A context sensitive real-time Spell Checker with language adaptability

Prabhakar Gupta Amazon prabhgup@amazon.com

Abstract—We present a novel language adaptable spell checking system which detects spelling errors and suggests context sensitive corrections in real-time. We show that our system can be extended to new languages with minimal language-specific processing. Available literature majorly discusses spell checkers for English but there are no publicly available systems which can be extended to work for other languages out of the box. Most of the systems do not work in real-time. We explain the process of generating a language's word dictionary and n-gram probability dictionaries using Wikipedia-articles data and manually curated video subtitles. We present the results of generating a list of suggestions for a misspelled word. We also propose three approaches to create noisy channel datasets of real-world typographic errors. We compare our system with industry-accepted spell checker tools for 11 languages. Finally, we show the performance of our system on synthetic datasets for 24 languages.

Index Terms—spell checker, auto-correct, n-grams, tokenizer, context-aware, real-time

I. INTRODUCTION

Spell checker and correction is a well-known and wellresearched problem in Natural Language Processing [1]-[4]. However, most state-of-the-art research has been done on spell checkers for English [5], [6]. Some systems might be extended to other languages as well, but there has not been as extensive research in spell checkers for other languages. People have tried to make spell checkers for individual languages: Bengali [7], Czech [8], Danish [9], Dutch [10], Finnish [11], French [12], [13], German [14], [15], Greek [16], Hindi [17], [18], Indonesian [19], Marathi [20], Polish [21], Portuguese [22], Russian [23], [24], Spanish [25], Swedish [26], Tamil [27], Thai [28], etc. This is due to the fact languages are very different in nature and pose different challenges making it difficult to have one solution that work for all languages [29]. Many systems do not work in real-time cases. There are some rule-based spell checkers (like LanguageTool¹) which try to capture grammar and spelling rules [30], [31]. This is not scalable and requires language expertise to add new rules. Another problem is evaluating the performance of the spell check system for each language due to lack of quality test data. Spelling errors are classified in two categories [32]: nonword errors where the word is unknown and real-word errors where the word itself is correct but used in a wrong form / context.

1www.languagetool.org

We present a context sensitive real-time spell-checker system which can be adapted to any language. One of the biggest problem earlier was absence of data for languages other than English, so we propose three approaches to create noisy channel datasets of real-world typographic errors. We use Wikipedia data for creating dictionaries and synthesizing test data. To compensate for resource-scarcity of most languages we also use manually curated movie subtitles since it provides information about how people communicate as shown in [33].

Our system outperforms industry-wide accepted English spell checkers (Hunspell and Aspell) and show our performance on benchmark datasets for English. We present our performance on synthetic dataset for 24 languages *viz.*, Bengali, Czech, Danish, Dutch, English, Finnish, French, German, Greek, Hebrew, Hindi, Indonesian, Italian, Marathi, Polish, Portuguese, Romanian, Russian, Spanish, Swedish, Tamil, Telugu, Thai and Turkish. We also compare 11 of these languages to one of the most popular rule-based systems. We did not customize our spell checker to suit local variants or dialects of a language. For example — the spelling "color" is used in American English whereas spelling "colour" is preferred in other versions of English. Our system will not flag any of these spellings.

The paper makes following contributions:

- We propose three different approaches to create typographic errors for any language which has never been done in multilingual setting (all earlier approaches have either been very simple [17] or language-specific [20]).
- We show system's time performance for each step in process, proving it's real-time effectiveness.
- Our system outperforms existing rule-based and industrywide accepted spell checking tools.
- We show that our system can be adapted to other languages with minimal effort showing precision@k for $k \in {1,3,5,10}$ and mean reciprocal rank (MRR) for 24 languages.

The paper is divided into four sections. Section II explains the preprocessing steps and approach to generate a ranked list of suggestions for any detected error. Section III presents different synthetic data-generation algorithms. Section IV describes the experiments and reports their results. Finally, Section V concludes the paper and discusses future endeavours.

II. APPROACH

Our system takes a sentence as input, tokenizes the sentence, identifies misspelled words (if any), generates a list of suggestions and ranks them to return the top k corrections. For ranking the suggestions, we use n-gram conditional probabilities. As a preprocessing step, we create frequency dictionaries which will aid in generation of n-gram conditional probabilities.

A. Preprocessing: Building n-gram dictionaries

We calculated unigram, bigram and trigram frequencies of tokens from corpus. Using these frequencies, we calculated conditional probabilities expressed in the equation 1 where P is conditional probability and c is the count of the n-gram in corpus. For unigrams, we calculate its probability of occurrence in the corpus.

$$P(w_i|w_{i-n+1}...w_{i-1}) = \frac{c(w_{i-n+1}...w_i)}{c(w_{i-n+1}...w_{i-1})}$$
(1)

We used Wikipedia dumps² along with manually curated movie subtitles for all languages. We capped Wikipedia articles to 1 million and subtitle files to 10K. On an average, each subtitle file contains 688 subtitle blocks and each block contains 6.4 words [33]. We considered words of minimum length 2 with frequency more than 5 times in the corpus. Similarly, only bigrams and trigrams where each token was known were considered.

