Decoding Unstructured Text: Enhancing LLM Classification Accuracy with Redundancy and Confidence

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Abstract

This paper develops guidelines for using Large Language Models (LLMs) in labeling and classifying complex, unstructured text. Researchers have choices of multiple configuration dimensions when employing LLMs for classification tasks. We propose a model where researchers optimize a utility function that includes two novel configuration dimensions: redundancy in classification and a confidence threshold based on the LLM self-reported confidence. The function also includes LLM version and whether prompts include detailed instructions. We propose researchers must balance increased accuracy with costs due to incomplete tasks and financial outlays. In an empirical test where we ask LLMs to classify whether press release headlines are about an acquisition, we find that applying thresholds for LLM self-reported confidence yields increases in accuracy, though with costs of incomplete tasks. Notably, we only find that redundancy increases accuracy when a strict confidence threshold is applied. For LLM classification, redundancy alone does not increase accuracy but does increase costs due to incomplete information and financial outlay. We also find that LLM version and detailed instructions shift the efficiency frontier of trade-offs between accuracy and costs of incomplete tasks when employing redundancy and confidence thresholds. Finally, we compare LLM classification results for different configurations to redundancy in human worker classification. We draw on our model and empirical results to develop guidelines for researchers and practitioners using LLM classification to create structured data from unstructured text.

1 Introduction

There are many settings in scholarly research and applied work where large amounts of unstructured data exist, too diverse to aggregate directly, yet containing elements needed for high-value structured data. Researchers have conducted search and labeling tasks on such data for decades, usually relying on human workers, undergraduate students, or even crowdsourced labelers ("mechanical turks" sourced over the Internet), who may lack expertise but are more cost effective (Geiger et al., 2021; Cegin et al., 2023; Li et al., 2023, e.g.,). More recently, considerations of cost and expertise have motivated researchers to seek automated solutions such as machine learning and natural language processing (NLP) algorithms, an approach drastically amplified after the advent of large language models (LLMs) and Generative AI (Zhikai Chen et al., 2023; Kolluri et al., 2019). The idea is that LLMs can provide more expertise at a lower cost, opening opportunities for researchers to develop structured data more quickly and easily than ever before. However, there remain outstanding questions about this approach. While researchers have years of experience to guide them to effectively use human workers, employing LLMs for these tasks is still in nascent stages.

This paper develops guidelines for effective use of LLMs in classification tasks using unstructured data. Our guidelines are based on experiments where we asked LLMs to classify press release headlines. As we iterated through various designs and observed LLM performance matched to "ground truth" created by the authors acting as subject matter experts, we recognized that any practitioner who wishes to deploy LLMs for classification tasks would confront a series of decision problems. The contributions of this paper are to articulate the decision problems and provide guidelines based on empirical tests that are specific to each decision problem. We develop novel decision points and solutions that practitioners should consider when employing LLMs for this purpose. In general, any practitioner needs to make a cost-quality trade-off when using any LLM (or more generally, an AI tool) for labelling unstructured data.

Typically, the practitioner will have a choice among multiple *configurations*, and seeks to optimize the cost-quality trade-off along some efficient frontier. Two straightforward configuration dimensions are: (1) the LLM version and (2) instructions required for accurate output (Del Arco et al., 2024). We also theorize and empirically study whether *redundancy* in classification and LLM self-reports of *confidence* increase accuracy–and if so, how they affect the researcher's cost-quality trade-off and efficient frontier. Redundancy in human responses is well studied and broadly incorporated for human worker classification tasks to increase accuracy (Agley et al., 2022; Alyakoob and Rahman, 2022). But, to our knowledge, whether redundancy increases accuracy for LLM classification has not been examined. This is critical information given the financial costs for LLMs to duplicate a task. Second, we theorize that asking LLMs to self-report confidence and applying a confidence threshold will further result in accuracy increases, a dimension that, to our knowledge, has neither been studied nor broadly employed in LLM classificaiton.

Our guidelines examine how a practitioner might set the configuration dimensions $(r, d; v, i)$ for a labeling project. Each configuration choice will affect two, generally conflicting, outcome measures: accuracy $a(r, d; v, i)$ and cost $C(r, d; v, i)$, where the cost measure comprises both direct financial costs $x(r, d; v, i)$ of applying the dimensions, and a delayed cost $C(U_n(r, d; v, i))$ for handling *unresolved* labeling tasks. Tasks remain unresolved when the LLM results fail to meet the required confidence threshold d for all r repetitions. Intuitively, higher accuracy implies higher cost (both direct and delayed), hence it is vital for the practitioner to pay special attention to the nature of non-linearity in accuracy (i.e., whether there are diminishing or increasing marginal returns for accuracy) when defining their two-dimensional utility function $U(r, d; v, i)$ over the configuration dimensions.

Our empirical analysis reveals that, as expected, more recent versions and more detailed instructions increase accuracy. Perhaps more intriguingly, these dimensions also reduce the costs of incomplete tasks, thus shifting the *efficiency frontier* in the accuracy-cost trade-off when employing redundancy and confidence. Our analysis further suggests that the practitioner should include a *blend* of redundancy and confidence to realize higher accuracy, i.e., a task is deemed *resolved* only when r repetitions exceed the confidence threshold d. Notably, we do not find evidence of increased accuracy when applying redundancy alone (unlike when employing human workers). This provides an important guideline for practitioners weighing the cost-accuracy trade-off when using LLMs. Redundant classification, in the absence of applying a strict confidence threshold, increases costs without increasing accuracy.

Based on our experiences, we emphasize that in most applications there will be some tasks that are quite nuanced and difficult to perform, for both human labellers and an LLM, and may require more costly expert review. Thus, the LLM can be used as a tool for a scalable approach for *isolating a small fraction of difficult tasks*, which can then be forwarded to experts, while performing relatively easier tasks at a low cost and with a machine's willingness to perform repetitive work. This is consistent with the idea that humans and AI can be an effective and efficient combination for cognitive work (Fügener et al., 2022).

Our guidelines were based on extensive experiments and analysis involving a large database of corporate press releases (over 27 million stories sourced from Lexis/Nexis archives spanning three decades). Our current study stemmed from a related investigation, where our intent was to examine small acquisitions by "big tech" companies such as Amazon, Facebook, and Google – ones that were not required to be reported and thus were difficult to track, but that are typically announced in press releases. Our first step was to identify acquisitions of small private companies from press release headlines. Since press releases cover hundreds of topics (not just acquisition related events), and because even an acquisition headline could be written in hundreds of ways, a vital element involved inferring acquisition-related actions from the press release headlines and text. We found that discerning that a headline described an acquisition (or not) was difficult, as evident in Table 1. We needed an automated reliable way to examine these releases for evidence of corporate acquisitions, their nature, intent, and post-acquisition events – and to be inclusive of acquisitions of small company and start-ups often missed by government databases and existing commercially available databases.

