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A WEIGHTED FINITE-STATE TRANSDUCER FOR CONTEXT-AWARE SYNONYM SELECTION: A HYBRID SYMBOLIC–NEURAL APPROACH

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Annotatsiya. Uşbu maqolada kontekstga mos sinonimlarni tanlaş çeklangan nomzodlar töplami doirasida ularni reytinglaş masalasi sifatida qaraladi. Sinonimlar luğati ikki qatlamli vaznli çekli holatlar transduseri (WFST) körinişida tuziladi: kiriş yoylari sözni uning ma'no holatlariga, nomzod yoylari esa har bir ma'no holatini muqobil sözlar bilan boğlaydi. Nomzod yoylarining vaznlari kompilyatsiya bosqiçida qat'iy belgilanmaydi, balki dekodlaş vaqtida kontekstning gap embeddinglari asosida hisoblanadi. FST-BUILD va FST-DECODE algoritmlari hamda ularning murakkablik çegaralari bayon etiladi. Özbek tilidagi 1 104 ta birlikdan iborat sinonimlar resursi asosida tuzilgan transduser 1 104 ta ma'no holati va 3 171 ta nomzod yoyiga ega bölib, 7,7 ms da quriladi hamda har bir sörov uçun köpi bilan 10 ta enkoder çaqiruvini talab qiladi. Tadqiqotning keyingi bosqiçi uçun semantik aniqlikni baholaş protokoli belgilangan.

Kalit sözlar: vaznli çekli holatlar transduseri, leksik almaştiriş, sinonim tanlaş, neyro-simvolik yondaşuv, hisoblaş murakkabligi, gap embeddinglari, resurslari kam tillar, özbek tili.

Аннотация. В данной статье выбор контекстно-зависимых синонимов рассматривается как задача ранжирования в рамках ограниченного множества кандидатов. Словарь синонимов преобразуется в двухслойный взвешенный конечный преобразователь (WFST): входные дуги связывают слово с его состояниями значений, а дуги кандидатов — каждое состояние значения с вариантами замены. Весовые коэффициенты дуг кандидатов не фиксируются на этапе компиляции, а вычисляются во время декодирования на основе эмбеддингов предложений, представляющих контекст. Представлены алгоритмы FST-BUILD и FST-DECODE, а также оценки их вычислительной сложности. На основе ресурса узбекских синонимов, содержащего 1 104 единицы, построенный преобразователь включает 1 104 состояния значений и 3 171 дугу кандидатов, строится за 7,7 мс и требует не более 10 вызовов энкодера на один запрос. Для следующего этапа исследования определён протокол оценки семантической точности.

Ключевые слова: взвешенный конечный преобразователь, лексическая замена, выбор синонимов, нейросимволический подход, вычислительная сложность, эмбеддинги предложений, языки с ограниченными ресурсами, узбекский язык.

Abstract. This paper treats context-aware synonym selection as a ranking problem over a constrained candidate space. A synonym dictionary is compiled into a two-layer weighted finite-state transducer (WFST): input arcs map a word to its sense states, and candidate arcs map each sense state to its substitutes. Candidate-arc weights are not fixed at compilation time but are computed at decoding time from sentence embeddings of the context. The FST-BUILD and FST-DECODE algorithms are presented with complexity bounds. On a 1,104-entry Uzbek synonym resource, the transducer has 1,104 sense states and 3,171 candidate arcs, builds in 7.7 ms, and requires at most 10 encoder calls per query. A protocol for evaluating semantic accuracy is specified for the next stage of the study.

Keywords: weighted finite-state transducer, lexical substitution, synonym selection, neuro-symbolic approach, computational complexity, sentence embeddings, low-resource languages, Uzbek.

INTRODUCTION

Replacing a word with the synonym that best fits its context supports text simplification, paraphrasing, machine-translation post-editing and educational text adaptation. In computational linguistics this task is known as *lexical substitution*: a system proposes meaning-preserving substitutes for a target word in context and ranks them by fit [6-8].