One issue we encountered while building these dictionaries using such a huge corpus was its size. For English, the number of unique unigrams was approx. 2.2M, bigrams was 50M and trigrams was 166M. If we store these files as uncompressed Python Counters, these files end up being 44MB, 1.8GB and 6.4GB respectively. To reduce the size, we compressed these files using a word-level Trie with hashing. We created a hash map for all the words in the dictionary (unigram token frequency) assigning a unique integer id to each word. Using each word's id, we created a trie-like structure where each node represented one id and its children represented n-grams starting with that node's value. The Trie ensured that the operation to lookup an n-gram was bounded in O(1)and reduced the size of files by 66\% on an average. For English, the hashmap was 14MB, unigram probabilities' file was 8.7MB, bigram was 615MB and trigram was 2.5GB.

B. Tokenization

There are a number of solutions available for creating tokenizer for multiple languages. Some solutions (like [34]–[36]), try to use publicly available data to train tokenizers, whereas some solutions (like Europarl preprocessing tools [37]) are rule-based. Both approaches are not extensible and typically are not real-time.

For a language, we create list of supported characters using writing systems information³ and Language recognition

charts⁴. We included uppercase and lowercase characters (if applicable) and numbers in that writing system, ignoring all punctuation. Any character which doesn't belong to this list is implied as foreign character to that language and will be tokenized as a separate token. Using regex rule, we extract all continuous sequences of characters in supported list.

C. Error Detection

We kept our error-search strictly to non-words errors; for every token in sentence, we checked for its occurrence in dictionary. However, to make system more efficient, we only considered misspelled tokens of length greater than 2. On manual analysis of Wikipedia misspellings dataset for English, we discovered misspelling of length 1 and 2 do not make sense and hence computing suggestions and ranking them is not logical.

D. Generating candidate suggestions

Given an unknown token, we generated a list of all known words within edit distance of 2, calling them candidate suggestions. We present the edit distance distribution of publicly available datasets for English in Section IV-C. Two intuitive approaches to generate the list of suggestions that work fairly well on a small-size dataset are checking edit-distance of incorrect spelling with all words in dictionary and second, generating a list of all words in edit-distance 2 of incorrect spelling⁵. The obvious problem with the first approach is with the size of corpus which is typically in range of hundreds of thousands and with the second approach is size of word because for longer words there can be thousands of suggestions and building a list of such words is also time consuming.

We considered four approaches — Trie data structure, Burkhard-Keller Tree (BK Tree) [38], Directed Acyclic Word Graphs (DAWGs) [39] and Symmetric Delete algorithm (SDA)⁶. In Table I, we represent the performance of algorithms for edit distance 2 without adding results for BK trees because its performance was in range of couple of seconds. We used Wikipedia misspelling dataset⁷ to create a list of 2062 unique misspellings of lengths varying from 3 to 16 which were not present in our English dictionary. For each algorithm, we extracted the list of suggestions in edit distance of 1 and 2 for each token in dataset.

E. Ranking suggestions

Using SDA, we generate a list of candidates which are to be ranked in order of relevance in the given context. Authors of [40], demonstrate the effectiveness of n-grams for English to auto-correct real-word errors and unknown word errors. However, they use high-order n-grams in isolation. We propose a weighted sum of unigrams, bigrams and trigrams to rank the suggestions. Authors in [41], use character embeddings to generate embeddings for each misspelling for clinical free-text

 $^{^2} Wiki media\ Downloads:\ https://dumps.wiki media.org$

³https://en.wikipedia.org/wiki/List_of_languages_by_writing_system

⁴https://en.wikipedia.org/wiki/Wikipedia:Language_recognition_chart

⁵https://norvig.com/spell-correct.html

⁶https://github.com/wolfgarbe/SymSpell

⁷https://en.wikipedia.org/wiki/Wikipedia:Lists_of_common_misspellings

TABLE I AVERAGE TIME TAKEN BY SUGGESTION GENERATION ALGORITHMS (EDIT DISTANCE = 2) (IN MILLISECOND)

Token	Trie	DAWGs	SDA
3	170.50	180.98	112.31
4	175.04	178.78	52.97
5	220.44	225.10	25.44
6	254.57	259.54	7.44
7	287.19	291.99	4.59
8	315.78	321.58	2.58
9	351.19	356.76	1.91
10	379.99	386.04	1.26
11	412.02	419.55	1.18
12	436.54	443.85	1.06
13	473.45	480.26	1.16
14	508.08	515.04	0.97
15	548.04	553.49	0.66
16	580.44	584.99	0.37

and then similar to [42], rank on basis of contextual similarity score.

