Probabilistic Record Linkage Using Pretrained Text Embeddings

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November 28, 2024

Abstract

Pretrained text embeddings are a fast and scalable method for determining whether two texts have similar meaning, capturing not only lexical similarity, but semantic similarity as well. In this paper, I show how to incorporate these measures into a probabilistic record linkage procedure that yields considerable improvements in both precision and recall over existing methods. The procedure even allows researchers to link datasets across different languages. I validate the approach with a series of political science applications, and provide open-source statistical software for researchers to efficiently implement the proposed method.

Keywords: Probabilistic Record Linkage, Fuzzy String Matching, Embeddings, Large Language Models, GPT-3, GPT-4, Text-As-Data

1 Introduction

Empirical social scientists frequently need to merge information from multiple datasets prior to conducting their analyses, but it is only in rare cases that two datasets contain a shared variable that unambiguously identifies which records belong to the same entity. In the absence of such exact matching variables, researchers must perform *fuzzy record linkage*—linking records based on some measure of similarity between variables. When working with text data, existing approaches commonly rely on *lexical* measures of string similarity (Jaro, 1989). These include "edit distance" measures like Jaro-Winkler and Levenshtein distance, string metrics that compare frequency distributions like cosine similarity, and set theoretic measures like Jaccard similarity, among many others. The most commonly used and cited fuzzy record linkage procedures in political science employ one or more of these metrics to capture the distance between pairs of records (Enamorado, Fifield and Imai, 2019; Kaufman and Klevs, 2022) .

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†Thanks to Elise Blasingame, Jason Byers, Rob Carroll, David Cottrell, Ted Enamorado, Kosuke Imai, Aaron Kaufman, George Krause, Avital Livny, Isaac Mehlhaff, Brandon Stewart, Maria Tislenko, Garrett Vande Kamp, and participants at Polmeth 2024 for their helpful comments and suggestions. The `fuzzylink` R package is available at `https://github.com/joeornstein/fuzzylink`.

Lexical similarity is a powerful tool for record linkage when datasets contain misspellings, typos, or other irregularities in data entry. But these measures have well-understood shortcomings, particularly in cases where lexically dissimilar strings can be used represent the same entity. For example, the name “James” is more lexically similar to the name “Jamel” than it is to the nickname “Jim”. Many record linkage problems that political scientists encounter have this property, in which semantically similar records can be represented by lexically dissimilar strings. Elected officials may be referenced by their legal name in one dataset and their nickname in another. An organization may be listed under its full name in one dataset and an acronym in another. For scholars of comparative and international politics, records may even appear in multiple languages. When faced with record linkage problems like these, a measure that captures not only the lexical similarity between strings, but their *semantic* similarity as well, would be highly desirable.

Fortunately, such measures have recently become widely available, thanks to rapid advances in large language models (LLMs) based on the transformer architecture (Vaswani et al., 2017). These models encode language using *text embeddings*, wherein each word is represented by a real-valued vector of numbers (Rodriguez and Spirling, 2021). Once trained, the distance between these text embeddings provides a useful measure of semantic similarity: words that are closer together in embedding space tend to have similar meaning. Formally, if two strings of text are represented by the vectors $\mathbf{a}$ and $\mathbf{b}$, then their cosine similarity $\frac{\mathbf{a}\cdot\mathbf{b}}{||\mathbf{a}||||\mathbf{b}||}$ measures how semantically related they are—with 0 being completely orthogonal and 1 being identical.

Table 1 provides several examples in which the cosine similarity between text embeddings provides a better measure of match quality than lexical similarity (see the next section for details on how these cosine similarities are computed). Consider, for example, the problem of linking an organization’s full name with its acronym (first four rows). Lexical measures of string distance will struggle with this sort of record linkage task, since an organization’s acronym may be lexically more similar to the acronym of another organization than it is to its own full name! By contrast, embedding vectors can encode the fact that AARP stands for American Association of Retired Persons, by representing those strings as vectors close to one another in space—this is how language models based on such embeddings (e.g., ChatGPT) “know” the relationship between those two concepts. In each of the examples in Table 1, the cosine similarity between text embeddings chooses the correct match, while lexical measures of string similarity do not. Consequently, a record linkage procedure that incorporates this measure of similarity may significantly outperform procedures that rely exclusively on lexical similarity.

Table 1: Examples where lexical similarity is a misleading measure of match quality. Best match according to four string distance measures in bold. In each case, lexical measures select the wrong match, while the cosine similarity between pretrained text embeddings selects the correct match.

String 1	String 2	Levenshtein	Jaro-Winkler	Jaccard	Embedding
AARP	American Association of Retired Persons	0.103	0.517	0.188	**0.837**
AARP	AAA	**0.500**	**0.722**	**0.333**	0.555
USPS	US Post Office	0.214	0.655	0.250	**0.814**
USPS	UPS	**0.750**	**0.806**	**1.000**	0.753
Mike Kelly	George Joseph "Mike" Kelly, Jr.	0.323	0.354	0.421	**0.827**
Mike Kelly	Mark Edward Kelly	**0.471**	**0.757**	**0.538**	0.616
Kit Bond	Christopher Samuel Bond	0.304	0.475	0.368	**0.605**
Kit Bond	Katie Britt	**0.364**	**0.627**	**0.455**	0.445

This is not the first paper to propose using text embeddings for record linkage. Indeed, there is by now an extensive literature applying transformer models to what computer scientists call *entity resolution*—determining whether two or more entries in a large dataset refer to the same entity (Zhou et al., 2021; Tang et al., 2022). These models have had significant practical applications in areas like e-commerce, where merging product records across multiple websites is a challenging large-scale problem. These approaches have been adapted to social science applications as well, most notably in the work of Arora and Dell (2023). What distinguishes the current paper from previous work is that it incorporates embedding similarity into a probabilistic record linkage procedure. Such procedures are preferable in social science for two main reasons: they do not rely on arbitrary thresholds to determine whether two records constitute a match, and they allow post-merge analyses to account for uncertainty introduced during record linkage (Enamorado, Fifield and Imai, 2019). For applications where there may be multiple correct matches for each observation, a method that can estimate match probabilities will provide a principled approach for determining which records to merge, and how strongly to weight each observation in a subsequent analysis.

In this paper, I propose a probabilistic record linkage procedure that incorporates pretrained text embeddings into an active learning algorithm (Bosley et al., 2022). The approach, which I call `fuzzylink`, is a variant of Adaptive Fuzzy String Matching (Kaufman and Klevs, 2022), an iterative process of fitting a model, labeling uncertain matches, refining the model, and repeating until there are no uncertain record pairs remaining. The labeling step is performed by zero-shot prompts to a language model, which significantly reduces time and expense compared to hand-labeling (Ornstein, Blasingame and Truscott, 2022). Across a series of political science applications, I show that this approach significantly improves both precision and recall over existing approaches, and can even perform some tasks—like multilingual record linkage—that would be impossible using lexical similarity measures alone. In this paper I focus on applications with a single fuzzy matching variable (and potentially multiple exact "blocking" variables), and conclude by discussing how one might extend the procedure to multiple fuzzy matching variables.