Symbolic approaches compile a dictionary into a finite-state transducer. Such systems are fast and interpretable, but classical WFST weights are fixed at compilation time [1, 2], so the same synonym pair cannot be preferred in one context and rejected in another. Neural approaches [9–11] adapt to context but require large models, draw candidates from the whole vocabulary or a generator, and make decisions harder to audit, which is a serious

limitation for low-resource languages such as Uzbek. Context-dependent WFST weights are known from neural-context transducers [3, 4] and from speech recognition [5], but these works target other tasks and are trained end to end. A formal construction that compiles an existing synonym dictionary into a WFST with a pluggable encoder, together with its complexity analysis, has not been considered separately.

The aim of the study is to develop a model, algorithms and architecture for interpretable synonym selection over a constrained candidate space and to validate them on an Uzbek resource. The objectives are: to formalise the problem; to define the two-layer WFST and its weight function; to develop the algorithms and estimate their complexity; and to validate the approach structurally. The contribution is a formal compilation model, a decoding algorithm whose number of neural scoring calls depends on the number of candidates of the word rather than on the vocabulary size, a modular architecture, and structural measurements on Uzbek data. Semantic-accuracy results are not reported here; their evaluation protocol is given in Section 2.5.

LITERATURE REVIEW

The foundations of WFSTs, including determinisation, minimisation and composition-based decoding, were laid by M. Mohri and co-authors [1, 2]. P. Rastogi, R. Cotterell and J. Eisner computed transduction weights from a neural encoding of the context [3], and C.-C. Lin and co-authors developed neural finite-state transducers [4]. In speech recognition, language-model weights are re-scored on the fly according to context [5]. The statement that WFST weights are static therefore holds only for the classical formalism. The present work differs not in the idea of context-dependent weights, but in applying it to compile a synonym dictionary and constrain the candidate space.

Lexical substitution was introduced at SemEval-2007 [6] and later supported by the CoInCo corpus [7] and the Swords benchmark [8]. BERT-based substitution [9] generates and ranks candidates with a masked language model; LexSubCon [10] combines lexical-resource knowledge with contextual embeddings; ParaLS [11] uses a pretrained paraphraser. J. Vladika and co-authors showed that synonym substitution is not the same as contextually appropriate substitution [12]. Surveys of hybrid symbolic–neural NLP describe embedding symbolic structure in the model architecture as one of the main integration strategies [13]; the proposed approach follows it, and lightweight distilled encoders such as LEALLA [14] and MiniLM [15] suit its weight function. For Uzbek, the UzWordNet database with about 28 thousand synsets has been created [16], but no annotated corpus for contextual lexical substitution is known to the author. Table 1 summarises the comparison.

Table 1.
Position of the proposed approach relative to the closest methods[1]

Approach	Symbolic structure	Context adaptation	Source of candidates
Classical WFST [1, 2]	yes	no	compiled dictionary
Neural-context WFST [3, 4]	yes	yes (trained)	task-specific transducer
BERT-based substitution [9]	no	yes	language-model vocabulary
LexSubCon [10]	partial	yes	resource and language model
Proposed approach	yes	yes (pluggable encoder)	existing synonym dictionary

RESEARCH METHODOLOGY

Problem statement and model. A resource R maps each word w to a set of senses $S(w)$, and each sense s to a candidate set $M(s) \subset \Gamma$. Let c be a sentence containing w, and $c[w \to t]$ the sentence with t substituted for w. The problem is stated as

$$(s^*, t^*) = \arg\max_{s \in S(w),\, t \in M(s)} \omega_c(s, t). \qquad 1)$$

For each fixed context c, the transducer $T_c = (\Sigma, \Gamma, Q, I, F, E, \omega_c)$ is defined over the Viterbi semiring $(\mathbb{R}_+, \max, \times, 0, 1)$, where $Q = \{q_0\} \cup Q_S \cup \{q_f\}$ contains one state q_s per sense, $I = \{q_0\}$, $F = \{q_f\}$, and

$$E_{in} = \{(q_0, w, \varepsilon, q_s) : s \in S(w)\}, \quad E_{cand} = \{(q_s, \varepsilon, t, q_f) : t \in M(s)\}. \qquad 2)$$

Input arcs have weight 1 and candidate arcs have weight $\omega_c(s, t) \in [0, 1]$, so the weight of each path $q_0 \to q_s \to q_f$ equals $\omega_c(s, t)$, and the best path solves (1). All T_c share one topology, which is compiled once, while the weights are computed per query (Figure 1). For a fixed c, T_c is a standard WFST, so classical algorithms [1] apply to it directly. The candidate weight is

1 Author's calculations.

$$\omega_c(s, t) = \alpha \cdot \sigma(\cos(E(c[w \to t]), E(c))) + (1 - \alpha) \cdot g(w, t), \quad 3)$$

where $E(\cdot)$ is a lightweight multilingual sentence encoder [14]; $\sigma(x) = (1 + x)/2$ keeps the weight in $[0, 1]$; $g \in [0, 1]$ is an optional prior such as normalised frequency; and $\alpha \in [0, 1]$ is tuned on a development set. The encoder can be replaced without changing the compiler.