We create a context score (S) for each suggestion and rank on decreasing order of that score, returning top k suggestions. Context score is weighted sum of unigram context score (S_1) , bigram context score (S_2) and trigram context score (S_3) defined by equation 2. This score is calculated for each suggestion by replacing token x_i with the suggestion. For n-grams where any token is unknown, the count is considered to be 0.

$$S_n = W_n \sum_{i=0}^{n-1} \frac{c(x_{i+j-n+1}^{i+j})}{c(x_{i+j-n+1}^{i+j-1})} = W_n \sum_{j=0}^{n-1} P(x_i | x_{i+j-n+1}^{i+j-1})$$
 (2)

where:

i = index of misspelled token $W_n = \text{the weight for } n^{th}\text{-gram's score}$

 $c(x_i^j)$ = occurrence frequency of sequence $(w_i \dots w_j)$

P =conditional probability.

III. SYNTHESIZING SPELLING ERRORS

The biggest challenge in evaluation of spell checker was quality test dataset. Most of the publicly available datasets are for English [43]. We propose three strategies to introduce typographical errors in correct words to represent noisy channel. We select all the sentences, where we did not find any spelling error and introduced exactly one error per sentence.

A. Randomized Characters

From a sentence, we pick one word at random and make one of the three edits: insertion, deletion or substitution with a random character from that language's supported character list. Since it is a completely randomized strategy, the incorrect words created are not very "realistic". For example — in English for edit distance 2, word "moving" was changed to "moviAX", "your" to "mouk", "chest" to "chxwt". We repeated the process for edit distance 1 (introducing only one error) and edit distance 2 (introducing two errors) and create dataset for 20,000 sentences each.

B. Characters Swap

On analyzing common misspellings for English [43], we discovered majority of edit-distance 2 errors are swap of two adjacent characters. For example — "grow" is misspelled as "gorw", "grief" as "greif". One swap imply edit distance of two, we created a dataset of 20,000 samples for such cases.

C. Character Bigrams

Introducing errors randomly produces *unrealistic* words. To create more realistic errors, we decided to use character bigram information. From all the words in dictionary for a language, we calculate occurrence probabilities for character bigrams. For a given word, we select a character bigram randomly and replace the second character in selected bigram with a possible substitute from pre-computed character bigram probabilities. This way, we were able to generate words which were more plausible. For example — in English for edit distance 1, word "heels" was changed to "heely", "triangle" to "triajgle", "knee" to "kyee". On shallow manual analysis of generated words, most of the words look quite realistic. For English, some of the words generated are representative of keyboardstrokes error (errors that occur due to mistakenly pressing a near-by key on keyboard/input device). For example, we generated some samples like — "Allow" to "Alkow", "right" to "riggt", "flow" to "foow" and "Stand" to "Stabd". We generated a sample of 40,000 sentences each for edit distance 1 and edit distance 2.

IV. EXPERIMENTS AND RESULTS

A. Synthetic Data evaluation

For each language, we created a dataset of 140,000 sentences⁸ with one misspelling each. The best performances for each language is reported in Table II. We present Precision@k⁹ for $k \in 1,3,5,10$ and mean reciprocal rank (MRR). The system performs well on synthetic dataset with a minimum of $80\% \ P@1$ and $98\% \ P@10$.

The system is able to do each sub-step in real-time; the average time taken to perform for each sub-step is reported in Table III. All the sentences used for this analysis had exactly one error according to our system. Detection time is the average time weighted over number of tokens in query sentence, suggestion time is weighted over misspelling character length and ranking time is weighted over length of suggestions generated.

Table IV presents the system's performance on each error generation algorithm. We included only P@1 and P@10 to show trend on all languages. "Random Character" and "Character Bigrams" includes data for edit distance 1 and 2 whereas "Characters Swap" includes data for edit distance 2. Table V presents the system's performance individually on edit distance 1 and 2. We included only P@1, P@3 and P@10 to show trend on all languages.

⁸With an exception of Czech, Greek, Hebrew and Thai where size of dataset was smaller due to unavailability of good samples