2 The Algorithm

Suppose we have two datasets $\mathcal{A}$ and $\mathcal{B}$, with sample sizes $n_\mathcal{A}$ and $n_\mathcal{B}$ respectively. The algorithm described below performs a fuzzy "left join", identifying every record in $\mathcal{B}$ that matches at least one record in $\mathcal{A}$. It proceeds in six steps.

Step 1: Embedding. Select the string variable that identifies each record in $\mathcal{A}$ and $\mathcal{B}$, and retrieve text embeddings for each unique string. In the analyses that follow, I use 256-dimensional pretrained embeddings from OpenAI.[1] Wherever possible, the strings representing records should *not* be pre-processed by stemming, converting to lowercase, or any other steps that one might take to reduce complexity in a bag-of-words representation (Grimmer and Stewart, 2013); performance will generally be improved if we embed text as it is most likely to appear in the training corpus (e.g. "Coca-Cola" instead of "cocacola"). The output from this step will be two matrices $\mathbf{M}_\mathcal{A}$ and $\mathbf{M}_\mathcal{B}$, with dimensions $n_\mathcal{A} \times 256$ and $n_\mathcal{B} \times 256$ respectively. Each row of these matrices is an embedding vector.

Step 2: Compute Similarity Metrics. For each pair of records in the set $\mathcal{A} \times \mathcal{B}$, compute the cosine similarity between their embedding vectors. If the embeddings are normalized to length 1, a matrix of cosine similarities can be efficiently computed by taking the product $\mathbf{M}_\mathcal{A}(\mathbf{M}_\mathcal{B})'$. If there are any variables that must match exactly to link a record from $\mathcal{A}$ to $\mathcal{B}$ ("blocking variables"), perform

[1] The most up-to-date embedding model offered by OpenAI as of March 2024 returns 3,072-dimensional embeddings, but one can reduce the dimensionality through "Matryoshka Representation Learning" (Kusupati et al., 2024), dramatically improving computation speed at little cost to accuracy. The most recent training data for these embedding models is September 2021, meaning the approach will underperform if successfully linking records requires knowledge of events that have occurred since that date.

this step only for pairs of records with exact matches on these variables. Since the computational complexity of this step scales with $n_{\mathcal{A}} \times n_{\mathcal{B}}$, exact blocking can significantly improve efficiency and as practical matter should be used whenever possible.

Step 3: Label a Training Set. Select a subset of record pairs and assign each pair a binary label, 1 if the records are a true match and 0 otherwise. For this paper's analyses, I begin with an initial training set of the 500 record pairs with the highest cosine similarity scores and generate labels using the following zero-shot prompt to OpenAI's GPT-4o:[2]

```
Decide if the following two names refer to the same {record_type}.
{additional_instructions} Think carefully.3 Respond with "Yes" or "No".


Name A: {A}
Name B: {B}
```

The placeholders `{record_type}` and `{additional_instructions}` will vary by application. The accuracy of LLM labels is often improved by including context-specific instructions or examples (Ornstein, Blasingame and Truscott, 2022), just as a researcher would include a detailed codebook if this step were conducted by human research assistants or crowd-coders.

Step 4: Fit Supervised Learner. Fit a probabilistic model to map these cosine similarities onto a match probability. In the analyses that follow, I fit a logistic regression, which has the advantage of being significantly faster at generating predictions for large datasets than other supervised learners. I include as predictors both embedding similarity and Jaro-Winkler similarity, to capture both semantic and lexical differences between records.[4]

Step 5: Label Uncertain Matches. Estimate match probabilities for all record pairs in the set $\mathcal{A} \times \mathcal{B}$ using the fitted model from Step 4. For any record pairs with estimated match probability in some range $[\underline{p}, \bar{p}]$, assign labels as in Step 3. Add these new labeled observations to the training set and refit the model as in Step 4. Repeat these steps until there are no uncertain matches remaining.

[2] In the Supplementary Materials, I replicate the paper's empirical applications using open-source language models for the embedding and labeling steps. The advantage of open-source models is that their results are fully reproducible, though this comes at the expense of poorer record linkage accuracy. I discuss this tradeoff more fully in Section 4.

[3] Bizarre as it may seem, prompts that include phrases like "Think carefully" often yield marginal gains in classification accuracy (Battle and Gollapudi, 2024).

[4] In Section C of the Supplementary Materials, I vary the model specification in Step 4 and show that this choice yields the best-calibrated probability estimates.

The choice of values for $\underline{p}$ and $\bar{p}$ is ultimately a pragmatic one—balancing precision, recall, and computational efficiency. Wider intervals will tend to yield higher recall rates at the expense of precision and speed. In the analyses that follow, I validate all records with match probabilities in the range $[0.1, 0.95]$. If there are any records in $\mathcal{A}$ without matches after Step 5, I label an additional twenty of the most probable matches in $\mathcal{B}$ to improve recall.

Step 6: Link Datasets. Return all record pairs with an estimated match probability greater than $\underline{p}$. This includes any record pairs labeled a true match in Steps 3 and 5.

3 Applications

In this section, I describe three applications of the method, testing its performance across a variety of record linkage tasks common in political science. The first application merges the names of over 9,000 candidates for public office with voter file records from tens of millions of registered voters in California. The second application merges the names of interest groups with ideology scores estimated from campaign contributions. And the final application explores how well the method can perform record linkage across multiple languages, merging the names of political parties from 32 countries in 30 different languages.

For each application, I evaluate performance by computing both precision and recall, where precision measures the fraction of identified matches that are correct, and recall measures the fraction of correct matches that are identified.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Any method that performs well on both of these metrics is likely to be particularly useful for researchers. Higher precision increases the quality of matches, reducing bias in subsequent empirical analyses. Higher recall reduces the amount of missing data in the linked dataset, increasing the statistical power of downstream analyses—and reducing bias whenever that missingness is non-random.

3.1 Linking Candidates to Voter File Records

Every year, hundreds of thousands of candidates are elected to local public office throughout the United States. Collecting data on these elections can be a painstaking process (Sumner, Farris and Holman, 2020; Einstein, Ornstein and Palmer, 2022; de Benedictis-Kessner et al., 2023), because unlike candidates for state and federal office, there is often very little information recorded about local candidates except their names. In this application, I merge the names of every candidate for mayor and city council in the state of California since 2016 with their corresponding records in the L2 voter file. There are a total of 9,025 unique candidate names, and roughly 22 million registered voters in the California voter file.[5] I merge these two datasets using full name as the fuzzy matching string and exact blocking on last name and city of residence. To make validation feasible, the author and a research assistant hand-coded matches from three counties—Alameda, Kern, and Ventura—to estimate precision and recall.

