 - 5)	0.68% (0.00% - 1.70%)	Possible
AND Technology Research	1980	United Kingdom	38 000	[0, 0, 0, 0, 0, 0]	2 (0 - 9)	0.01% (0.00% - 0.02%)	Possible
RedMane Technology LLC	2000	United States	351	[0, 5, 6, 0, 1, 1]	2 (0 - 5)	0.57% (0.00% - 1.42%)	Possible
Closer Consulting	2006	Portugal	361	[2, 8, 14, 0, 1, 7]	2 (0 - 5)	0.55% (0.00% - 1.39%)	Possible
VRIZE	2020	United States	373	[1, 4, 2, 0, 0, 1]	2 (0 - 5)	0.54% (0.00% - 1.34%)	Possible
Charter Global	1994	United States	395	[0, 0, 3, -, -, -]	2 (0 - 6) *	0.61% (0.20% - 1.76%)	Probable
Technology Control Corporation	2008	Saudi Arabia	418	[0, 1, 5, 1, 2, 6]	2 (0 - 6)	0.48% (0.00% - 1.44%)	Possible
LeewayHertz Technologies	2007	United States	211	[0, 5, 9, 0, 0, 7]	2 (0 - 5)	0.95% (0.00% - 2.37%)	Possible
Stratpoint Technologies	1998	Philippines	522	[1, 6, 5, 0, 1, 4]	2 (0 - 6)	0.38% (0.00% - 1.15%)	Possible
Coherent Solutions	1995	United States	1 100	[1, 7, 6, 0, 2, 4]	2 (0 - 5)	0.18% (0.00% - 0.45%)	Possible
Mobcoder	2014	United States	219	[0, 4, 3, -, -, -]	2 (0 - 5) *	1.10% (0.00% - 2.56%)	Possible
Spatialedge	2016	South Africa	134	[6, 21, 23, 0, 0, 15]	2 (0 - 5)	1.49% (0.00% - 3.73%)	Possible
Q agency	2013	Croatia	261	[0, 0, 2, 0, 1, 2]	2 (0 - 5)	0.77% (0.00% - 1.92%)	Possible
Itransition	1998	United States	1 500	[0, 7, 6, -, -, -]	2 (0 - 6) *	0.16% (0.00% - 0.43%)	Possible
Kainos	1986	United Kingdom	2 900	[0, 16, 26, 0, 3, 5]	2 (0 - 6)	0.07% (0.00% - 0.21%)	Possible

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Company	Year	Country	Staff	Individual Estimates	ML q50 (CI)	ML %	Category
NeuroSYS	2010	Poland	52	[1, 2, 0, 2, 2, 1]	1 (0 - 3)	1.92% (0.00% - 5.77%)	Possible
ANDRO Computational Solutions	1994	United States	41	[0, 3, 4, 1, 2, 4]	1 (0 - 3)	2.44% (0.00% - 7.32%)	Possible
BigThinkCode Technologies	2021	India	51	[1, 1, 2, 0, 0, 1]	1 (0 - 3)	1.96% (0.00% - 5.88%)	Possible
KAMTECH	1997	India	296	[0, 0, 2, 0, 0, 0]	1 (0 - 3)	0.34% (0.00% - 1.01%)	Possible
Fraktal Norge	2014	Norway	52	[0, 0, 1, 0, 1, 1]	1 (0 - 2)	1.92% (0.00% - 3.85%)	Possible
Software Systems	1991	Oman	264	[0, 0, 0, 0, 0, 0]	1 (0 - 3)	0.38% (0.00% - 1.14%)	Possible
Cloud Temple	2017	France	302	[1, 5, 1, 0, 1, 2]	1 (0 - 4)	0.33% (0.00% - 1.32%)	Possible
TechAhead	2009	United States	310	[0, 2, 6, 0, 0, 1]	1 (0 - 4)	0.32% (0.00% - 1.29%)	Possible
Markovate Inc.	2015	United States	57	[0, 0, 5, 0, 0, 1]	1 (0 - 3)	1.75% (0.00% - 5.26%)	Possible
Konverge.AI	2018	India	130	[1, 6, 15, 0, 0, 8]	1 (0 - 4)	0.77% (0.00% - 3.08%)	Possible
Orobix	2009	Italy	38	[1, 0, 3, 1, 2, 4]	1 (0 - 3)	2.63% (0.00% - 7.89%)	Possible
Edvantis	2005	Germany	343	[0, 2, 1, 0, 0, 1]	1 (0 - 4)	0.29% (0.00% - 1.17%)	Possible
InData Labs	2014	Cyprus	59	[0, 5, 4, 0, 4, 5]	1 (0 - 4)	1.69% (0.00% - 6.78%)	Possible
Applied Data Science Partners	2016	United Kingdom	33	[0, 3, 4, 0, 1, 1]	1 (0 - 3)	3.03% (0.00% - 9.09%)	Possible
Tech Valley	2014	France	2 300	[0, 0, 0, 0, 0, 0]	1 (0 - 5)	0.04% (0.00% - 0.22%)	Possible
Atmo	2020	United States	30	[0, 6, 7, 1, 1, 1]	1 (0 - 3)	3.33% (0.00% - 10.00%)	Possible
MI-6	2017	Japan	130	[6, 19, 0, 0, 0, 6]	1 (0 - 4)	0.77% (0.00% - 3.08%)	Possible
DataRoot Labs	2016	Ukraine	28	[1, 9, 1, 0, 3, 5]	1 (0 - 4)	3.57% (0.00% - 14.29%)	Possible
Infer Solutions	2002	United States	20	[0, 1, 0, 0, 0, 1]	1 (0 - 2)	5.00% (0.00% - 10.00%)	Possible
LBox Co	2019	South Korea	25	[0, 0, 0, 2, 3, 3]	1 (0 - 2)	4.00% (0.00% - 8.00%)	Possible
UMD	1983	Australia	1 300	[3, 6, 11, 0, 0, 0]	1 (0 - 3)	0.08% (0.00% - 0.23%)	Possible