Headline Text	Comment
BWI - Completion of Winery Purchase purchase	Appears to represent an acquisition, but not clear if it is a property or a company
Vantex Acquires the Lac Fortune West Property	Property acquisition, not a corporate acquisition
SYB - Sigma consortium's superior bid for Symbion businesses 1/1	Suggests an effort to acquire, and is "about" acquisition, although outcome is not clear
BPC - Sale of Hartland Cables Business	Could be the sale of a company or a business line
Crosshair Announces Termination Of Purchase and Sale Agreement with Strathmore Minerals Corp.	Does not indicate what was intended to be purchased
JDSU Completes Sale of Hologram Business to OpSec Security	This is likely the sale of a business unit but could be an independent company.
Orrick Advises Instagram on Acquisition by Facebook	Does not convey if an acquisition is in progress or it is about a potential acquisition.
Acquires Significant Ownership Stake In Network	Indicates an acquisition but not whether it is majority control.
LAF - Acquisition & Financing of the Rapu Rapu	This could be a company acquisition or property.
Acquires Tervita's Drilling Fluids Business And Forms Strategic Alliance	Unclear whether this is an acquisition of a company or a division within a company.

Table 1: Sample Press Release Headlines Potentially About a Corporate Acquisition.

This prompted us to use LLM classification, inputting press release headlines and asking the LLM to output whether the headline was about a corporate acquisition (and if so, for which entities). These proved to be daunting tasks which required substantial expertise to perform correctly because, similar to BNER work (Zhou et al., 2021), acquisition-related headlines have a lot of nuances, entity (company) names evolve, acquisitions are stated in multiple ways, and acquisition-related words do not always refer to a corporate acquisition. We uncovered more challenges than we expected in realizing necessary accuracy levels for our structured data–challenges that using the latest LLM version and crafting targeted instructions did not adequately address.

Thus, we embarked on a series of experiments that led to systematic guidelines that should be employed by a researcher or practitioner who employs generative AI tools for labeling unstructured text. We also compared LLM results to human worker classification, based on data from an initiative where we recruited and trained over a dozen undergraduate student assistants to classify the headlines. This provided an important benchmark for assessing LLM accuracy, as well as potential pathways for evaluating cost-accuracy trade-offs of using human workers to classify data "left out" when applying redundancy and confidence thresholds.

We draw on our results to create guidelines for researchers and practitioners who employ generative AI tools for labeling. Our results suggest that by following these guidelines researchers can employ LLMs to achieve high accuracy even for moderately complex classification tasks that require background information or special handling.

2 Emerging Literature on LLMs for Labelling

Our work contributes to the growing area of research on the use of Generative AI for labeling and for making comparisons between human and machine techniques. Several recent studies show promising results for advanced LLMs. Cegin et al. (2023) report that for "paraphrase generation for intent classification," GPT creates more robust and diverse answers as compared to human labelers. Ringel (2023) experiment with using GPT-4 as a surrogate for human expertise in identifying marketing mix variables in consumers' posts on Twitter, and find GPT labels – unlike crowdsourced labels – are in high agreement with expert labels. Le Mens et al. (2023) finds that GPT-4 without training closely tracks human judgement in classifying book descriptions as similar to a genre. Li et al. (2023) find that with suitable prompt engineering, generative AI models can match the performance of human surveys in generating perceptual maps, and do so more cost effectively.

Other studies show more nuanced effects. Zenan Chen and Chan (2023) tasked expert and non-expert users to write ad copy either on their own or using LLMs. They find improved outcomes when the LLM served as a sounding board to comment on human-created content, but detrimental performance when used as a ghostwriter with primary responsibility for the content. Relatedly, Brynjolfsson et al. (2023) examine the use of AI for customer service agents and show substantial productivity gains for less experienced agents but little to negative gains for highly experienced ones.

Previous studies compare human vs machine performance, but it is an open question whether and when researchers can effectively apply LLMs to create structured data, especially for complex tasks. An example of complicated but important labeling is *Biomedical Named Entity Recognition* (BioNER), a data labeling task that is vital to scale and automate downstream biomedical natural language processing tasks (Zhou et al., 2021). It is non-trivial and difficult because of "... various ways of naming biomedical entities, ambiguities caused by the frequent occurrences of abbreviations, and new entities constantly and rapidly reported in scientific publications." Similarly, in the corporate sector, companies are employing machine learning and NLP to automatically process vast amounts of customer reviews to understand sentiment and customer perceptions. Our research group faced a similar challenge in working with corporate press releases.

3 LLM Design for Labeling: Configurations and Objectives

In a project where an LLM is deployed for large-scale labeling of unstructured data, a typical practitioner will care about both the *accuracy* of the LLM's work and its *cost*, with the cost comprising both immediate costs of execution as well as a delayed cost of dealing with tasks that the LLM was unable to resolve. In general, higher accuracy will result in higher execution cost and, as we discuss below, may also create higher delayed costs. What is critical, however, is that the practitioner has multiple ways to deploy the LLM, which vary in the accuracy-cost tradeoffs they present. These alternate ways of deployment reflect different combinations along the following 4 dimensions.

- **Version of the tool (v).** In 2023, we considered GPT-3.5 and 4, the latter with higher cost and a promise of better quality.
- **Level of instructions given to the LLM (i).** Ideally, more detailed instructions should improve quality with relatively little increase in cost.
- **Redundancy Level (r).** Assign the same task multiple (r) times (with the LLM set at a high "creative" level to enable variety in answers) then, consider the task as resolved only upon agreement among the r repetitions, and compute accuracy $a(r; v, i)$ based on the performance of this subset of tasks against ground truth. This approach requires defining a redundancy level and a resolution rule (e.g., unanimity).
- **Confidence threshold (d).** Ask the LLM to self-report *confidence*, accept only those responses that exceed a defined *confidence threshold* d, and compute accuracy $a(d; v, i)$ based on the performance of this subset of tasks against ground truth.