 $^{^{9}}$ Percentage of cases where expected output was in top k results

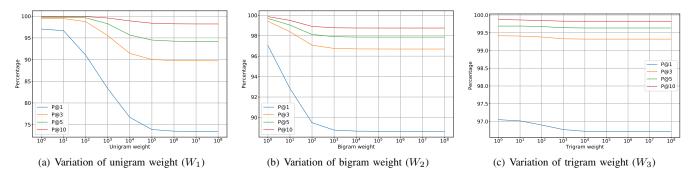


Fig. 1. Importance of n-grams weights towards system accuracy

TABLE II Synthetic Data Performance results

TABLE III
SYNTHETIC DATA TIME PERFORMANCE RESULTS

Language	# Test Samples	P@1	P@3	P@5	P@10	MRR	Language	Detection Time (μs)	Suggesti ED=1 (ms)	on Time ED=2 (ms)	Ranking Time (ms)
Bengali	140000	91.30	97.83	98.94	99.65	94.68	Bengali	7.20	0.48	14.85	1.14
Czech	94205	95.84	98.72	99.26	99.62	97.37	Czech	7.81	0.75	26.67	2.34
Danish	140000	85.84	95.19	97.28	98.83	90.85	Danish	7.28	0.67	23.70	1.96
Dutch	140000	86.83	95.01	97.04	98.68	91.32	Dutch	10.80	0.81	30.44	2.40
English	140000	97.08	99.39	99.67	99.86	98.27	English	7.27	0.79	39.36	2.35
Finnish	140000	97.77	99.58	99.79	99.90	98.69	Finnish	8.53	0.46	15.55	1.05
French	140000	86.52	95.66	97.52	98.83	91.38	French	7.19	0.82	32.02	2.69
German	140000	87.58	96.16	97.86	99.05	92.10	German	8.65	0.85	41.18	2.63
Greek	30022	84.95	94.99	96.88	98.44	90.27	Greek	7.63	0.86	25.40	1.87
Hebrew	132596	94.00	98.26	99.05	99.62	96.24	Hebrew	22.35	1.01	49.91	2.18
Hindi	140000	82.19	93.71	96.28	98.30	88.40	Hindi	8.50	0.60	18.51	1.72
Indonesian	140000	95.01	98.98	99.50	99.84	97.04	Indonesian	12.00	0.49	20.75	1.22
Italian	140000	89.93	97.31	98.54	99.38	93.76	Italian	6.92	0.72	29.02	2.17
Marathi	140000	93.01	98.16	99.06	99.66	95.69	Marathi	7.16	0.43	10.68	0.97
Polish	140000	95.65	99.17	99.62	99.86	97.44	Polish	6.44	0.64	24.15	1.74
Portuguese	140000	86.73	96.29	97.94	99.10	91.74	Portuguese	7.14	0.66	28.92	2.20
Romanian	140000	95.52	98.79	99.32	99.68	97.22	Romanian	10.26	0.63	18.83	1.79
Russian	140000	94.85	98.74	99.33	99.71	96.86	Russian	6.79	0.68	22.56	1.72
Spanish	140000	85.91	95.35	97.18	98.57	90.92	Spanish	7.19	0.75	31.00	2.41
Swedish	140000	88.86	96.40	98.00	99.14	92.87	Swedish	7.76	0.83	32.17	2.57
Tamil	140000	98.05	99.70	99.88	99.98	98.88	Tamil	11.34	0.23	4.83	0.31
Telugu	140000	97.11	99.68	99.92	99.99	98.38	Telugu	6.31	0.29	7.50	0.54
Thai	12403	98.73	99.71	99.78	99.85	99.22	Thai	11.60	0.66	18.75	1.33
Turkish	140000	97.13	99.51	99.78	99.92	98.33	Turkish	7.40	0.49	17.42	1.23

We experimented with the importance of each n-gram. Figure 1 presents the results for this experiment. We kept two weights constant varying one weight to compare the performance. For example to determine unigram weight (W_1) importance, we set bigram weight (W_2) and trigram (W_3) to 1, varying W_1 $(10^i, i \in [0,8])$. As shown in Figure 1(a) and Figure 1(b), if unigram or trigram are given more importance, the performance of system worsens. Figure 1(c) shows removing lower order n-grams and giving more importance to only trigram also decreases performance. Therefore, finding the right balance between each weight is crucial for system's best performance.

B. Comparison with LanguageTool

We compared the performance of system with one of the most popular rule-based systems, LanguageTool (LT). Due to some license issues, we could only run LT for 11 lan-

guages *viz.*, Danish, Dutch, French, German, Greek, Polish, Portuguese, Romanian, Russian, Spanish and Swedish.

As shown in Figure 2, LT doesn't detect any error in many cases. For example — for German, it did not detect any error in 42% sentences and for 25% (8% (No Match) + 17% (Detected more than one error)), it detected more than one error in a sentence out of which in 8% sentences, the error detected by our system was not detected by LT. Only for 33% sentences LT detected exactly one error which was same as detected by our system. Results for Portuguese seem very skewed which can be due to the fact Portuguese has two major versions, Brazilian Portuguese (pt-BR) and European Portuguese (pt-PT); LT has different set of rules for both versions whereas dataset used was a mix of both.