Of the 840 candidates that ran for office in these three counties, `fuzzylink` identified 793 potential matches in the voter file. 154 of these were exact matches, and the research team determined that 597 of the remaining fuzzy matches were valid, for an estimated precision of 94.7%. In addition, the research team was able to locate 21 matches in the L2 voter file that `fuzzylink` failed to identify, for a near-perfect recall rate of 97.2%. By comparison, the `fastLink` approach (Enamorado, Fifield and Imai, 2019)—which links records based on predetermined cutoffs in Jaro-Winkler scores—identifies only 448 potential matches, with an estimated precision of 98.6% and recall of 58.2%. The dramatically improved recall is largely due to `fuzzylink` successfully linking a variety of nicknames from the candidate list with legal names in the voter file (e.g., "Vinnie" with "Vinton", "Chuck" with "Charles", "Libby" with "Elizabeth", "Trish" with "Patricia", "Mel" with "Carmelita", "Sri" with "Sricharana", "Teddy" with "Theadora"). There are also a number of cases where candidates go by their middle name (e.g., "Jeffrey Benjamin Gould" listed as "Ben Gould" on the ballot, "Gregory Tod Abbott" listed as "Tod Abbott") and are correctly paired by the LLM prompt.

It is worth noting, in light of ongoing debates over algorithmic bias in language models (Abid, Farooqi and Zou, 2021; Grossmann et al., 2023), that a disproportionate share of false positive matches (33 out of 42) are Asian, Hispanic, or African American names. As with any record linkage

[5]The California Election Data Archive (CEDA) is available at `http://www.csus.edu/isr/projects/ceda.html`.

procedure, researchers should take the time to carefully examine a subset of the merged dataset and ensure that the method is performing as expected. Fortunately, the estimated match probabilities are well-calibrated (see Appendix Section C) and can serve as a useful guide during validation: the false positives had a median match probability of just 18.4%, compared to 61% for the true positives. One could eliminate over half of the false positives in the merged dataset by manually validating only the 150 least-probable matches.

3.2 Linking Amicus Cosigners to Campaign Donations

Next, I replicate the record linkage from Abi-Hassan et al. (2023), who estimate the ideology of interest groups by merging the names of organizations that cosigned Supreme Court amicus curiae briefs (Box-Steffensmeier, Christenson and Hitt, 2013) with ideal point estimates (DIME scores) from campaign donations (Bonica, 2014). There are 15,376 organizations in their dataset and 2.9 million organizations with recorded campaign donations in the DIME dataset. To make validation feasible, I focus here on the 1,388 organizations that cosigned amicus briefs in the year 2012. To reduce computational complexity during fuzzy matching, I also restrict the DIME dataset to organizations with at least eight distinct campaign contributions.[6]

Through a combination of exact matching and fuzzy string matching, Abi-Hassan et al. (2023) were able to locate DIME scores for 376 of these 1,388 organizations, approximately 27% of the total. By comparison, despite restricting its search to only 8% of the DIME dataset, `fuzzylink` is able to locate DIME scores for 444 unique organizations. As in the first application, this dramatically improved recall is largely the result of correctly identifying alternative names for the same organization (e.g., "Utah Association for Justice" and the "Utah Trial Lawyers Association", "California Forestry Association' and "CA Forestry Assoc PAC", "Ojibwe" and "Chippewa" tribes) and even former names of the same organization (e.g., "The Association of Magazine Media" formerly "Magazine Publishers Association", "California Construction Trucking Association" formerly "California Dump Truck Owners Association", "United States Telecom Assocation" formerly "United States Telephone Assn", "PacifiCorp" formerly "Pacific Power & Light", "RELX" formerly "Reed Elsevier"). This improved recall does not appear to come at the expense of precision: the research

[6]According to Bonica (2023), "donating to eight or more distinct recipients is [typically] sufficient to recover a reliable ideal point estimate".

team identified only 7 false positives out of 1,058 proposed matches, for an estimated precision of 99.3%. Note that this estimate considers chapters or subsidiaries of larger organizations to be true matches (for example, linking "NAIOP" and "NAIOP New Jersey Chapter"), under the assumption that one can use campaign donations of local chapters to make inferences about the parent organization's ideology. If one were unwilling to make such an assumption, those matches could easily be filtered out post-merge, or one could modify the LLM prompt in Step 3 to ignore such matches.

3.3 Linking Political Party Names Across Multiple Languages

For record linkage problems involving multiple languages, lexical similarity measures tend to be a poor guide to match quality. The strings "LDP" and "Jiyū Minshutō", for example, share no lexical features at all, but both refer to the same Japanese political party. Pretrained text embeddings, by comparison, can naturally accommodate this sort of problem by representing text from multiple languages in the same embedding space. This makes transformer models particularly adept at machine translation tasks (Vaswani et al., 2017). In this application, I demonstrate that the approach proposed here can successfully link the names of political parties across 30 languages—though performance is better for some languages than for others.

To test the method, I take the ParlGov dataset of parliamentary elections since 1900 (Döring and Manow, 2018), splitting it into two datasets as illustrated in Table 2. The first dataset contains each party's name in its native language, the election year, and the number of seats the party won in parliament that year. The second dataset contains the English translation of the party's name along with its estimated left-right ideology on a ten-point scale. I include all parties from non-English speaking countries that won seats in parliament, for a total of 4,972 observations across 32 countries and 663 elections. Because text embeddings may be closer in space for some language pairs than others[7], I perform this record linkage separately for each country, blocking on election date.

The resulting dataset correctly matches 4,805 name pairs out of 4,972—a recall rate of 96.6%. There are, however, a large number of false positive matches (209 in total), for an overall precision of 95.8%. As expected, the method's accuracy varies somewhat by language: precision and recall

[7]For example, as measured by cosine similarity, the phrase "Social Democratic Party" is much closer to the Portuguese "Partido Social Democrata" (0.80) than it is to the Icelandic Social Democratic Party "Alþýðuflokkurinn" (0.44). However, "Alþýðuflokkurinn" is closest to "Social Democratic Party" *relative* to other Icelandic parties, so the probabilistic model will perform best if we avoid pooling embedding distances across language pairs.

Table 2: Multilingual Record Linkage Application: Splitting the Parlgov data into two sets with 4,972 observations each.