An LLM configuration is a specific combination of $(r, d; v, i)$, and the number of combinations depends on the choice set within each dimensions. Each configuration imposes an immediate execution cost $x(r, d; v, i)$, delivers an associated accuracy level $a(r, d; v, i) \in [0, 1]$ for tasks it can resolve, but it leaves a fraction $U_n(r, d; v, i) \in [0, 1]$ of unresolved tasks because of failure to achieve the confidence threshold d for all r repetitions. These unresolved tasks impose a delayed cost $C(U_n(r, d; v, i))$ representing unfinished tasks or the cost of labeling via some expensive human experts. These functions can be estimated by running all configurations over a sample of tasks. We propose practitioners should define their utility function for accuracy $U(a(r, d; v, i))$, along with execution and unresolved-task cost functions. Utility for accuracy should be framed with attention to the nature of non-linearity (i.e., whether there are diminishing or increasing marginal returns for accuracy). For instance, diminishing marginal returns can be captured by a function such as $\sqrt{a}$; increasing returns can be reflected via a^2; and a logistic-like function $\frac{2}{1+e^{-x}} - 1$ can be used to get increasing returns with an asymptotic maximum. Likewise, there is a need to estimate the cost function for unresolved tasks.

The practitioner needs to pick a best-fit configuration over the space of configurations. This best configuration could be one that maximizes net utility $(U(a(r, d; v, i)) - w_1 x(r, d; v, i) - w_2 C(U_n(r, d; v, i)))$, where w_i are relative weights assigned to costs. Alternately, it could maximize accuracy subject to a cost (budget) constraint, or minimize cost for a desired level of accuracy. Since the specific optimization goals, and cost and accuracy functions, are practitioner-specific, we do not make specific recommendations on which configuration to use. Instead, we leverage our experimental work to create an abstract description of tradeoffs by computing an efficient frontier between accuracy and percent of unresolved tasks.

One important contribution of this study is the investigation of the role of redundancy in increasing the accuracy of LLM classification. When human workers are deployed for labeling of complex unstructured data, they are usually recruited under tight budget constraints. Affordable workers — undergraduate students with extra time or strangers sourced over the Internet using tools such as Prolific or AMT – often have limited expertise on the topic (Agley et al., 2022; Alyakoob and Rahman, 2022). Hence it is common to assign each labeling task to multiple workers, because an identical label from multiple (n) researchers implies a higher *confidence* that the label is correct. For instance, Alyakoob and Rahman (2022) initially assigned each labeling task to 3 workers; in case of disagreement it was assigned to another 2 (total 5); and if at least 4 out of 5 responses weren't identical, another 5 subjects were sought; if 7 out of 10 agreed, the task was assigned that label and otherwise considered unresolved. Similarly, professional news organizations require at least 2 convergent sources to publish a claim. In the US, the jury system requires unanimity among 12 jurors to render a verdict in a criminal case, otherwise resulting in a hung jury and possible retrial.[1] Patients often seek a second medical opinion, though often without much thought to what would occur if the opinions diverged. Radiology readings of complex images often require multiple radiologists or a mix between machine and human experts.

The idea that redundancy increases quality draws from the French intellectual Marquis de Concordet's demonstration, two and a half centuries ago, that "that there are situations in which it is advisable to entrust a decision to a group of individuals of lesser competence than to a single individual of greater competence" (Boland, 1989). When redundancy is implemented by assigning a task to multiple human subjects, it is reasonable to assume that each subject's response on a task is independent and that subjects have identical probability p of an accurate response. Then, if the same task is assigned to n subjects, the probability that all n agree and provide the *correct* response is p^n; that all n agree and provide an *incorrect* response is $(1-p)^n$; and the task remains unresolved with probability $1 - p^n - (1-p)^n$. Further, the *conditional probability* (i.e., conditional on all n subjects providing the same response) of a correct vs. incorrect response is $\frac{p^n}{(p^n+(1-p)^n)}$.

With this background of redundancy in human labeling projects, we asked: what is the role of redundancy when an LLM does the labeling? One might initially think redundancy is unnecessary with LLMs because a machine, given the same input, should produce the same output each time. This determinism would imply that multiple iterations of the same task by an LLM would yield identical responses, negating the benefits of redundancy seen with human labelers. However, LLMs can be configured to introduce variability through a parameter called "temperature." The temperature setting controls the randomness of the model's predictions. A lower temperature results in more deterministic outputs, while a higher temperature increases randomness, allowing the model to generate different responses to the same prompt. By setting a higher temperature, we can simulate redundancy where the LLM provides varied responses. There is a question of how similar this is to having multiple human labelers evaluate the same task, specifically whether LLM redundancy also improves accuracy. A second contribution of this study is to prompt the LLM to self-report its confidence in its response. In practice, prompting a model for its confidence helps users filter out less reliable answers, thereby improving the overall accuracy of the task at hand. High-confidence responses typically mean the model finds strong alignment with familiar patterns, making these responses more dependable. This is particularly useful in applications where precision is crucial, such as data classification or decision support systems. By using confidence assessments, users can focus on high-confidence answers for critical tasks, while flagging low-confidence responses for further review, thus optimizing the balance

[1] relaxed to a $\frac{5}{6}th$ agreement for some civil trials, with the caveat that a panel with only 6 jurors must produce a unanimous outcome (Andres v. United States, 333 U.S. 740, 748 (1948).

between automation efficiency and accuracy. Therefore, we include a confidence threshold in our model, theorizing that conditioning on confidence should improve accuracy (while incurring a cost of incomplete tasks).

A novel element our analysis uncovers is that combining *redundancy* with self-reported *confidence* enhances this approach further. By leveraging multiple responses generated at a higher temperature and applying a confidence threshold, we select only the most confident and varied responses. This combined strategy mitigates the limitations of both methods when used alone, providing a more robust framework for accurate and efficient data labeling. This ensures that tasks are resolved with high reliability, optimizing the balance between automation efficiency and accuracy.

4 Data and Methodology

We developed our guidelines from our observations of LLM performance classifying unstructured data based on the configuration dimensions described above.

4.1 Lexis Nexis Dataset of Press Releases

The data for our study is a comprehensive text corpus comprising over 27 million press release headlines from Lexis-Nexis. This corpus represents a broad spectrum of corporate communications spread over several decades, providing a large and varied initial set of articles for our analysis. Our motivation is to evaluate the performance of LLMs in *differentiating between headlines pertaining to corporate acquisitions and mergers, and those that do not*. With 27 million headlines, a random selection large enough to yield a substantial number of acquisition-related headlines from human or LLM labelers is cost-prohibitive. Therefore, we first appliy automated methods for an initial filter to generate a set of headlines for review that oversampled those likely to be acquisition-related.