C. Public Datasets results

We used four publicly available datasets for English — **birkbeck**: contains errors from Birkbeck spelling error cor-

TABLE IV $\begin{tabular}{ll} \textbf{Synthetic Data Performance on three error generation} \\ \textbf{Algorithm} \end{tabular}$

Language	Random	Character	Charact	ers Swap	Characte	Character Bigrams		
Language	P@1	P@10	P@1	P@10	P@1	P@10		
Bengali	91.243	99.493	82.580	99.170	93.694	99.865		
Czech	94.035	99.264	91.560	99.154	97.795	99.909		
Danish	84.605	98.435	71.805	97.160	90.103	99.444		
Dutch	85.332	98.448	72.800	96.675	91.159	99.305		
English	97.260	99.897	93.220	99.700	98.050	99.884		
Finnish	97.735	99.855	94.510	99.685	98.681	99.972		
French	84.332	98.483	72.570	97.215	91.165	99.412		
German	86.870	98.882	73.920	97.550	91.448	99.509		
Greek	82.549	97.800	71.925	96.910	90.291	99.386		
Hebrew	94.180	99.672	88.491	99.201	95.414	99.706		
Hindi	81.610	97.638	67.730	96.200	86.274	99.169		
Indonesian	94.735	99.838	89.035	99.560	96.745	99.910		
Italian	88.865	99.142	78.765	98.270	93.400	99.775		
Marathi	92.392	99.493	85.145	99.025	95.449	99.905		
Polish	94.918	99.743	90.280	99.705	97.454	99.954		
Portuguese	86.422	98.903	71.735	97.685	90.787	99.562		
Romanian	94.925	99.575	90.805	99.245	97.119	99.845		
Russian	93.285	99.502	89.000	99.240	97.196	99.942		
Spanish	84.535	98.210	71.345	96.645	90.395	99.246		
Swedish	87.195	98.865	76.940	97.645	92.828	99.656		
Tamil	98.118	99.990	96.920	99.990	99.284	99.999		
Telugu	97.323	99.990	93.935	99.985	97.897	99.998		
Thai	97.989	99.755	97.238	99.448	98.859	99.986		
Turkish	97.045	99.880	93.195	99.815	98.257	99.972		

TABLE V
SYNTHETIC DATA PERFORMANCE ON DIFFERENT EDIT DISTANCE OF ERRORS

Language	Edit	t Distance	= 1	Edit Distance $= 2$		
Language	P@1	P@3	P@10	P@1	P@3	P@10
Bengali	97.475	99.883	99.998	86.581	96.282	99.395
Czech	98.882	99.914	99.996	93.016	97.611	99.271
Danish	95.947	99.692	99.970	78.272	91.797	97.960
Dutch	96.242	99.653	99.958	79.790	91.528	97.722
English	99.340	99.985	99.998	95.400	98.954	99.750
Finnish	99.398	99.968	99.998	96.549	99.280	99.820
French	95.645	99.658	99.985	79.706	92.664	97.959
German	96.557	99.807	99.983	80.866	93.431	98.345
Greek	94.964	99.538	99.964	76.102	90.980	97.096
Hebrew	97.643	99.715	99.990	90.217	96.883	99.313
Hindi	93.127	99.590	99.997	73.731	89.276	97.025
Indonesian	98.687	99.955	99.995	92.091	98.231	99.716
Italian	95.818	99.670	99.978	84.585	95.370	98.912
Marathi	96.262	99.700	99.993	89.524	96.834	99.401
Polish	96.925	99.728	99.997	93.246	98.585	99.749
Portuguese	95.903	99.872	99.995	79.889	93.597	98.436
Romanian	98.690	99.897	99.988	93.156	97.942	99.439
Russian	97.568	99.830	99.992	92.257	97.851	99.499
Spanish	95.190	99.627	99.977	78.950	92.140	97.520
Swedish	96.932	99.778	99.968	82.836	93.865	98.511
Tamil	97.120	99.873	99.998	98.204	99.808	99.996
Telugu	95.985	99.853	99.998	95.662	99.445	99.989
Thai	96.994	99.470	99.983	97.786	99.450	99.725
Turkish	98.635	99.927	99.998	95.521	99.164	99.865

pus¹⁰, **hollbrook**: contains spelling errors extracted from passages in book, *English for the Rejected*, **aspell**: errors collected to test GNU Aspell¹¹ [44], **wikipedia**: most common spelling errors on Wikipedia. Each dataset had a list of misspelling and the corresponding correction. We ignored all the entries which had more than one tokens. We extracted 5,987 unique correct words and 31,589 misspellings. Figure 3(a) shows

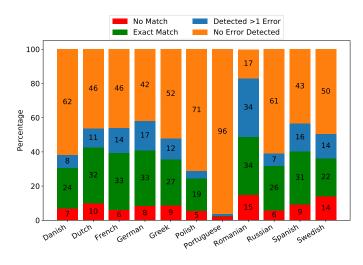


Fig. 2. Performance Comparison with LT for 11 languages

the distribution of edit distance between misspelling and its correction. Figure 3(b) shows the same distribution excluding **birkbeck** dataset leaving 2,081 unique words and 2,725 misspellings. **birkbeck** dataset is the biggest out of four but the quality of this dataset is questionable. As explained by the dataset owners, the dataset is created using poor resources. From Figure 3(b), our assumption of most of the common misspelling being in maximum edit-distance of 2 is correct.