Native Party Names:

country_name	election_date	party_name	seats
Austria	1919-02-16	Sozialdemokratische Partei Österreichs	72
Austria	1919-02-16	Österreichische Volkspartei	69
Austria	1919-02-16	Deutschnationale	8
Austria	1919-02-16	Deutsche Freiheits und Ordnungspartei	5
.	.	.	.
.	.	.	.
Turkey	2023-05-14	Zafer Partisi	0

English Party Names:

country_name	election_date	party_name	left_right
Austria	1919-02-16	Social Democratic Party of Austria	3.7293
Austria	1919-02-16	Austrian People's Party	6.4733
Austria	1919-02-16	German-Nationals	7.4000
Austria	1919-02-16	German Freedom and Order Party	8.8000
.	.	.	.
.	.	.	.
Turkey	2023-05-14	Victory Party	8.8000

are lower for countries like Israel (93.6% precision, 91.7% recall) and Japan (85.2% precision and 94% recall) than for Italy (99.1% precision, 99.6% recall) or Portugal (100% precision, 99.1% recall). See Appendix Table A1 a complete list of these evaluation metrics by country.

In addition to computing these accuracy metrics, one can evaluate whether the record linkage procedure allows us to recover downstream quantities of interest. Figure 1 plots the seat-share weighted ideology of every parliament in the ParlGov dataset (lines) along with each parliament's estimated ideology following the record linkage (points).[8] The correlation between the estimates and their true values is 0.987, and the estimates are perfectly correlated with the truth in most countries. Only a few country-years stand out as severely mis-estimated. In Switzerland, the model incorrectly links the FDP ("Freisinnig-Demokratische Partei der Schweiz") with both the Liberal Party of Switzerland and the Radical Democratic Party. These two parties merged in 2009, but they were separate parties throughout the prior century, which biases our estimates rightwards for much of the 20th century.

[8]For each party in $\mathcal{A}$, estimated ideology is computed as the average ideology of its matches in $\mathcal{B}$, weighted by match probability.

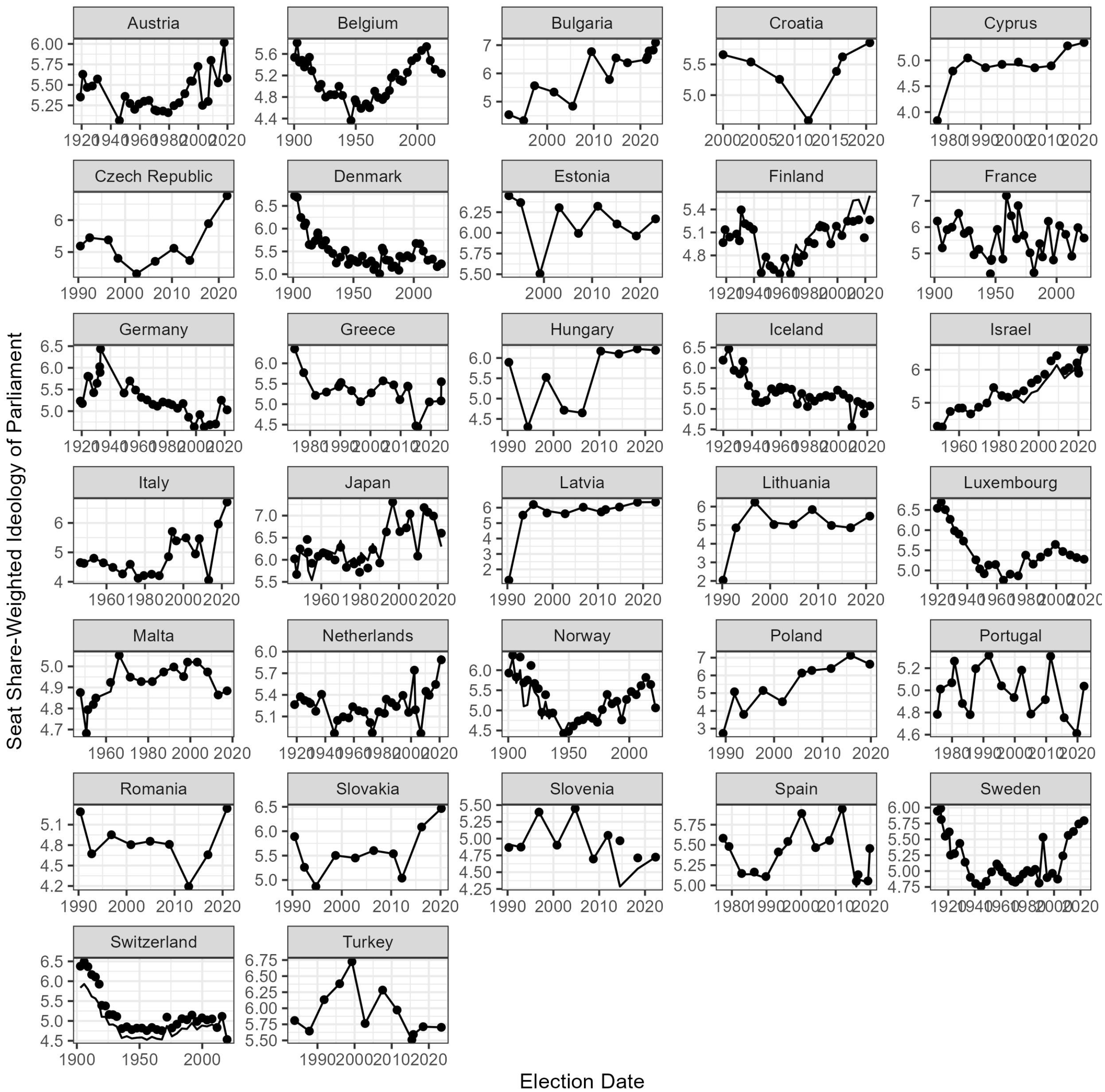

Figure 1: Estimated seat-weighted parliamentary ideology following merge (points) plotted over true values (lines).

In practice, errors like these can be easily corrected by conducting a post-merge manual validation, focusing on records in $\mathcal{A}$ that did not match to a single unique record in $\mathcal{B}$. In this case, it would require manually checking only 111 proposed matches, roughly 2% of the total.

4 Discussion

The approach I propose here has significant advantages over methods that rely on lexical similarity measures alone. Social scientists often encounter record linkage problems where matching records may be lexically dissimilar from one another, whether it's due to alternative names, acronyms, or even different languages. Under such conditions, the `fuzzylink` procedure can significantly improve both precision and recall. And it does so without requiring significant expenditure in time or money. None of the applications described in the previous section took longer than a few hours to execute on a personal computer or cost more than $10 in API fees.

There are, however, two limitations of the method that should be addressed in future work. First, I have focused in this paper on applications where there is a single fuzzy string matching variable, but the sorts of record linkage problems faced by social scientists often include many such variables. Fortunately, the method can be extended in a number of ways. One approach would be to re-express multiple fuzzy variables as a single string, which can then be represented as an embedding. For example, a record with {name} and {address} fields might be represented by the string "My name is {name} and I live at {address}." Another approach would be to estimate a match probability separately for each variable as I have done here, and then use those match probabilities as inputs in a second probabilistic record linkage procedure, like `fastLink` (Enamorado, Fifield and Imai, 2019). Further research is needed to determine which approach yields better results.