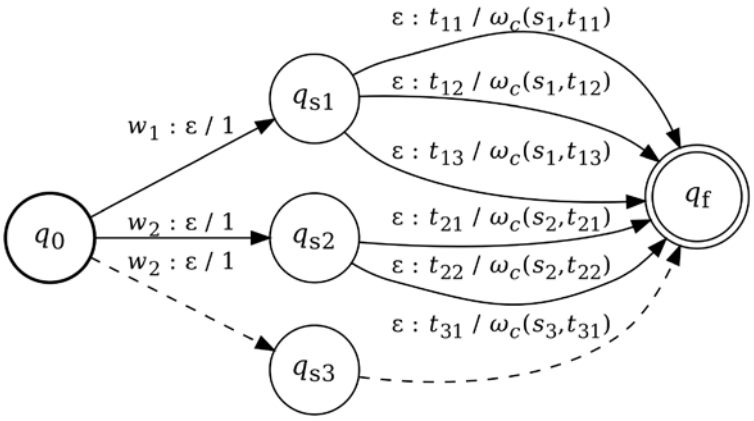


Figure 1. Topology of the two-layer WFST (the dashed line shows the second sense of a polysemous word)[2]

Algorithms

Algorithm 1. FST-BUILD(R)

1: $Q \leftarrow \{q_0, q_f\}$; $E \leftarrow \emptyset$; $D \leftarrow$ empty hash table
2: **for each** $w \in R$, **for each** $s \in S(w)$ **do**
3: create state q_s; $E \leftarrow E \cup \{(q_0, w, \varepsilon, q_s)\}$; $D[w] \leftarrow D[w] \cup \{q_s\}$
4: **for each** $t \in M(s)$ **do** $E \leftarrow E \cup \{(q_s, \varepsilon, t, q_f)\}$ ▷ weight set at decoding
5: **return** (Q, E, D)

Algorithm 2. FST-DECODE(Q, E, D, c, w)

1: **if** $w \notin D$ **then return** $\perp$; $e_0 \leftarrow E(c)$; $L \leftarrow \emptyset$
2: **for each** $q_s \in D[w]$, **for each** $(q_s, \varepsilon, t, q_f) \in E$ **do**
3: $L \leftarrow L \cup \{(t, s, \alpha \cdot \sigma(\cos(E(c[w \to t]), e_0)) + (1 - \alpha) \cdot g(w, t))\}$
4: sort L by score; **return** the best (t^*, s^*), the ranking L and the path $q_0 \to q_{s^*} \to q_f$

The implementation separates four modules: a resource loader with a quality audit, a transducer compiler (Algorithm 1), a stateless contextual weighting service implementing (3), and a decoder/API (Algorithm 2) that returns the selected candidate, the full ranking and the explaining path.

Complexity analysis

Proposition 1. FST-BUILD requires $O(|E|)$ expected time and $O(|Q| + |E|)$ space, since each sense and each pair (s, t) is processed once with an expected $O(1)$ hash insertion.

Proposition 2. Let $D(w) = \Sigma_{s \in S(w)} |M(s)|$ and let T_{enc} be the cost of encoding one sentence. FST-DECODE calls the encoder $D(w) + 1$ times, so

$$T_{decode}(w) = O(D(w) \cdot T_{enc} + D(w) \log D(w)), \quad 4)$$

which does not depend on the vocabulary size $|V|$. Compared with unconstrained ranking that re-encodes the sentence for every candidate, the number of encoder calls drops from $|V|$ to $D(w)$. A masked language model [9], however, scores the whole vocabulary in one forward pass, so relative to it the advantage lies in verified candidates and interpretable decisions rather than in asymptotic speed (Table 2).