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Company	Year	Country	Staff	Individual Estimates	ML q50 (CI)	ML %	Category
Neural Magic	2018	United States	21	[2, 3, 5, 1, 1, 1]	1 (0 - 2)	4.76% (0.00% - 9.52%)	Possible
BigData Republic	2015	Netherlands	23	[0, 4, 4, 0, 2, 4]	1 (0 - 3)	4.35% (0.00% - 13.04%)	Possible
ELEKS	1991	Ukraine	1 900	[1, 12, 5, 0, 0, 3]	1 (0 - 4)	0.05% (0.00% - 0.21%)	Possible
Pyramid Consulting Group	1996	United States	226	[0, 0, 0, 0, 0, 0]	1 (0 - 3)	0.44% (0.00% - 1.33%)	Possible
GalaxE.Solutions	1990	United States	1 300	[0, 9, 4, 0, 0, 0]	1 (0 - 3)	0.08% (0.00% - 0.23%)	Possible
Binariks	2014	United States	203	[0, 3, 0, 0, 0, 0]	1 (0 - 2)	0.49% (0.00% - 0.99%)	Possible
kineo.ai	2020	Germany	12	[0, 1, 2, 0, 1, 1]	1 (0 - 4)	8.33% (0.00% - 33.33%)	Possible
Strong Analytics	2016	United States	9	[1, 1, 3, 1, 2, 1]	1 (0 - 3)	11.11% (0.00% - 33.33%)	Possible
Schafer Corporation	1972	United States	176	[0, 0, 0, 0, 0, 2]	1 (0 - 2)	0.57% (0.00% - 1.14%)	Possible
Altrium	2022	United States	91	[0, 2, 6, 0, 0, 4]	1 (0 - 3)	1.10% (0.00% - 3.30%)	Possible
AI Consult	2019	Brazil	203	[0, 1, 0, 0, 0, 0]	1 (0 - 2)	0.49% (0.00% - 0.99%)	Possible
Qvik	2008	Finland	92	[0, 1, 3, 0, 0, 1]	1 (0 - 2)	1.09% (0.00% - 2.17%)	Possible
Guardians Infotech	2022	United States	81	[0, 0, 0, 0, 0, 0]	1 (0 - 2)	1.23% (0.00% - 2.47%)	Possible
Xaion Data	2020	Japan	80	[0, 0, 0, 0, 0, 0]	1 (0 - 2)	1.25% (0.00% - 2.50%)	Possible
Closeloop Technologies	2011	United States	95	[0, 0, 3, 0, 0, 1]	1 (0 - 3)	1.05% (0.00% - 3.16%)	Possible
XenonStack	2016	United States	96	[0, 2, 3, 0, 0, 2]	1 (0 - 3)	1.04% (0.00% - 3.12%)	Possible
Avertra	2007	United States	207	[0, 1, 0, 0, 0, 1]	1 (0 - 3)	0.48% (0.00% - 1.45%)	Possible
247 Labs	2013	Canada	76	[0, 1, 1, -, -, -]	1 (0 - 4) *	2.11% (0.00% - 5.26%)	Possible
Megamax Services	2015	India	210	[0, 2, 0, 0, 0, 0]	1 (0 - 3)	0.48% (0.00% - 1.43%)	Possible
Sahana System	2012	India	158	[1, 7, 4, 0, 0, 3]	1 (0 - 4)	0.63% (0.00% - 2.53%)	Possible
Sieger	2004	Germany	220	[0, 1, 1, -, -, -]	1 (0 - 4) *	0.73% (0.00% - 1.82%)	Possible