Another limitation of the method as presented is its reliance on proprietary language models. Because these models are closed-source and operated by for-profit entities, they can be deprecated or modified at any time without the consent of their users. Consequently, the results that `fuzzylink` produces—including those presented in this paper—are not fully reproducible. Though a researcher could replicate the steps I used to generate the results, within a few years it will be impossible to reproduce them exactly. For this reason, many scholars in our discipline have urged using open-source language models wherever possible (Spirling, 2023).

Unfortunately, as of writing, it is difficult to see how the method presented here could be undertaken using open-source language models. Frankly, the level of accuracy I demonstrate here would not have been possible even using the previous generation of *proprietary* language models. In the Supplementary Materials, I attempt to replicate the paper's empirical applications using one of the highest performing open-source language models currently available (Mistral 8x22B), as well as the previous generation of language models released by OpenAI as of early 2023 (GPT-3.5). These variants significantly underperform the results reported in the previous section, particularly for the organization matching and multilingual record linkage applications. Given the rapid development of open-source language models, it is likely that there will be an acceptable open-source solution in the coming years, but until that time the accuracy gains from proprietary models outweigh their drawbacks.

When a research method falls short of full computational reproducibility, one must insist that it meet standards of *replicability* (procedures are transparently documented so that other scholars can independently replicate them) and *reliability* (repeated application of the procedure yields similar, if not identical, outcomes). Indeed, these are the standards that our discipline applies to other non-reproducible research methods, like those that rely on human research assistants or crowd-coders. The `fuzzylink` software package[9] was developed to help researchers implement the method proposed here in a straightforward and replicable manner, and I hope that it will enable much useful social science research in the coming years.

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[9]Implemented in the `R` programming language, the package is available at `https://github.com/joeornstein/fuzzylink`.

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A Additional Figures and Tables

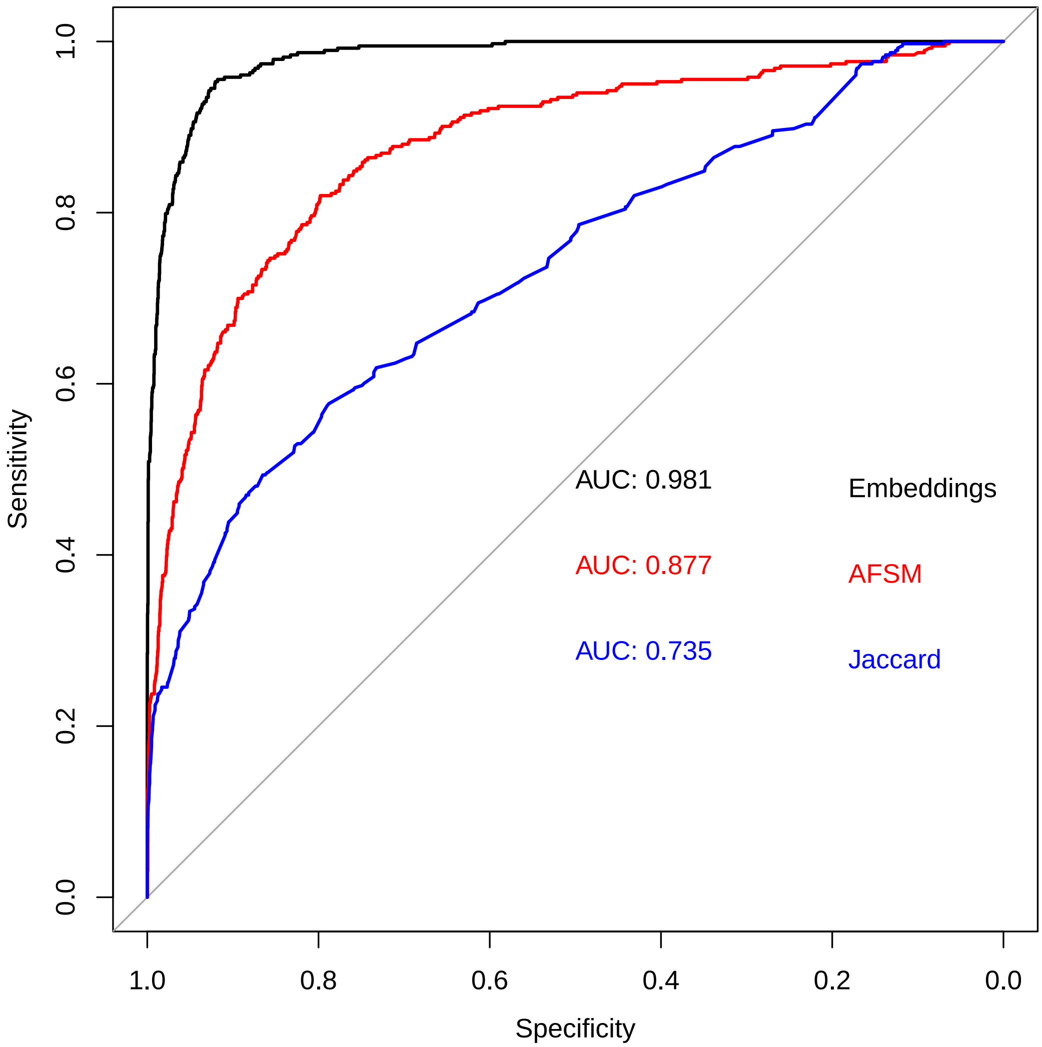


Figure A1: Receiver Operator Curves (ROC) for three fuzzy string similarity metrics on hand-labeled organization name pairs from Kaufman and Klevs (2022).

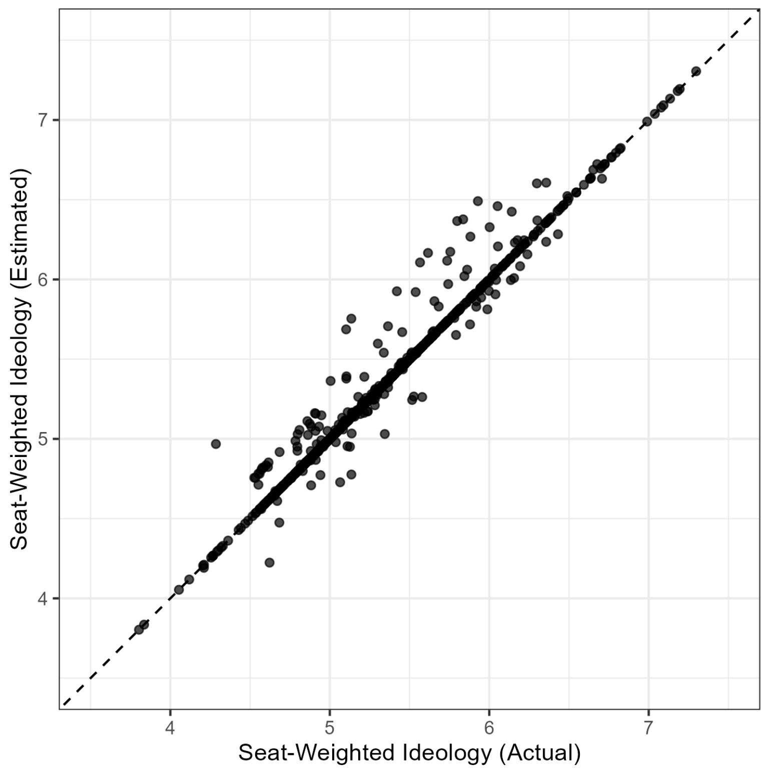


Figure A2: The actual seat-weighted ideology of each parliament in the ParlGov dataset (x-axis) plotted against estimated seat-weighted ideology following the probabilistic record linkage. Red points are those with absolute error greater than 1-point.