This task was addressed through a two-stage process, each targeting specific aspects of the classification challenge. In the first stage, we employed a pretrained Bidirectional Encoder Representations from Transformers (BERT) named entity recognition model, combined with part-of-speech (POS) tagging heuristics. This approach focused on identifying key elements indicative of acquisitions, such as organizational names and relevant linguistic markers. The criteria for considering a headline as potentially related to an acquisition were based on the detection of specific verbs, nouns, company names, and terminologies typically associated with acquisition activities.

The second stage involved using Word2Vec for generating detailed headline embeddings to grasp the semantic context more effectively. We supplemented this with a standard BERT classifier, enhanced by data augmentation techniques to address class imbalances. Despite challenges in data accuracy and potential overfitting, this comprehensive approach laid the groundwork for our subsequent analysis by narrowing down the dataset to a more relevant subset.

Throughout the development of these methodologies, there was an ongoing process of refinement, where we continually adjusted the training data and classification thresholds to improve accuracy and precision. While the automated methods helped filter and preprocess the dataset, the primary aim was to create a manageable dataset for comparing the performance of human labelers and LLMs. This comparison required high-quality training data verified by human labelers, which was essential for benchmarking the performance of the LLMs. Additionally, involving human labelers allowed us to evaluate and compare their accuracy directly against LLM performance, which is a core objective of our study.

With this methodology, we identified a focused set of headlines that included roughly 50% likely acquisition-related headlines and 50% randomly selected headlines. Given that acquisition-related headlines are rare in the original dataset, this approach created a balanced and manageable dataset, allowing us to effectively study the performance of LLMs while maintaining a representative sample of the overall data.

4.2 Empirical Analysis

To develop guidelines, we ask an LLM to classify the set of press release headlines as about an acquisition or not. We focus on evaluating *accuracy* and *costs* based on unresolved tasks, as a function of the configuration dimensions (as outlined in section 3). Financial costs can then be calculated based on costs to running the LLM at the desired redundancy level and employing human worker or expert classification to fill in incomplete tasks.

We first define our dependent and independent variables, and then describe data collection for *Expert Classification* and *LLM Classification*. For additional analyses, we compare LLM Classification accuracy to *Human Worker Classification* based on assessments of undergraduate RAs.

4.2.1 Dependent Variables

- **Accuracy ($a(r, d; v, i)$).** The correlation between LLM and Expert classification for headlines accepted based on the independent variables, where the classification task is whether a headline is about an acquisition or not.

- **Cost of incomplete tasks $C(U_n(r, d; v, i))$.** $U_n(r, d; v, i)$ is the number of headlines left unresolved based under the given configuration or independent variables.

4.2.2 Independent Variables

- **Version of the LLM (v).** A categorical variable, with 1 indicating the LLM classifier is GPT-4, and 0 indicating the classifier is GPT-3.5.

- **Level of instructions (i).** We employ two prompts, one with very basic directions of inputs and outputs (hereby referred to as no instructions), and another that includes an in-depth instructions describing what constitutes an acquisition and examples. This is a categorical variable with 1 indicating the LLM was given detailed instructions, and 0 indicating it was not.

- **Redundancy Level (r).** This is the number of times the LLM was asked to perform the same classification task (with the LLM set at a high "creative" level), between 1 and 25 times. Redundant classification of a headline required defining a resolution rule for accepting the LLM response and assigning classification. We use unanimous agreement, only including headlines with 100% consistent classification as acquisition or not across all trials.[2]

- **Confidence threshold (c).** This is the threshold of self-reported confidence required to accept the LLM response. Again, we need to employ an aggregation rule and we use average confidence over redundant trials. The LLM reports confidence as a percentage from 0-100 (described below). We test five confidence thresholds: (1) all headlines (no threshold), (2) 85 percent, (3) 90 percent, and (4) 100 percent confidence.[3]

4.2.3 Estimation

We use OLS regression to assess whether, and the extent to which, our theorized configurations impact accuracy and cost due to incomplete tasks, as theorized in our utility functions.

$$a = \beta_1 * v + \beta_2 * i + \beta_3 * r + \beta_4 * c$$

$$U_n = \gamma_1 * v + \gamma_2 * i + \gamma_3 * r + \gamma_4 * c$$

[2] We only include consistently classified headlines because otherwise average confidence is not meaningful. The LLMs are highly consistent in their classification; with redundancy of 25 trials, between 85 and 95 percent of headlines are always classified as acquisition or not (depending on the version and level of instructions). We do not find accuracy differences based only on the consistency level of the LLM response across redundant trials. Appendix XX provides details.

[3] We find self-reported confidence is highly skewed toward 100 percent, which is why our first cut-off is at 85 percent. Appendix XX provides details of confidence distributions.

With these results, we then provide guidance for how a researcher can assess the cost-quality trade-off along an efficient frontier. If β is positive and γ negative, this configuration dimension presents a trade-off, and the researcher must weigh the value of increased accuracy with incurring increased costs. If both β and γ are positive, this represents a shift in the efficiency frontier, such that the configuration results in accuracy increases and reductions in costs due to incomplete tasks.

4.2.4 Expert Classification

To assess accuracy, we compare classification by LLMs to expert classification as determined by the authors of this paper. Two authors independently reviewed each headline for a sample of 1,155 headlines and agreed on the classification for 1,022 headlines. We conduct our analysis on the 1,022 headlines with expert agreement. This excludes the subset of headlines (133) where the underlying meaning is ambiguous.

4.2.5 LLM Classification

For LLM classification, we study classification from two versions: GPT-3.5 and GPT-4. We also devised two distinct experimental setups: a "with instructions" prompt and a "no instructions" prompt, resulting in the first four configurations (see Appendix A). All prompts ask the LLM to report its confidence in its classification as a percentage between 0 and 100. For each of the four version/instruction configurations, we ran the prompts 25 times ($n = 25$) to generate 25 separate classification responses. We consider classification for the n requested runs for the respective redundancy level ($n = 1$ through $n = 25$).

We evaluate accuracy by computing the correlation between expert classification and LLM classification for the headlines retained based on the four independent variables. For example, for version GPT-3.5, no instructions, confidence 85 and redundancy 10, the LLM classification is based on headlines consistently classified as acquisition or not across 10 requested trials, which also had average confidence of at least 85. We compute the correlation of LLM and Expert classification for this set of headlines, and the correlation, number of unresolved headlines, and respective configuration dimensions are one observation.