TABLE VI PUBLIC DATASET COMPARISON RESULTS

	P@1	P@3	P@5	P@10
Aspell	60.82	80.81	87.26	91.35
Hunspell	61.34	77.86	83.47	87.04
Ours	68 99	83 43	87.03	90.16

We use every correct and incorrect token in this dataset to check if they are present and absent in our dictionary respectively in order to prove if our detection system is able to detect correctness/incorrectness of tokens efficiently. The detection system was able to detect 99.13% of correct tokens and 88.37% of incorrect tokens accurately. The percentage of incorrect token detection is comparatively low is because there are many tokens in dataset which were actually correct but were added in misspelling dataset — "flower", "representative", "mysteries", etc. Some correct words in dataset which were detected incorrect were also noise due to the fact some words start with a capital letter but in dataset they were in lowercase — "beverley", "philippines", "wednesday" etc. Comparison of most popular spell checkers for English (GNU Aspell and Hunspell¹²) on this data is presented in Table VI. Since these tools only work on word-error level, we used only unigram probabilities for ranking. Our system outperforms both the systems.

¹⁰http://ota.ox.ac.uk/

¹¹ http://aspell.net/

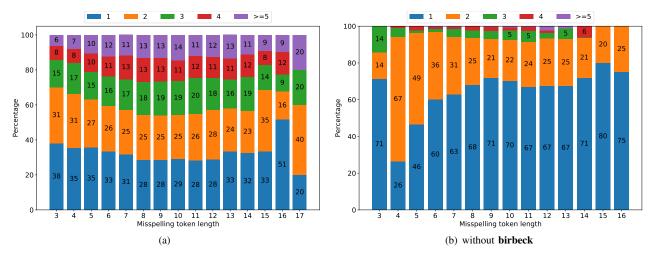


Fig. 3. Edit distance distribution for Public English Datasets

D. False Positive evaluation

For a spell checker system, false positives is when spelling error is detected but there was none. We experimented with a mix of three public datasets — **OpenSubtitles dataset** [45], **OPUS Books dataset** [46] and **OPUS Tatoeba dataset** [46] to generate a dataset with minimum 15,000 words for each of 24 languages. Since these datasets are human curated, we can safely assume every token should be detected as a *known* word.

As shown in Table VII, most of the words for each language were detected as known but still there was a minor percentage of words which were detected as errors. For English, the most frequent errors in complete corpus were either proper nouns or foreign language words — "Pencroft", "Oblonsky", "Spilett", "Meaulnes" and "taient". This proves the effectiveness of system against false positives.

V. CONCLUSION

We presented a novel context sensitive spell checker system which works in real-time. Most of the available literature majorly discuss spell checkers for English and sometimes for some European (like German, French) and Indian languages (like Hindi, Marathi), but there are no publicly available systems (non-rule based) which can work for all languages.

Our proposed system outperformed industry-wide accepted spell checkers (GNU Aspell and Hunspell) and rule-based spell checkers (LanguageTool). First, we proposed three different approaches to create typographic errors for any language which has not been done earlier in multilingual setting. Second, we divide our proposed system in 5 steps — Preprocessing; tokenization; error detection; candidate suggestion generation; and suggestion ranking. We used n-gram conditional probability dictionaries to understand context to rank suggestions and present top suggestions.

We showed the adaptability of our system to 24 languages using precision@k for $k \in 1, 3, 5, 10$ and mean reciprocal rank (MRR). The system performs at a minimum of 80% P@1 and

TABLE VII
FALSE POSITIVE EXPERIMENT RESULTS

Language	# Sentences	# Total Words	# Detected	%
Bengali	663748	457140	443650	97.05
Czech	6128	36846	36072	97.90
Danish	16198	102883	101798	98.95
Dutch	55125	1048256	1004274	95.80
English	239555	4981604	4907733	98.52
Finnish	3757	43457	39989	92.02
French	164916	3244367	3187587	98.25
German	71025	1283239	1250232	97.43
Greek	1586	43035	42086	97.79
Hebrew	95813	505335	494481	97.85
Hindi	5089	37617	37183	98.85
Indonesian	100248	84347	82809	98.18
Italian	36026	718774	703514	97.88
Marathi	17007	84286	79866	94.76
Polish	3283	34226	32780	95.78
Portuguese	1453	25568	25455	99.56
Romanian	4786	34862	34091	97.79
Russian	27252	384262	372979	97.06
Spanish	108017	2057481	2028951	98.61
Swedish	3209	66191	64649	97.67
Tamil	40165	21044	19526	92.79
Telugu	30466	17710	17108	96.60
Thai	16032	67507	49744	73.69
Turkish	163910	794098	775776	97.69

 $98\% \ P@10$ on synthetic dataset. We showed the robustness of our system to false-positives. In future, we can further increase the support to real-word errors and compound word errors.