	Country	Precision	Recall
1	Austria	100.00	98.31
2	Belgium	95.27	96.58
3	Bulgaria	100.00	94.94
4	Croatia	100.00	97.62
5	Cyprus	96.49	100.00
6	Czech Republic	100.00	100.00
7	Denmark	95.25	94.31
8	Estonia	100.00	98.21
9	Finland	100.00	91.37
10	France	97.73	95.13
11	Germany	95.93	100.00
12	Greece	100.00	95.45
13	Hungary	100.00	100.00
14	Iceland	98.74	99.37
15	Israel	93.56	91.69
16	Italy	99.16	99.58
17	Japan	85.22	94.02
18	Latvia	100.00	98.53
19	Lithuania	96.67	100.00
20	Luxembourg	90.48	95.00
21	Malta	97.96	100.00
22	Netherlands	94.82	97.99
23	Norway	93.09	93.95
24	Poland	97.50	96.30
25	Portugal	100.00	99.10
26	Romania	92.68	97.44
27	Slovakia	100.00	100.00
28	Slovenia	100.00	96.81
29	Spain	96.02	94.94
30	Sweden	97.16	100.00
31	Switzerland	90.00	98.78
32	Turkey	100.00	100.00

Table A1: Precision and Recall for Multilingual Record Linkage Application By Country

B Replicating Results Using Alternate Language Models

B.1 Linking Candidates to Voter File Records

When linking these datasets using labels from GPT-3.5 instead of GPT-4, `fuzzylink` returns fewer matches, but with slightly better precision. Out of the 840 candidates that ran for office in the three California counties, the method identified 566 potential matches in the voter file. 154 of these were exact matches, and the research team determined that 411 of the non-exact matches were valid, for an estimated precision of 99.8%. However, this improved precision comes at the cost of recall. The research team was able to locate 139 matches in the L2 voter file that `fuzzylink` failed to identify, for an estimated recall rate of 80.3%.

When linking these datasets using labels and embeddings from the open-source Mistral 8x22B language model (released April 17, 2024), `fuzzylink` returns far fewer matches, but with improved precision. Out of the 840 candidates that ran for office in the three California counties, the method identified 518 potential matches in the voter file. 154 of these were exact matches, and the research team determined that 362 of the non-exact matches were valid, for an estimated precision of 99.6%. However, this improved precision comes at the cost of recall. The research team was able to locate 187 matches in the L2 voter file that the model failed to identify, for an estimated recall rate of 73.4%.

B.2 Linking Amicus Cosigners to Campaign Donors

When linking these two datasets using labels from GPT-3.5 instead of GPT-4, the method returns matches for a much larger number of organizations (695 instead of 444), but the precision of these matches is unacceptably low. In a random sample of 100, only 37% were deemed a valid match by the research team.

B.3 Linking Party Names Across Languages

When linking these two datasets using labels from GPT-3.5 instead of GPT-4, the method returns a tremendous number of false positive matches—6,284 in total. As a result, estimated recall is slightly higher than that reported in the paper (97.1%), but those true positives are swamped by false positives, for an estimated precision of 43.5%.

When linking these two datasets using labels and embeddings from the open-source Mistral 8x22B language model (released April 17, 2024), `fuzzylink` returns only 216 false positive matches, for an estimated precision of 95.2% (roughly as precise as the 95.8% reported in the main text). Recall, however, is somewhat lower, at 85.7%, and this reduced ability to identify matches yields significantly worse performance on the ideology estimation task—particularly in countries like Estonia, Finland, and Iceland—as illustrated in Figures A3 and A4.

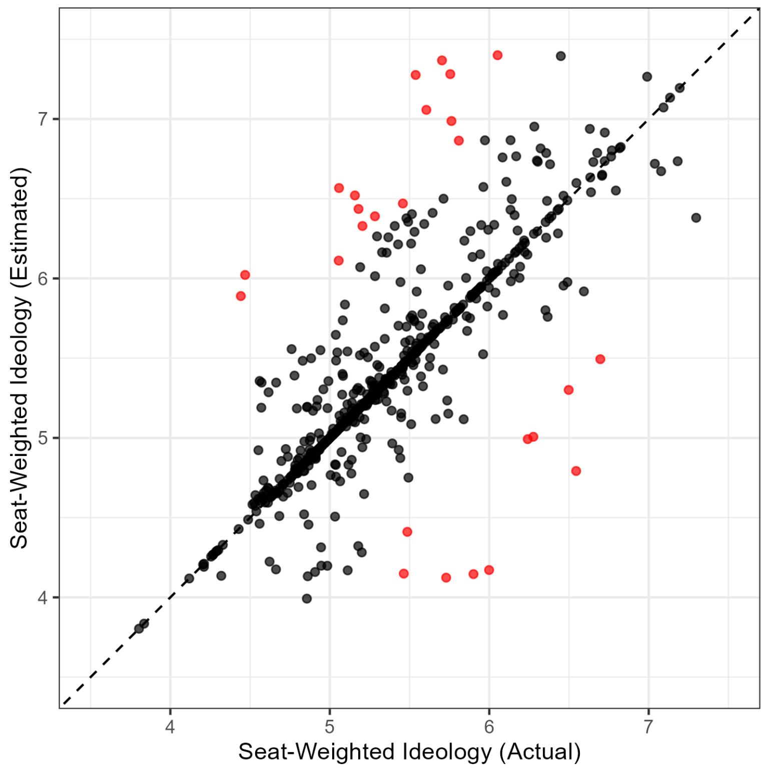


Figure A3: The actual seat-weighted ideology of each parliament in the ParlGov dataset (x-axis) plotted against estimated seat-weighted ideology estimated using labels and embeddings from open-source Mixtral 8x22B model (y-axis). Red points are those with absolute error greater than 1-point.