We repeat the entire set of $n = 1$ through $n = 25$ redundant *trials* over multiple *runs*. We employ 11 runs for GPT-3.5 and 5 runs for GPT-4, with fewer runs for GPT-4 due to cost considerations. This results in 4,000 observations.[4] Table 2 summarizes our approach. For all configurations we use the parameter temperature $= 1.0$, which controls the randomness of the generated responses. A temperature of 1.0 indicates a higher

[4] 2 instruction configurations, 5 confidence thresholds, 25 redundancy levels, 11 runs for GPT-3.5 and 5 runs for GPT-4: 2x5x25x(11+5) = 4,000

	with minimal instructions	with detailed instructions
GPT-3.5	11 trials	11 trials
GPT-4	5 trials	5 trials

Table 2: Number of trials performed under 4 configurations. Each trial involved 25 repetitions.

level of randomness, allowing for more varied and creative responses. This setting was chosen to increase the LLMs' capability to generate diverse interpretations of the headlines.

The text of the prompts are in Appendix A. The prompt with instructions provided detailed definitions and examples to explain how we wanted the LLM to classify headlines as acquisitions (coded as ”A”), mergers (coded as ”M”), or neither (coded as ”N”), along with its confidence in the classification, and to identify the names of the companies involved, if applicable.[5] This prompt included examples of each type, additional instructions on specific cases (e.g., partial acquisitions, acquisitions of assets not constituting a company acquisition), and guidelines for identifying company names involved in these events. The aim was to provide the LLM with comprehensive contextual understanding before classification. The prompt without instructions presented a more straightforward task to the LLMs without additional context or examples. It instructed the LLM to read a headline and classify it as an acquisition, merger, or neither, its confidence in the classification, and to identify the names of the companies involved, if applicable. This prompt tested the LLMs' inherent capabilities in headline classification without instructions, examples, or other context.

4.2.6 Human Worker Classification

In additional analyses, we compare LLM classification accuracy to human workers. This provides a baseline for assessing the levels of LLM accuracy that can be achieve with our guidelines. It also provides a potential pathway for resolving the incomplete tasks.

We recruited thirteen undergraduate research assistants from a west coast university to read a random sample of the headlines selected by our algorithm and label them as describing described a company merger and acquisition (whether it was impending or already completed), or not. We ask them to classify each headline as either: (1) about a company merger or acquisition, (2) about an acquisition of property, (3) not about a merger or acquisition, or (4) unclear/unsure.[6] We also asked them to enter into a text box the company names for the acquirer or acquiree, if applicable. Unfortunately, we did not collect data on RA self-

[5] For our analysis, we combined the acquisition and merger classifications.

[6] As described above, some headlines use terms like ‘acquire’ to describe acquiring property, rather than a corporate acquisition. We thought it might be useful for subsequent algorithm development if our training data separately classified property acquisition. For the purposes of this paper, this category is grouped with ‘not about a about merger or acquisition.’

reported confidence because we conducted this data collection before we theorized about this configuration dimension with LLM classification. The RAs attended a two-hour instructional session where we explained criteria for classifying headlines into the above categories. During the session, the RAs classified a set of test headlines and then we presented the correct classifications and answered questions. Details of the RA training are included in Appendix A.

The RAs worked remotely. We created an interface using a Google spreadsheet where the RAs could fetch a set of 50 headlines at a time to classify. The interface provided a drop-down box with the four classification choices and columns to copy and paste the acquirer and acquiree names when applicable. When the RAs finished classifying the 50 headlines they would click the ”submit” button that recorded their answers in our database. The RAs then had the option of retrieving another set of 50 headlines. Each headline was reviewed by between one to eight RAs.

5 Results

5.1 LLM Classification

We conduct our analysis on the 1,022 headlines where there was expert agreement. As described in section 4.2.3, we use OLS regression to analyze whether the configuration dimensions predict (i) classification accuracy, measured by the correlation between LLM and expert classification, and (ii) costs incurred later due to incomplete responses, measured by the number of headlines not accepted. We also ran additional regressions to consider the interaction between two of the dimensions, redundancy and confident threshold. Table 3 summarizes the statistical results from all regressions.

Redundancy and confidence thresholds: Results in table 3 show an accuracy/cost trade-off for employing redundancy and confidence thresholds. Every unit of increased redundancy increases the accuracy correlation by 0.001 (column 1) such that redundancy of 25 results in a .025 increased correlation. The cost of incomplete tasks also increases with each unit of redundancy by 5.5 (column 3) such that redundancy of 25 results in an incomplete task cost of 139. There is also an accuracy/cost trade-off to applying a higher confidence threshold: employing a 100% confidence threshold increases the accuracy correlation by .135 compared to a 95% threshold and by .19 compared to no threshold. The trade-off is that costs also increase by 223 and 452, respectively.

LLM version and level of instructions: Results also show that both the advanced LLM version (GPT-4) and detailed instructions *increase accuracy* while *reducing costs* of unresolved tasks. The advanced LLM

	Corr Model	Corr Model (I)	Cost Model	Cost Model (I)
Intercept	0.680^{***}	0.623^{***}	608.760^{***}	497.199^{***}
	(0.003)	(0.004)	(5.281)	(7.722)
Confidence Threshold: 0	-0.193^{***}	-0.130^{***}	-452.639^{***}	-318.624^{***}
	(0.003)	(0.005)	(5.361)	(10.565)
Confidence Threshold: 0.85	-0.199^{***}	-0.127^{***}	-393.015^{***}	-237.026^{***}
	(0.003)	(0.005)	(5.361)	(10.565)
Confidence Threshold: 0.90	-0.179^{***}	-0.107^{***}	-336.183^{***}	-190.265^{***}
	(0.003)	(0.005)	(5.361)	(10.565)
Confidence Threshold: 0.95	-0.135^{***}	-0.058^{***}	-222.656^{***}	-100.774^{***}
	(0.003)	(0.005)	(5.361)	(10.565)
Version: 4.0	0.062^{***}	0.062^{***}	-189.233^{***}	-189.233^{***}
	(0.002)	(0.002)	(3.657)	(3.496)
Instructions: Detailed	0.039^{***}	0.039^{***}	-82.018^{***}	-82.018^{***}
	(0.002)	(0.002)	(3.390)	(3.241)
Redundancy	0.001^{***}	0.006^{***}	5.546^{***}	14.127^{***}
	(0.000)	(0.000)	(0.235)	(0.503)
Confidence Threshold 0 x Redundancy		-0.005^{***}		-10.309^{***}
		(0.000)		(0.711)
Confidence Threshold 0.85 x Redundancy		-0.006^{***}		-11.999^{***}
		(0.000)		(0.711)
Confidence Threshold 0.90 x Redundancy		-0.006^{***}		-11.224^{***}
		(0.000)		(0.711)
Confidence Threshold 0.95x Redundancy		-0.006^{***}		-9.376^{***}
		(0.000)		(0.711)
R^2	0.698	0.724	0.761	0.781
Adj. R^2	0.697	0.723	0.760	0.781
Num. obs.	4000	4000	4000	4000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 3: OLS regressions to evaluate effects of configuration dimensions on LLM classification accuracy (Correlation) and "inverse cost" (Number included). Columns 2 and 4 add the interaction between LLM version and level of instructions. Confidence threshold effects are compared to employing a 100% threshold (baseline) and Detailed instructions are compared with minimal (baseline).