REFERENCES

- C. Whitelaw, B. Hutchinson, G. Chung, and G. Ellis, "Using the web for language independent spellchecking and autocorrection," in *EMNLP*, 2009
- [2] Q. Chen, M. Li, and M. Zhou, "Improving query spelling correction using web search results," in Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL), 2007.
- [3] J. Gao, X. Li, D. Micol, C. Quirk, and X. Sun, "A large scale ranker-based system for search query spelling correction," in *Proceedings of the 23rd International Conference on Computational Linguistics*. Association for Computational Linguistics, 2010, pp. 358–366.

- [4] P. Gupta, M. Sharma, K. Pitale, and K. Kumar, "Problems with automating translation of movie/tv show subtitles," ArXiv, vol. abs/1909.05362, 2019
- [5] M. Choudhury, M. Thomas, A. Mukherjee, A. Basu, and N. Ganguly, "How difficult is it to develop a perfect spell-checker? a cross-linguistic analysis through complex network approach," 2007.
- [6] M. D. Dunlop and J. Levine, "Multidimensional pareto optimization of touchscreen keyboards for speed, familiarity and improved spell checking," in CHI, 2012.
- [7] M. Islam, M. Uddin, M. Khan et al., "A light weight stemmer for bengali and its use in spelling checker," 2007.
- [8] M. Richter, P. Straňák, and A. Rosen, "Korektor-a system for contextual spell-checking and diacritics completion," *Proceedings of COLING* 2012: Posters, pp. 1019–1028, 2012.
- [9] E. Bick, "A constraint grammar based spellchecker for danish with a special focus on dyslexics," A Man of Measure: Festschrift in Honour of Fred Karlsson on his 60th Birthday. Special Supplement to SKY Jounal of Linguistics, vol. 19, pp. 387–396, 2006.
- [10] A. M. Bosman, S. de Graaff, and M. A. Gijsel, "Double dutch: The dutch spelling system and learning to spell in dutch," in *Handbook of orthography and literacy*. Routledge, 2013, pp. 149–164.
- [11] T. Pirinen, K. Lindén et al., "Finite-state spell-checking with weighted language and error models," in Proceedings of LREC 2010 Workshop on creation and use of basic lexical resources for less-resourced languages, 2010.
- [12] M. Starlander and A. Popescu-Belis, "Corpus-based evaluation of a french spelling and grammar checker." in *LREC*, 2002.
- [13] T. Fontenelle, "Developing a lexicon for a new french spell-checker," 2006
- [14] A. Rimrott and T. Heift, "Evaluating automatic detection of misspellings in german," *Language Learning & Technology*, vol. 12, no. 3, pp. 73–92, 2008
- [15] G. Kodydek, "A word analysis system for german hyphenation, full text search, and spell checking, with regard to the latest reform of german orthography," in TSD, 2000.
- [16] G. Petasis, V. Karkaletsis, D. Farmakiotou, G. Samaritakis, I. Androut-sopoulos, and C. Spyropoulos, "A greek morphological lexicon and its exploitation by a greek controlled language checker," in *Proceedings of the 8th Panhellenic Conference on Informatics*, 2001, pp. 8–10.
- [17] P. Etoori, M. Chinnakotla, and R. Mamidi, "Automatic spelling correction for resource-scarce languages using deep learning," in *Proceedings of ACL 2018, Student Research Workshop*, 2018, pp. 146–152.
- [18] S. Kabra and R. Agarwal, "Auto spell suggestion for high quality speech synthesis in hindi," CoRR, vol. abs/1402.3648, 2014.
- [19] M. Y. Soleh and A. Purwarianti, "A non word error spell checker for indonesian using morphologically analyzer and hmm," in *Proceedings* of the 2011 International Conference on Electrical Engineering and Informatics. IEEE, 2011, pp. 1–6.
- [20] V. Dixit, S. Dethe, and R. K. Joshi, "Design and implementation of a morphology-based spellchecker for marathi, and indian language," ARCHIVES OF CONTROL SCIENCE, vol. 15, no. 3, p. 301, 2005.
- [21] R. Grundkiewicz, "Automatic extraction of polish language errors from text edition history," in *International Conference on Text, Speech and Dialogue*. Springer, 2013, pp. 129–136.
- [22] R. T. Martins, R. Hasegawa, M. d. G. V. Nunes, G. Montilha, and O. N. De Oliveira, "Linguistic issues in the development of regra: A grammar checker for brazilian portuguese," *Natural Language Engineering*, vol. 4, no. 4, pp. 287–307, 1998.
- [23] A. Sorokin and T. Shavrina, "Automatic spelling correction for russian social media texts," in *Proceedings of the International Conference Dialog(Moscow*, 2016, pp. 688–701.
- [24] A. Sorokin, "Spelling correction for morphologically rich language: a case study of russian," in *Proceedings of the 6th Workshop on Balto-Slavic Natural Language Processing*, 2017, pp. 45–53.
- [25] F. R. Bustamante and E. L. Díaz, "Spelling error patterns in spanish for word processing applications." in *LREC*. Citeseer, 2006, pp. 93–98.
- [26] V. Kann, R. Domeij, J. Hollman, and M. Tillenius, "Implementation aspects and applications of a spelling correction algorithm," Text as a Linguistic Paradigm: Levels, Constituents, Constructs. Festschrift in honour of Ludek Hrebicek, vol. 60, pp. 108–123, 2001.
- [27] T. Dhanabalan, R. Parthasarathi, and T. Geetha, "Tamil spell checker," in Sixth Tamil Internet 2003 Conference, Chennai, Tamilnadu, India, 2003.