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Company	Year	Country	Staff	Individual Estimates	ML q50 (CI)	ML %	Category
FS Studio	2013	United States	64	[0, 0, 0, 0, 0, 2]	1 (0 - 3)	1.56% (0.00% - 4.69%)	Possible
DeepMetis	2020	Germany	13	[0, 0, 0, 0, 1, 2]	1 (0 - 4)	7.69% (0.00% - 30.77%)	Possible
HydroMind	2021	India	4	[0, 1, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 25.00%)	Non-zero
Finolity Consultancy Services	2017	India	4	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
iiNumbers	2014	Taiwan	4	[0, 1, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Double Check Consulting	2011	United States	10	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Technology	2001	Lebanon	3	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Q-Noon	2017	Turkey	3	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Chi SquareX	2021	India	10	[1, 3, 4, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 10.00%)	Non-zero
HatchWorks	2016	United States	0	[0, 2, 4, -, -, -]	0 (0 - 0) *	-	Not Detected
we-do.ai	2007	Germany	9	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
YouNeeD	2014	Colombia	4	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
HyQuest Consulting Solutions	2007	United States	9	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Xaigi Technology	2021	India	3	[0, 0, 6, 0, 1, 2]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Polixir	2018	China	10	[0, 1, 1, -, -, -]	0 (0 - 1) *	0.00% (0.00% - 16.00%)	Non-zero
Kmeleon	2017	United States	10	[0, 1, 2, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Solid Software Solutions	2011	Poland	3	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
FlowPlus	2018	United Kingdom	3	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
AIQRATE	2019	India	3	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Royal Caliber	2011	United States	10	[0, 0, 1, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 8.00%)	Non-zero
The Quantitative Consulting & Solutions	2013	Hong Kong	3	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected

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Company	Year	Country	Staff	Individual Estimates	ML q50 (CI)	ML %	Category
Downtown Consulting	2011	United Kingdom	3	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Japan Data Science Consortium	2018	Japan	3	[0, 0, 0, 0, 0, 4]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
RBC Group	2008	Ukraine	9	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
IT Consulting Group	2011	United States	3	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
□ □ □ □ □ □ □ □	2021	Taiwan	7	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Taris Technologies	2022	India	4	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Azati Corporation	2002	Poland	4	[0, 1, 0, 0, 0, 2]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Digiwise	2012	Iran	7	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Gefatec	2012	Brazil	7	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
NEC Research Institute		Unknown	7	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Eigen partners		United States	7	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Qexpert	2015	Brazil	6	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Lukasa	2021	United States	8	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Ignous	2012	Chile	8	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Vertex Laboratories	2016	United States	6	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Thinking Machines	2015	Philippines	8	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Evergo	2006	Poland	3	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Springbok AI	2017	United Kingdom	6	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Courart Informática	1991	Brazil	8	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Information Workers Group	2006	Italy	6	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Toncent Information Technology Service	2015	China	6	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected