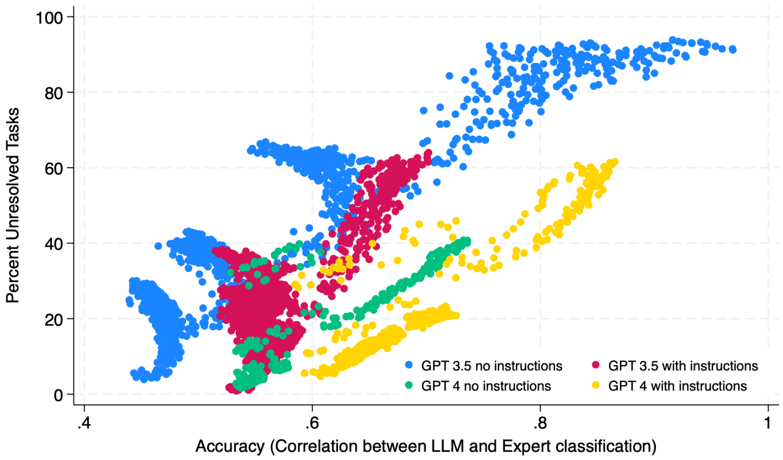

Figure 1: Efficiency frontier. Correlation accuracy and unresolved tasks for each trial and run, by LLM version and instructions.

increases the accuracy by .062 (column 1) while also decreasing the costs due to incomplete tasks by 189 (column 3). Providing detailed instructions increases accuracy by .039 (column 1) with an accompanying cost decrease of 82.

Together, these results indicate that the advanced LLM and instructions shift the efficiency frontier in terms the accuracy and cost of unresolved task trade-offs. Figure 1 plots the accuracy and unresolved tasks for each observation. The color of the datapoint indicates the first two configuration dimensions: whether GPT-3.5 or 4 was used and if the prompt contained detailed instructions. The cost/accuracy trade-off is due to employing different confidence thresholds and redundancy (variance is also due to stochasticity across runs). The graph shows that version and instructions shifts the efficiency frontier: there is a larger increase in cost from unresolved tasks per increment of accuracy for the less advanced LLM and basic instruction prompts. For example, with GPT-4 with detailed instructions, accuracy levels increase to over .8 correlation while losing half the tasks, whereas for GPT-3.5 without instructions, high accuracy comes at a very high cost of retaining less than 10% of tasks. Also interesting to note: only GPT-3.5 without instructions yields such large sacrifices in cost of incomplete observations to realize high exceptionally high accuracy – for this version redundancy and confidence thresholds result in correlations that approach 1, but with only a handful of tasks resolved.

Using the advanced LLM and detailed instructions to shift the efficiency frontier does incur a *financial cost*. The cost comparison for OpenAI API access to (standard) GPT models is as follows:

Standard Models:

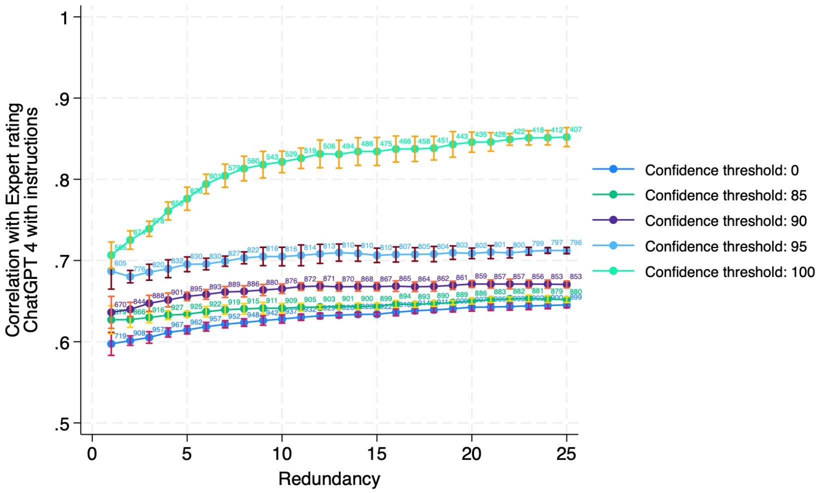

Figure 2: Accuracy by redundant runs for each confidence threshold for classification by GPT4 with instructions. Averages taken over 5 runs at each redundancy level. Error bars 95%CI. The average number of resolved (included) tasks are indicated at each datapoint, out of 1022 requested. Tasks are excluded both because of stochasticity in questions the LLM answers as well as conditioning on consistent classification and confidence threshold.

- GPT-3.5: $1 to $1.50 per 1 million input tokens and $2 per 1 million output tokens.[7]
- GPT-4: $30 per 1 million input tokens and $60 per 1 million output tokens.

Thus, GPT-4 is approximately 20 to 30 times more expensive for both input and output tokens compared to GPT-3.5. In our case, for 1000 tasks, using GPT-4 with detailed instructions would incur an additional $970.

Figure 2 plots the relationship between accuracy and redundancy by confidence threshold for classification by GPT4 with instructions.[8] This plots the average accuracy and 95% confidence intervals for all runs at the redundancy level, for different confidence thresholds. The graph reveals that trends are fairly flat with redundancy except when the confidence threshold is 100%; that is only including responses with full confidence for all redundant trials.