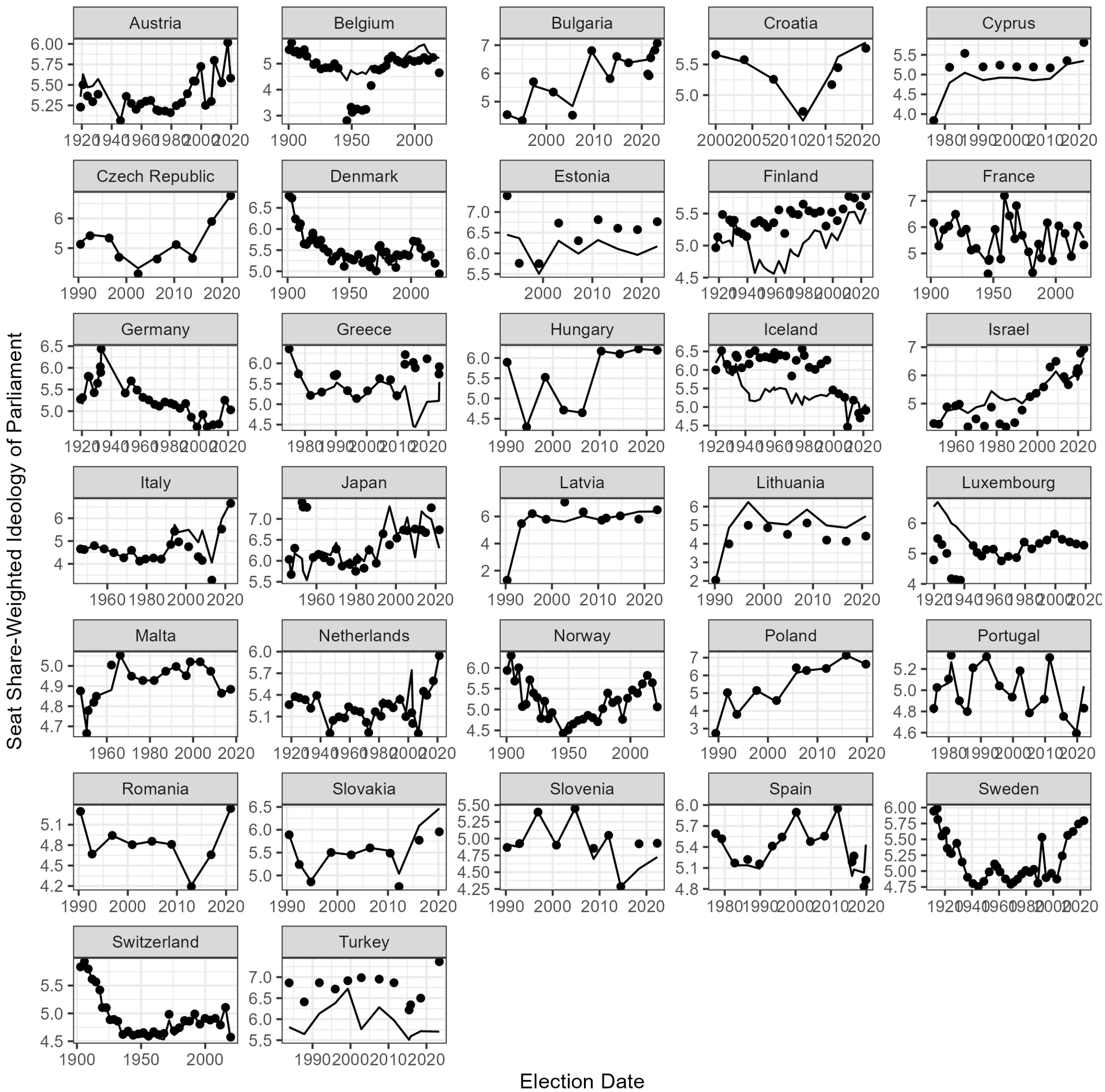


Figure A4: Estimated seat-weighted parliamentary ideology following merge (points) plotted over true values (lines), using labels and embeddings from open-source Mixtral 8x22B model.

C Match Probability Calibration

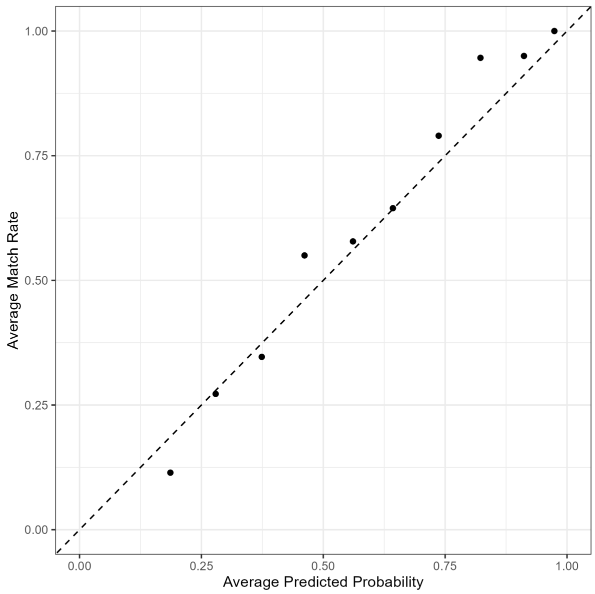
In the main text, I argue that a key advantage of a probabilistic approach to record linkage is that the estimated match probabilities can be used in downstream statistical analyses as a measure of confidence in the match quality. But in order for match probabilities to be useful in this manner, they must be well calibrated—record pairs that `fuzzylink` assigns a 90% match probability should be true matches roughly 90% of the time. To assess calibration, I extract estimated match probabilities for every within-block pair of records from the first and third applications (linking candidates with voter file records and the multilingual record linkage application). I exclude record pairs that are exact matches, and compare the estimated match probabilities with the true rate of matching.

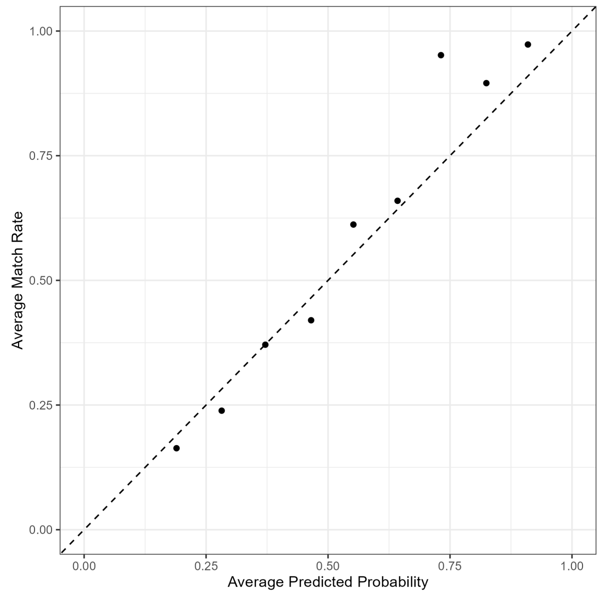
As Figures A5 and A6 illustrate, the estimated match probabilities are strongly correlated with hand-validated match rates, though they tend to be somewhat underconfident relative to perfect calibration (dashed line). In each figure, panel (a) plots the performance of the record linkage using the model specification as described in the main text—a logistic regression using a linear combination of embedding similarity and Jaro-Winkler similarity as predictors. Panel (b) uses only embedding similarity as a predictor, and panel (c) uses only Jaro-Winkler distance as a predictor.