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Data-Sleek	2020	United States	8	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
USC	1991	Japan	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
New Outcome	2001	Germany	5	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Accord Business Group	2014	United Arab Emirates	5	[0, 0, 7, 0, 1, 2]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
GENIA	2019	Trinidad and Tobago	5	[0, 2, 0, -, -, -]	0 (0 - 1) *	16.00% (0.00% - 32.00%)	Possible
PBQ Oilfield Services	2013	United Arab Emirates	5	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Muons Technology		United States	8	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Arena Technologies	2002	United States	5	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Tumult Labs	2019	United States	5	[0, 0, 0, 0, 0, 2]	0 (0 - 1)	0.00% (0.00% - 20.00%)	Non-zero
Allogic Tecnologia	2016	Brazil	5	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
H&W Consulting	2017	China	7	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
ONE LOGIC	2013	Germany	6	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Inftech		Germany	2	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Sevn3.ai	2021	India	2	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Inttao	2003	United States	0	[0, 0, 0, 0, 0, 0]	0 (0 - 0) *	-	Not Detected
Chapel Hill Tech	2002	United States	1	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Rubentis	2015	South Korea	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
Technologies	2014	Japan	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
ROA Intelligence	2003	South Korea	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
Geeks Data Consulting	2016	Tunisia	0	[0, 0, 0, 0, 0, 0]	0 (0 - 0) *	-	Not Detected
curious.ai	2013	Unknown	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
Xihu Xinchen	2021	China	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
BitAddict AB	2014	Sweden	0	[0, 0, 0, 0, 0, 1]	0 (0 - 0) *	-	Not Detected
ANewD.ai	2017	United States	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
Inavan India Technologies	2003	India	0	[1, 2, 3, 1, 1, 2]	0 (0 - 0) *	-	Not Detected

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Company	Year	Country	Staff	Individual Estimates	ML q50 (CI)	ML %	Category
NivoNexus	2021	Unknown	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
RedMaxx Consultoria	2008	Brazil	0	[0, 0, 0, 0, 0, 0]	0 (0 - 0) *	-	Not Detected
ClearSource	2008	United States	11	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
NeXT'S	2014	Burkina Faso	0	[0, 0, 0, 0, 0, 0]	0 (0 - 0) *	-	Not Detected
NUMERICUBE	2009	France	1	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Automators GmbH	2018	Austria	0	[0, 0, 0, 0, 0, 0]	0 (0 - 0) *	-	Not Detected
Defour Analytics Pvt. Ltd.	2016	India	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
Visual IT Solutions	2008	India	0	[0, 0, 1, 0, 0, 0]	0 (0 - 0) *	-	Not Detected
RK Software Services	2010	United States	0	[0, 0, 0, 0, 0, 0]	0 (0 - 0) *	-	Not Detected
Argonaut AI	2021	El Salvador	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
Woyitech.com	2005	China	0	[0, 0, 0, 0, 0, 0]	0 (0 - 0) *	-	Not Detected
Innovacio Technologies	2019	India	0	[0, 1, 1, -, -, -]	0 (0 - 0) *	-	Not Detected
Machine Learning Solutions	2018	Italy	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
Boostalgo	2015	United States	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
AROUSAL Tech.	2013	Japan	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
Spectra Analytics	2014	United Kingdom	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
AritaWeb Inc.	2015	United States	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
Globe Geosolution	2014	India	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected
Lipon Technologies	2021	India	1	[0, 0, 0, -, -, -]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Alexander Thamm	2012	Germany	1	[0, 0, 1, 2, 7, 17]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
AI Research	2018	United States	2	[0, 0, 1, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
LinkUp Studio	2013	Ukraine	2	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Amplient Labs	2016	United States	2	[0, 0, 1, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Webpragma	2004	United States	2	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Element AI	2016	Canada	2	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
EXCEEDDATA	2015	China	2	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected

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Resileo	2014	India	2	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Makes.ai	2020	Brazil	2	[0, 0, 0, 0, 1, 2]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Data Cowboys	2014	United States	2	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Exometrics	2016	United Kingdom	2	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Kantic Analytics	2020	France	2	[0, 1, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
aiso-lab	2017	Unknown	2	[0, 0, 1, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Biz Digital Connection	2014	Colombia	0	[0, 0, 0, 0, 0, 0]	0 (0 - 0) *	-	Not Detected
Pathway Intelligence	2005	Unknown	2	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Albitech Consulting	2008	Finland	2	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Stowe Research International	1998	United States	2	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Intrinsic Algorithm	2001	United States	1	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
HubThunder	2015	Canada	1	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Strategic Machine, Inc.		Unknown	1	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
AITN	2014	United States	1	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Knowm	2002	United States	1	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Gen Y Solutions	2013	Unknown	1	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
TED Consulting	2016	France	1	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
Pttrner	2021	Japan	1	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Developower	1990	United States	1	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
StatHack	2021	Japan	1	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
CantabPi	2017	United Kingdom	1	[0, 2, 0, 0, 0, 1]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
eoda	2010	Germany	1	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected

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Tarah AI	2010	India	1	[0, 0, 0, 0, 1, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
exvy	2017	United States	1	[0, 0, 1, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Kapahi Industries	2018	India	10	[0, 0, 0, 0, 0, 0]	0 (0 - 0)	0.00% (0.00% - 0.00%)	Not Detected
GRPS Lab	2018	India	28	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 3.57%)	Non-zero
IntelligiChain	2017	United States	11	[0, 0, 0, 0, 0, 2]	0 (0 - 1)	0.00% (0.00% - 9.09%)	Non-zero
Pitt Technology Group	1991	United States	34	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 2.94%)	Non-zero
Searchmetrics	2005	United States	50	[0, 0, 1, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 4.00%)	Non-zero
HackSoft	2014	Bulgaria	46	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 2.17%)	Non-zero
Tapptitude	2013	Romania	45	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 2.22%)	Non-zero
Netguru	2008	Poland	43	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 4.65%)	Non-zero
Objetiva Solução	2009	Brazil	42	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 2.38%)	Non-zero
EuroCC	2008	Spain	42	[0, 1, 8, -, -, -]	0 (0 - 3) *	1.90% (0.00% - 7.62%)	Possible
League of Digital Economy	2001	Russia	38	[0, 0, 0, 0, 0, 1]	0 (0 - 1)	0.00% (0.00% - 2.63%)	Non-zero
Ventagium Data Consulting	2017	Mexico	38	[0, 1, 0, 0, 0, 1]	0 (0 - 1)	0.00% (0.00% - 2.63%)	Non-zero
3Alica	2010	United States	38	[0, 2, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 5.26%)	Non-zero
Archiot	2018	India	38	[0, 1, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 2.63%)	Non-zero
Eigen	2016	China	36	[0, 1, 0, -, -, -]	0 (0 - 2) *	2.22% (0.00% - 6.67%)	Possible
Beeby Clark+Meyler	2005	United States	35	[0, 2, 0, -, -, -]	0 (0 - 2) *	2.29% (0.00% - 6.86%)	Possible
Perfsol	2018	Ukraine	33	[1, 1, 1, -, -, -]	0 (0 - 2) *	2.42% (0.00% - 7.27%)	Possible
Systemware Innovation	1978	Canada	26	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
RCI Analytics Intelligence	1989	Brazil	32	[0, 1, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 3.12%)	Non-zero

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Kaeyros Analytics	2019	Germany	31	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 3.23%)	Non-zero
Siali	2018	Unknown	31	[0, 4, 0, 0, 0, 2]	0 (0 - 2)	0.00% (0.00% - 6.45%)	Non-zero
Bys Grup	2010	Turkey	30	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 3.33%)	Non-zero
Datapy	2019	France	29	[0, 1, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 3.45%)	Non-zero
XCALE Tech	2016	Spain	29	[0, 0, 2, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 3.45%)	Non-zero
NuAIg AI Consulting	2020	United States	29	[1, 1, 2, 0, 0, 2]	0 (0 - 2)	0.00% (0.00% - 6.90%)	Non-zero
Chase Consultancy Services	2006	India	29	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Lucient	2002	United States	27	[0, 1, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 3.70%)	Non-zero
Chipside	2003	United Kingdom	27	[0, 0, 0, 0, 1, 1]	0 (0 - 2)	0.00% (0.00% - 7.41%)	Non-zero
Jaam Automation	2021	United Kingdom	26	[0, 0, 1, 1, 1, 1]	0 (0 - 2)	0.00% (0.00% - 7.69%)	Non-zero
Droids Agency	2017	Denmark	26	[1, 2, 1, 0, 1, 3]	0 (0 - 2)	0.00% (0.00% - 7.69%)	Non-zero
ESSI Integrated Technologies	2003	India	50	[0, 1, 2, -, -, -]	0 (0 - 3) *	1.60% (0.00% - 6.40%)	Possible
etalytics	2020	Germany	51	[0, 0, 1, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 3.92%)	Non-zero
CREA pro	2010	Slovenia	52	[1, 1, 1, -, -, -]	0 (0 - 3) *	1.54% (0.00% - 6.15%)	Possible
Wednesday Solutions	2020	India	55	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 3.64%)	Non-zero
Physics	2021	Belgium	47 000	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
PricewaterhouseC	1998	United Kingdom	5 100	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Lucent Technologies		United States	1 000	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
NEXTGEN	2010	United States	167	[0, 0, 1, -, -, -]	0 (0 - 3) *	0.48% (0.00% - 1.92%)	Possible
Hcube Conseil	2018	Algeria	140	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 1.43%)	Non-zero
INT	1999	United States	140	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 1.43%)	Non-zero