Interactions: Based on the trends revealed in figure 2, we investigate whether interactions between redundancy and confidence thresholds affect accuracy and costs. Table 3 presents effects. Column 2 reveals an interaction such that redundancy only increases accuracy when the confidence threshold is set to 100% (baseline condition), and the size of the effect increases by 6 times, to .006. For the 100% confidence thresh-

[7] Think of tokens as words. They are roughly equivalent.

[8] Plots for other versions and instructions show similar trends.

No. RAs	1	2	3	4	5	6	7	8
No. Headlines	167	265	274	175	92	36	12	1

Table 4: Headline Frequency for Number of RA Reviewers

old, redundancy of 25 increases correlation accuracy by .15 compared to no redundancy. When we run the estimation excluding the 100% confidence conditions from our risk set, the effect of redundancy decreases by two orders of magnitude and is no longer significant ($\beta = .00007; p = .35$).

This result indicates that for LLM classification *redundancy alone does not improve accuracy*. Unlike human worker classification, running redundant trials without conditioning on confidence does not provide benefits for the additional financial cost. Moreover, although there is also an interaction between redundancy and confidence threshold for the costs of incomplete tasks, the coefficients do not net to zero (see table 3 column 4), and the estimation excluding the 100% confidence conditions from our risk set yields an effect that is smaller but still significant both statistically and economically ($\beta = 3.4; p < .001$).

This means, absent a high confidence threshold, redundancy yields no increase in accuracy but does increase both costs of incomplete tasks and financial costs of running the redundant tasks.

5.2 Comparing LLM and Human Worker Classification

One question might be how LLM classification accuracy compares to employing human workers to classify headlines. To this end, we asked human workers to complete the same classification task, as described in section 4.2.6. Table 4 shows the number of headlines reviewed by RAs, or RA redundancy (the number of RAs that reviewed each headline), for the set of 1,022 headlines. We aggregate responses in a comparable manner to LLM classification, coding a headline as about an acquisition if all RAs code it as such, otherwise the headline is coded as neither.

Figure 3 shows the correlation between Human worker and Expert classification by worker redundancy.[9] As expected, for human workers, accuracy increases with redundancy, providing a contrast to the finding for LLM classification described above. Redundancy of 2-3 workers leads to modest accuracy, with correlations around .5 or .6 and comparable to LLM classification by GPT-3.5 with instructions or GPT-4 without instructions. Redundancy of 5 or 6 workers yields correlations above .7, comparable to those realized by GPT-4 with instructions.

[9] Headlines reviewed by 6-8 RAs are collapsed into a single group due to low numbers (see table 4).

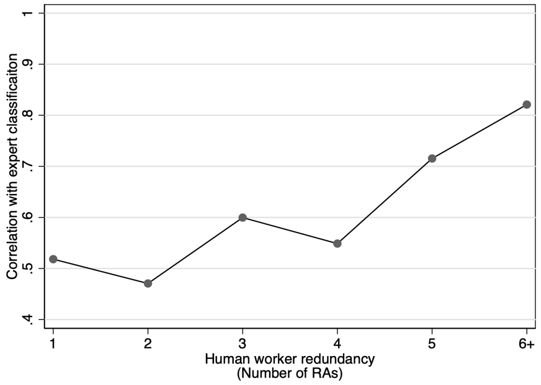

Figure 3: Correlation between human worker and expert classification by human worker redundancy (number of RAs to review a headline)

6 Guidelines

As researchers increasingly use (Gen) AI in labeling and classification tasks to create structured data sets there is a need for guidelines for best practices. Our findings provide important insights as to how LLMs can be best used in these tasks. They reveal areas where best practices that work with human labelers do not directly extend to LLMs (for example in terms of redundant classification). We develop guidelines based on our findings for researchers to best utilize LLMs for classification tasks as well as areas where LLMs might be less reliable or consistent.

Self-Reported Confidence

Researchers should employ "self-reported confidence," pick a confidence threshold that fits the needs of their project, and use the results to identify the subset of their data that needs deeper human evaluation. A key finding from our empirical analysis is that researchers can use LLM self-reported confidence to increase classification accuracy. Of course, there is an inherent trade-off to having an LLM classify a large number of objects (quantity) versus having high accuracy in each classification (quality). Researchers therefore need to examine and pick a confidence threshold for accepting accuracy based on the needs of their project. Moreover, our findings that self-reported confidence improves accuracy means researchers can identify the subset of their data that can be satisfactorily classified by an LLM as opposed to what needs to be reviewed by a human. This should lead to higher accuracy at lower cost.

Redundancy with Multiple Trials

Unlike human classification, where multiple subjects increases accuracy, there is little value in deploying redundant trials with an LLM for classification only. A second important finding is that redundancy in LLM classification across multiple trials only leads to small improvements in accuracy (at best). In this way, LLMs are different from human classifiers. Figure 3 shows that human worker redundancy increases accuracy, in line with our theoretical predictions and historical research. For LLMs, however, we find no evidence that redundancy increases accuracy in the absence of a confidence threshold (*see* table 3 and figure 2). Based on these findings, we do not recommend that researchers incur costs of asking an LLM to perform the same classification over multiple trials without a confidence threshold.

There is value in deploying redundant trials with an LLM to compute average self-reported confidence. At the same time, our findings show substantial increases in accuracy when considering LLM self-reported confidence averaged across multiple trials. We find classification accuracy increases when the LLM has high confidence across redundant trials (*see* table 3 and figure 2). For the highest classification accuracy, we recommend researchers ask the LLM to self-report confidence *across multiple trials*, and implement a confidence threshold based on classifications that are both consistently classified and have high average self-reported confidence across the multiple trials. At the same time, redundancy and a confidence threshold also increase costs of incomplete tasks. Since the efficiency frontier shifts with an advanced LLM and detailed instructions, we recommend researchers use this combination with those configuration dimensions. Further, this combination can be used in contexts where it is adequate to study a subset of data from unstructured text, or in combination with expert review for the subset of incomplete tasks.

Instructions

For nuanced classification tasks that require expertise, researchers should include instructions in their prompts. Our results also suggest that, for classification tasks that are somewhat nuanced or require special handling, accuracy improves when the LLM is provided with instructions. Our specific task, in asking whether a headline is classified as about an acquisition, was by no means difficult, but did require some background knowledge. In our case, we found that providing detailed instructions improved classification accuracy, for both the basic and advanced LLM (*see* figure 1, table 3). We believe many classification tasks for which researchers employ human and machine labelers are of a comparable level of difficulty and require similar handling and expertise. Based on our results, we suggest researchers create detailed prompts with clear and concise instructions, including definitions and examples, if classification that requires some level of expertise.

