Week 5: Comparing Strings

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# Comparing Strings

Micheal Jordan, M. Jordan, and M.J. are three names for the same person. Humans can quickly examine these variations and conclude this fact. Meanwhile, computers need specialized fuzzy string comparison algorithms to make the same deductions. These entity name comparison algorithms focus on either name variations or misspellings. Gong, Wang, and Oard (2009) propose a hybrid solution that addresses both aspects (see Figure 1).

Figure 1: High-level Process

Their process imports and tokenizes names into “names” and “name formats.” Next, they use a directed graph to represent all permutations. Then, weighted edges between the nodes quantify the similarity to the original text. This configuration enables Dijkstra’s shortest path algorithm to find the right combination for fuzzy comparisons. Finally, the comparison determines if the match candidates are equivalent (Boolean value).

## Success Criterion

The process’s core use-case determines if two names are similar, regardless of spelling or variations (e.g., initials). Therefore, Gong, Wang, and Oard (2009) must maximize the solution’s recall and precision by minimizing false positives or negatives. Additionally, the system must be efficient and performant. Each imported name produces dozens of potential permutations, expanding the total data volume.

## Measuring Correctness

The authors assess multiple machine learning algorithms for determining the appropriate edge weights. Similar to previous publications, they use an F-measurement to assess the accuracy of each algorithm. Data scientists use F-Score as a “way of combining the precision and recall of the model, and [defines] the harmonic mean of the model’s precision and recall (Wood, n.d.).” Researchers can trade-off in their solution to optimize this value for their specific scenario. For instance, a regulated industry might enforce higher penalties on false positives over negatives.

## Measuring Efficiency

The name comparison process must store and retrieve numerous tokens during its assessment. According to the authors, their DBLP data set contains 227 million possible pairs, but only 0.7% are helpful (pg. 1878). This situation requires efficient data structures that can scale across large data sets. However, the researchers do not measure their efficiency and predominately rely on a NoSQL Data Management System (called Flamingo). They claim that initializing and comparing the most extensive test set completes within five minutes.

## Test Cases

The researchers collected the author’s names and citations from three academic publication sources (see Table 1). Next, they hand-labeled ground truths for the learning algorithms (Soft-TFIDF, Jaro-Winkler, recursive JW, Monge-Elkan, and recursive M.E.). Finally, the fuzzy comparison process ran across all combinations of data sets and methods.

Table 1: Data sources

|  |  |  |  |
| --- | --- | --- | --- |
|  | CiteSeer | arXiv | DBLP |
| References | 2892 | 58515 | 58399 |
| Authors | 1165 | 9200 | 21688 |

These test cases provide coverage over a vast corpus of English names. This situation could miss standard name formats for African or European nations. However, that limitation is outside the project’s scope.

# Create a different string algorithm

## Problem Statement

Young children are difficult to understand because they lack conversational experience. Their speech places the wrong tonal inflections or omits critical syllables. Similar challenges exist with disabled adults and people learning new languages. String comparison algorithms and machine learning can examine phrases and suggest possible translations.

## Value-Prop

These capabilities would enable parents, guardians, and other caretakers to better understand their wards. As a result, those custodians could provide more accurate support with uninhibited communication, directly improving the ward’s quality of life. It also opens the door for more focused vocal coaching. For instance, when a toddler asks about “ah-paans,” it becomes a perfect opportunity to enunciate “airplane.”

## Success Criteria

Novice speakers use a finite vocabulary that is dependent on age and experience. Child developmental experts maintain this information in a standardized format. The research team can use those lists as benchmarks for assessing the translation system coverage.

## Success Measurement

After the solution supports 80% of a specific benchmark, then it is considered passing. Each word within the benchmark requires sufficiently high precision and recall scores. It is unlikely that all benchmarks will be equally passing. Consider the clarity difference between a three and four-year-old. On the other hand, younger age groups have fewer words to match and could accurate by random chance. The system needs to filter low confidence predictions to mitigate this risk.

## Validating Correctness and Efficiency

Users can interact with the translation service through their mobile phones. First, the app will upload audio recordings to receive the top translations. Next, the user clicks the most accurate translation or selects “these are wrong.” The survey responses influence the benchmark tracking and coverage requirements.

This research project has a finite budget, and it must economically process each request. Users expect the app to be responsive and promptly return the list (e.g., less than 30 seconds).

## Test Coverage

The initial pilot program will focus on a single new parent support group. These are available in most urban communities and contain several children under five. Once the basic functionality is verified, a broader study could include additional crowdsourcing. An ideal cohort would cover fifty children between one to five years old. This amount does not cover all household diversity scenarios but is sufficient for the prototype phase.

# References

Gong, J., Wang, L., & Oard, D. (2009). Matching person names through name transformation. *Information and Knowledge Management* (pp. 1875–1878). New York, NY. USA: ACM. doi:10.1145/1645953.1646253

Wood, T. (n.d.). *What is the F-score*? Retrieved from Deep A.I.: https://deepai.org/machine-learning-glossary-and-terms/f-score