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Company	Year	Country	Staff	Individual Estimates	ML q50 (CI)	ML %	Category
Dragonfly	2018	United Kingdom	134	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 1.49%)	Non-zero
Intelliarts	1999	Ukraine	113	[0, 0, 1, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 1.77%)	Non-zero
InfoPower	1995	Taiwan	112	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 1.79%)	Non-zero
Dextra	1995	Spain	109	[0, 1, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 1.83%)	Non-zero
STME	1982	Saudi Arabia	109	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 1.83%)	Non-zero
Probe Group	1979	Australia	107	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 1.87%)	Non-zero
GOX	2006	United Kingdom	103	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 1.94%)	Non-zero
Metric	2019	Armenia	94	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
MojoTech	2008	United States	80	[0, 0, 1, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 2.50%)	Non-zero
Techspert	2016	United Kingdom	73	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
ReqPOOL	2001	Austria	71	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
TeamOne Group	2009	China	71	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 2.82%)	Non-zero
Exposit	2012	Poland	66	[0, 1, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 3.03%)	Non-zero
TechSource	1998	United States	66	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 3.03%)	Non-zero
VS Data	2000	Brazil	64	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 3.12%)	Non-zero
Exposé	2016	Australia	61	[0, 0, 4, 0, 0, 1]	0 (0 - 2)	0.00% (0.00% - 3.28%)	Non-zero
Partnership on AI	2016	United States	61	[0, 0, 5, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 3.28%)	Non-zero
LaunchPad Lab	2012	United States	59	[0, 0, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 3.39%)	Non-zero
Tagtoo Technology	2013	Taiwan	56	[0, 1, 0, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 3.57%)	Non-zero
Bravinci	2020	Netherlands	26	[0, 0, 3, 0, 0, 1]	0 (0 - 1)	0.00% (0.00% - 3.85%)	Non-zero
IceApple Technology Solutions	2020	India	24	[0, 0, 1, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 4.17%)	Non-zero

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Analytics Town	2016	United States	11	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 9.09%)	Non-zero
Business Data Solutions	2013	Chile	13	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 7.69%)	Non-zero
MindTitan	2016	Estonia	16	[0, 3, 1, -, -, -]	0 (0 - 2) *	5.00% (0.00% - 15.00%)	Possible
Priority Technologies	2015	India	16	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
TechnoPro India	2019	India	15	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 6.67%)	Non-zero
Xpert Data Works	2013	United States	15	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 6.67%)	Non-zero
craftworks	2014	Austria	15	[0, 0, 0, 0, 0, 1]	0 (0 - 1)	0.00% (0.00% - 6.67%)	Non-zero
Seedbox	2020	Germany	15	[1, 1, 1, -, -, -]	0 (0 - 1) *	5.33% (0.00% - 10.67%)	Possible
AITIL	2004	Peru	15	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 6.67%)	Non-zero
Sigma Software	2002	Ukraine	15	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Plantech	2021	United States	14	[0, 1, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 7.14%)	Non-zero
Cybersift	2017	United Kingdom	14	[0, 0, 1, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 7.14%)	Non-zero
Pentadata Infokom Persada	2007	Indonesia	14	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 7.14%)	Non-zero
TalenTech Digital	2017	United States	14	[0, 0, 2, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 7.14%)	Non-zero
idalab	2016	Germany	13	[0, 2, 0, 0, 1, 1]	0 (0 - 1)	0.00% (0.00% - 7.69%)	Non-zero
ITsPeople	2016	Netherlands	23	[0, 1, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 4.35%)	Non-zero
NİBGAT®	2010	Turkey	12	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 8.33%)	Non-zero
Isazi Consulting	2012	South Africa	12	[1, 1, 1, -, -, -]	0 (0 - 1) *	0.00% (0.00% - 13.33%)	Non-zero
Latam Digital	2017	Panama	12	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 8.33%)	Non-zero
AI Superior	2019	Germany	12	[0, 1, 5, 0, 1, 1]	0 (0 - 1)	0.00% (0.00% - 8.33%)	Non-zero
Saige Research	2017	South Korea	12	[1, 0, 1, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 6.67%)	Non-zero