Version

Advanced LLMs, in our case GPT 4, provide higher accuracy with reducd costs due to incomplete tasks. At the same time, advanced LLMs also incur higher financial costs (*see* section 5). Evaluating this trade-off will depend on the researchers utility function in terms of their value of high accuracy and lowering incomplete tasks. The results we present provide information for a data-driven approach for a researcher to answer this question.

7 Conclusion

The use of LLMs and Generative AI in labeling and classification tasks is in nascent stages and will likely increase dramatically over the coming years. This creates a pressing need for guidelines and insights to best practices when using LLM classification. We propose a model where researchers optimize a utility function to balance accuracy and costs. Our model includes four configuration dimensions, two of which provide novel insights that, to our knowledge, have not previously been empirically tested for LLM classification.

Our empirical analysis provide important insights regarding redundancy and confidence. First, our results provide no evidence that redundancy in LLM classification increases accuracy in the absence of a confidence threshold. This is unlike human worker redundancy, and provides an important guideline to researchers to best allocate resources. Second, we introduce a novel dimension, self-reported confidence, and find that accuracy increases with stricter confidence levels. Third, we find that *redundancy in self-reported confidence* yields the most accurate results.

Our model also highlights that increasing accuracy by applying redundancy and confidence thresholds incurs the trade-off of costs based on incomplete tasks. Our model and empirical analysis provides valuable information for researchers to define their utility functions to balance this trade-off, given the unique needs of their project.

We also find that both advanced LLMs and including detailed instructions in the prompt *both* increase accuracy and reduce costs of incomplete tasks, such that these configurations shift the *efficiency frontier*. That these increase accuracy increases is in line with previous research, but the finding that they also reduce the cost of incomplete tasks is, to our knowledge, a novel contribution.

Overall, this study provides important guidelines as researchers increasingly turning to LLMs and generative AI, rather than using human labellers, to classify unstructred text in order to develop high-value structured data.

A Appendix: Prompts

A.1 No Instructions

A.1.1 Prompt 0

You are a helpful acquisition/merger analyst.

Read and analyze the following headline. Create a table with 4 columns.

In column 1, put “A” if the headline describes a company acquisition, “M” if the headline describes a company merger, or “N” if the headline describes neither a company acquisition nor a merger.

In column 2, indicate your confidence in the previous classification (“A”, “M”, or “N”) in percent (value between 0% and 100%)

In column 3, identify the acquiring company (if acquisition), one of the merged companies (if merger), or “NA” (if neither).

”In column 4, identify the acquired company (if acquisition), the other merged company (if merger), or “NA” (if neither).

Don’t provide reasoning/comments. Just provide the markdown table.

This is the headline:

```
\<series of headlines here\>
```

A.2 With Instructions

A.2.1 Prompt 0

You are a helpful acquisition/merger analyst. Your job is to classify if a headline is about a company acquisition (“A”), a company merger (“M”), or neither a company acquisition nor a merger (“N”). An acquisition is when one company buys another company. A merger is when two companies join together as equals. Before you start, carefully review the following examples and instructions.

- For example, this headline refers to a company acquisition: “BEWiSynbra acquires the recycling company EcoFill.” One company, BEWiSynbra, is acquiring another, EcoFill. We code it as acquisition (“A”).

- For example, this headline refers to a company merger: “Kroger and Albertsons Companies Announce Definitive Merger Agreement”. The two companies, Kroger and Albertsons, agreed to merge. We code it as merger (“M”).

- For example, this headline is not about an acquisition nor merger: “-Nevada Geothermal Power Inc. Announces Gordon Bloomquist Stepping Down as Director”. We code it as neither (“N”).

- For example, this headline refers to an acquisition, but it is unclear whether it is about a particular company acquiring another: “Determination for taxation purposes of acquisition cost of the shares of Qt Group Plc, established through partial demerger from Digia Plc”. We code it as neither (“N”).

Sometimes a headline refers to acquiring assets or property, but not a company acquisition. This should be coded as neither (“N”).

- For example, this headline refers to a company acquiring a set of programs: “Medivir strengthens its clinical pipeline by entering into agreement to acquire a portfolio of clinical stage oncology programs”. We code it as neither (“N”).

- For example, this headline refers to a company acquiring property: “Arizona Metals Corp to Acquire Additional Private Lands at its Kay Mine Project”. We code it as neither (“N”).

Additional information:

(1) Headlines that announce that an acquisition or merger is about to take place or already completed should be coded as acquisition (“A”) or merger (“M”).

(2) Headlines that announce that an acquisition or merger is not happening should be coded as acquisition (“A”) or merger (“M”).

(3) Some acquisitions are partial, meaning a company is acquiring a percentage of another company. We code these headlines as acquisition (“A”) if more than 50% were acquired, and as neither (“N”) if 50% or less were acquired or if the percentage is not clear from the headline.

(4) There may be some headlines that are not straightforward in a different way. If the headline cannot be classified as company acquisition (“A”) or company merger (“M”), code it as neither (“N”).

Company Names: If the headline was coded as acquisition or merger, capture the names of the companies involved. In an acquisition, one company buys another. Sometimes the headline does not name one or both companies. For example, the headline “DDM provides additional information related to its Hungarian acquisition” reports the name of the acquiring company (DDM) but not the name of the acquired company. In this case, leave the acquired company blank. In the case of a merger, two companies are coming together (or merging), but one is not buying another. In this case, enter the names of the companies if they are mentioned in the headline. If only one company is mentioned, enter only one name. If both companies are mentioned, enter both names.

Now start to classify headlines.

Read and analyze the following headline. Create a table with 4 columns.

In column 1, put “A” if the headline describes a company acquisition, “M” if the headline describes a company merger, or “N” if the headline describes neither a company acquisition nor a merger.

In column 2, indicate your confidence in the previous classification (“A”, “M”, or “N”) in percent (value between 0% and 100%).

In column 3, identify the acquiring company (if acquisition), one of the merged companies (if merger), or “NA” (if neither).

In column 4, identify the acquired company (if acquisition), the other merged company (if merger), or “NA” (if neither).

Don’t provide reasoning/comments. Just provide the markdown table.

This is the headline:

```
\<series of headlines here\>
```

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