Table 2.
Asymptotic complexity per query[3]

Method	Scoring	Space
Unconstrained, re-encoding each candidate	$O(\|V\| \cdot T_{enc})$	$O(\|V\|)$
Masked language model [9]	$O(T_{enc} + \|V\| \cdot d)$	$O(\|V\| \cdot d)$
Static WFST	$O(D(w))$, context-blind	$O(\|Q\| + \|E\|)$

2 Author's calculations.
3 Author's calculations.

Proposed WFST + encoder	$O(D(w)\cdot T_{enc})$	$O(\|Q\| + \|E\|)$ + model

Data and measurement setup. The experiments used a 1,104-entry Uzbek synonym resource structured as word → part of speech → senses → candidates. Every entry has a single sense; about 1.9% of candidate arcs (59) contain malformed tokens, and one of four grammatical categories has no entries. Construction time was measured for the full resource; decoding latency was measured without the neural encoder, which has not yet been integrated.

Semantic-accuracy evaluation protocol. The next stage will use at least 300 real Uzbek corpus sentences with 100 target words, annotated by at least three native speakers (agreement measured with Krippendorff's α). Baselines will include a random choice, the first candidate, a frequency prior, static-embedding cosine similarity, mBERT/XLM-R masked-language-model substitution [9], encoder ranking without the transducer constraint, and zero-shot selection with a large language model. The ablation will vary α and the transducer constraint and measure oracle coverage of gold substitutes in $M(w)$. Metrics will be GAP, P@1 and best/oot [6] together with per-query latency including the encoder, with paired bootstrap and McNemar tests under Holm correction ($p < 0.05$).

ANALYSIS AND RESULTS

Table 3 reports the results. "Measured" values come from the implementation; "derived" values follow from the definition in Section 2.1.

Table 3.
Structural and computational indicators of the transducer[4]

Indicator	Value	Type
Sense states |QS| (dictionary entries)	1,104	measured
Candidate arcs |Ecand|	3,171	measured
Input arcs |Ein|	1,104	derived
Mean / maximum candidates per sense	2.87 / 9	measured
Encoder calls per query, D(w) + 1	≤ 10 (mean ≈ 3.87)	derived
FST-BUILD time	7.7 ms	measured
FST-DECODE latency (without encoder)	0.0017 ms/ query	measured

Compiling the full resource takes milliseconds, so the topology can be built once and reused. The symbolic part of decoding takes far less than a microsecond, so the total query time is determined in practice by the encoder: by (4), approximately $(D(w) + 1)\cdot T_{enc}$, with at most 10 encoder calls on this resource. A single timing at one resource size does not confirm the asymptotic bound of Proposition 1; measurements on 10–100% subsets of the resource are planned for that purpose.

Each decision is explained by one explicit path $q_0 \to q_s \to q_f$ and its score, which end-to-end neural rankers do not provide. Unlike LexSubCon [10], which also combines a lexical resource with contextual scoring, the proposed approach compiles the resource into a symbolic transducer and never proposes candidates outside it.

The study has limitations. The encoder has not yet been integrated, so the semantic accuracy of the approach and its advantage over the baselines have not been demonstrated; this is the main limitation. The resource contains no polysemous entries, so joint sense selection has not been tested; this can be addressed by compiling UzWordNet [16]. The transducer cannot propose substitutes absent from the resource, and a synonym is not always a contextually appropriate substitute [12]. Finally, the results were obtained for one language and one resource.

CONCLUSIONS AND RECOMMENDATIONS

The paper proposed a hybrid approach to context-aware synonym selection that compiles a synonym dictionary into a two-layer WFST with context-dependent weights. The model was formally defined and shown to be a standard WFST for every fixed context; the FST-BUILD and FST-DECODE algorithms were developed with bounds of $O(|E|)$ for construction and $O(D(w)\cdot T_{enc})$ for decoding. On the Uzbek resource the transducer was built in 7.7 ms, and the number of encoder calls per query was bounded by 10.

It is recommended to integrate a lightweight multilingual encoder and evaluate semantic accuracy with the protocol of Section 2.5, to create and openly release an Uzbek contextual lexical-substitution test set, to compile a

4 Author's calculations.

polysemous resource for joint sense and substitute selection, and to publish the code and data for reproducibility.

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