- [28] T. Karoonboonyanan, V. Sornlertlamvanich, and S. Meknavin, "A thai soundex system for spelling correction," in *Proceeding of the National Language Processing Pacific Rim Symposium*, 1997, pp. 633–636.
- [29] A. Helfrich and B. Music, "Design and evaluation of grammar checkers in multiple languages," in COLING, 2000.
- [30] D. Naber et al., A rule-based style and grammar checker. Citeseer, 2003.
- [31] M. Miłkowski, "Developing an open-source, rule-based proofreading tool," Software: Practice and Experience, vol. 40, no. 7, pp. 543–566, 2010
- [32] K. Kukich, "Techniques for automatically correcting words in text," ACM Comput. Surv., vol. 24, pp. 377–439, 1992.
- [33] P. Gupta, S. Shekhawat, and K. Kumar, "Unsupervised quality estimation without reference corpus for subtitle machine translation using word embeddings," in 2019 IEEE 13th International Conference on Semantic Computing (ICSC), Jan 2019, pp. 32–38.
- [34] E. Moreau and C. Vogel, "Multilingual word segmentation: Training many language-specific tokenizers smoothly thanks to the universal dependencies corpus," in *LREC*, 2018.
- [35] B. Snyder and R. Barzilay, "Unsupervised multilingual learning for morphological segmentation," in ACL, 2008.
- [36] P.-C. Chang, M. Galley, and C. D. Manning, "Optimizing chinese word segmentation for machine translation performance," in WMT@ACL, 2008.
- [37] P. Koehn, "Europarl: A parallel corpus for statistical machine translation," 2005.
- [38] W. A. Burkhard and R. M. Keller, "Some approaches to best-match file searching," *Commun. ACM*, vol. 16, pp. 230–236, 1973.
- [39] M. Balík, "Implementation of directed acyclic word graph," Kybernetika, vol. 38, pp. 91–103, 2002.
- [40] A. Carlson and I. Fette, "Memory-based context-sensitive spelling correction at web scale," Sixth International Conference on Machine Learning and Applications (ICMLA 2007), pp. 166–171, 2007.
- [41] P. Fivez, S. Suster, and W. Daelemans, "Unsupervised context-sensitive spelling correction of clinical free-text with word and character n-gram embeddings," in *BioNLP*, 2017.
- [42] H. Kilicoglu, M. Fiszman, K. Roberts, and D. Demner-Fushman, "An ensemble method for spelling correction in consumer health questions," AMIA ... Annual Symposium proceedings. AMIA Symposium, vol. 2015, pp. 727–36, 2015.
- [43] R. Grundkiewicz and M. Junczys-Dowmunt, "The wiked error corpus: A corpus of corrective wikipedia edits and its application to grammatical error correction," in Advances in Natural Language Processing – Lecture Notes in Computer Science, A. Przepirkowski and M. Ogrodniczuk, Eds., vol. 8686. Springer, 2014, pp. 478–490. [Online]. Available: http://emjotde.github.io/publications/pdf/mjd.poltal2014.draft.pdf
- [44] S. Deorowicz and M. Ciura, "Correcting spelling errors by modelling their causes," 2005.
- [45] P. Lison and J. Tiedemann, "Opensubtitles 2016: Extracting large parallel corpora from movie and tv subtitles," in *LREC*, 2016.
- [46] J. Tiedemann, "Parallel data, tools and interfaces in opus," in Proceedings of the Eight International Conference on Language Resources and Evaluation (LREC'12), N. C. C. Chair), K. Choukri, T. Declerck, M. U. Dogan, B. Maegaard, J. Mariani, J. Odijk, and S. Piperidis, Eds. Istanbul, Turkey: European Language Resources Association (ELRA), may 2012.