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Irrevo	2005	United States	12	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 8.33%)	Non-zero
Sharpware	2020	Turkey	12	[0, 0, 1, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 8.33%)	Non-zero
SR International	2002	United States	12	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 8.33%)	Non-zero
OVERCODE	2023	Unknown	12	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 8.33%)	Non-zero
Augur IT Consulting	2015	India	12	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 8.33%)	Non-zero
Gamax Laboratory Solutions	1996	Hungary	11	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
The Moonshot Factory		United States	11	[0, 0, 1, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 9.09%)	Non-zero
Rotunda Solutions	2014	United States	16	[1, 0, 3, 0, 1, 1]	0 (0 - 1)	0.00% (0.00% - 6.25%)	Non-zero
pims.ai	1972	United Kingdom	16	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
lexoro	2017	Germany	16	[1, 1, 1, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 6.25%)	Non-zero
Projak Infotech	2016	India	16	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 6.25%)	Non-zero
Cosmos Thrace	2019	Bulgaria	23	[0, 1, 1, 0, 0, 1]	0 (0 - 1)	0.00% (0.00% - 4.35%)	Non-zero
Softtact	2003	India	23	[0, 0, 1, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 4.35%)	Non-zero
Monadical	2006	United States	23	[0, 0, 3, 1, 1, 1]	0 (0 - 2)	0.00% (0.00% - 8.70%)	Non-zero
Digital Strategy Innovation	2020	Italy	22	[0, 4, 6, 0, 0, 1]	0 (0 - 1)	0.00% (0.00% - 4.55%)	Non-zero
Alltegrio	2012	United Kingdom	22	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 4.55%)	Non-zero
Rare Mile Technologies	2011	India	22	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 4.55%)	Non-zero
Grenoble Partners		United States	21	[0, 2, 1, 0, 1, 1]	0 (0 - 2)	0.00% (0.00% - 9.52%)	Non-zero
IBM Consulting	1995	United States	21	[0, 3, 0, -, -, -]	0 (0 - 3) *	3.81% (0.00% - 15.24%)	Possible
Total Synergy Consulting	1988	India	21	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
SpecTal	1999	United States	20	[0, 2, 0, -, -, -]	0 (0 - 2) *	4.00% (0.00% - 12.00%)	Possible

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Kifwat India	2018	India	20	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 5.00%)	Non-zero
ISB Optimus	2011	South Africa	20	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 5.00%)	Non-zero
Austin Technology	2012	Australia	20	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 5.00%)	Non-zero
The Idea Works	1981	United States	20	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
SoftShark	2021	Armenia	19	[0, 0, 1, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 5.26%)	Non-zero
Data Innovation Labs	2018	United States	19	[0, 0, 0, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 0.00%)	Not Detected
Tensorleap	2020	Israel	19	[1, 5, 1, 0, 1, 2]	0 (0 - 2)	0.00% (0.00% - 10.53%)	Non-zero
onepredict	2016	South Korea	19	[1, 2, 2, 0, 0, 3]	0 (0 - 1)	0.00% (0.00% - 5.26%)	Non-zero
CourtCorrect	2019	United Kingdom	18	[0, 0, 2, -, -, -]	0 (0 - 0) *	0.00% (0.00% - 4.44%)	Non-zero
Miracle Finland	2007	Finland	18	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 5.56%)	Non-zero
Dain	2023	United States	18	[0, 4, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 5.56%)	Non-zero
Spark Wave	2016	United States	18	[0, 0, 3, 0, 0, 0]	0 (0 - 2)	0.00% (0.00% - 11.11%)	Non-zero
5ONE Analytics	2015	India	17	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 5.88%)	Non-zero
Hexafold Technologies	2022	India	17	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 5.88%)	Non-zero
Lund&Bendsen	2001	Denmark	17	[0, 0, 0, 0, 0, 0]	0 (0 - 1)	0.00% (0.00% - 5.88%)	Non-zero
Computer Business System Research	1975	Japan	0	[0, 0, 0, -, -, -]	0 (0 - 0) *	-	Not Detected