Table C reports Brier Scores and Log Likelihoods for each model variant. In both applications, the model variant that uses both embedding similarity and lexical similarity as predictors yields match probabilities that are better-calibrated than the other two model variants. Unsurprisingly, the model variant that only uses Jaro-Winkler similarity as a predictor performs significantly worse in the multilingual record linkage application (Figure A6).

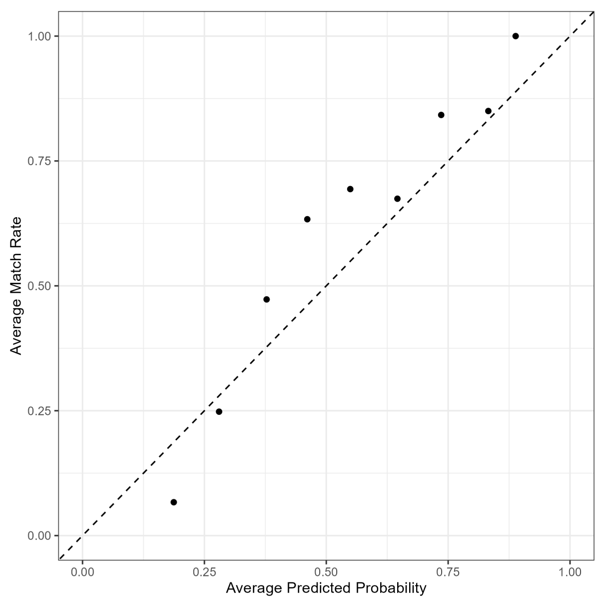
Table A2: Estimated match probability calibration in two applications, varying model specification.

Application	**Predictors**	**Brier Score**	**Log Likelihood**
Voter File	Both	0.157	-566.08
Voter File	Embedding Similarity Only	0.162	-633.68
Voter File	Lexical Similarity Only	0.164	-685.77
Multilingual Record Linkage	Both	0.051	-8150.81
Multilingual Record Linkage	Embedding Similarity Only	0.054	-8467.359
Multilingual Record Linkage	Lexical Similarity Only	0.073	-11465.13



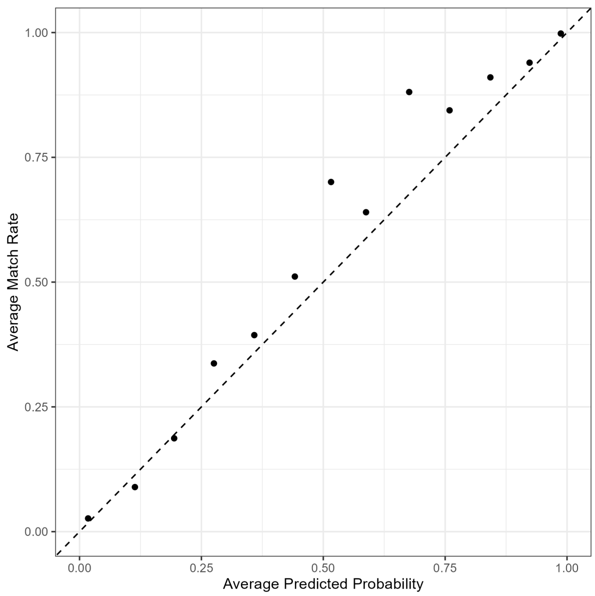


(a) (b)

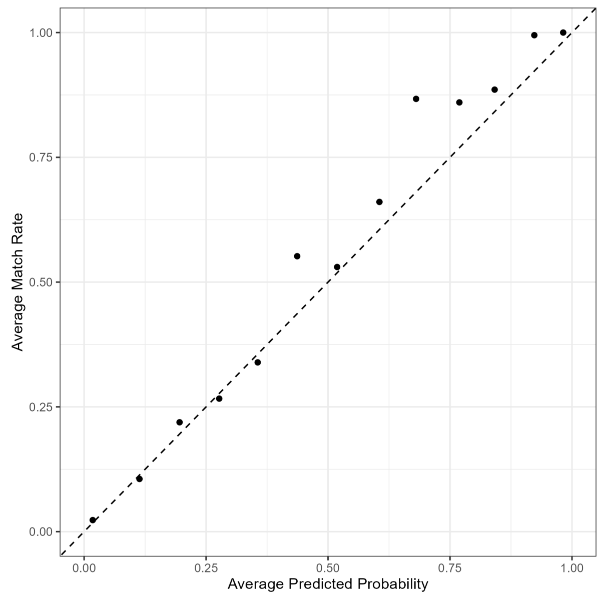


(c)

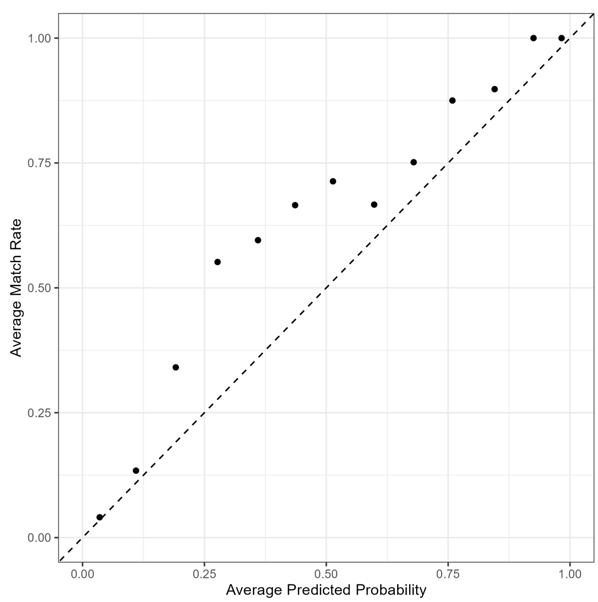
Figure A5: Binned calibration plot for voter file record linkage application, using three different sets of predictors: (a) both embedding similarity and Jaro-Winkler similarity, (b) embedding similarity only, and (c) Jaro-Winkler similarity only.



(a)



(b)



(c)

Figure A6: Binned calibration plot for multilingual record linkage application, using three different sets of predictors: (a) both embedding similarity and Jaro-Winkler similarity, (b) embedding similarity only, and (c) Jaro-Winkler similarity only.