Comparing nondeterministic and quasideterministic finite-state transducers built from morphological dictionaries*

Alicia Garrido-Alenda and Mikel L. Forcada Departament de Llenguatges i Sistemes Informàtics Universitat d'Alacant E-03071 Alacant, Spain

SEPLN 2002, Valladolid

*Funded by Caja de Ahorros del Mediterráneo, Universitat d'Alacant and CICyT (project TIC2000-1599-C02-02).

Lexical transformations in NLP systems

Aligned and unaligned dictionaries

Transducers: quasideterministic and nondeterministic

Building transducers from dictionaries

Comparing quasi- and non-deterministic transducers

Lexical transformations in NLP systems

Aligned and unaligned dictionaries

Transducers: quasideterministic and nondeterministic

Building transducers from dictionaries

Comparing quasi- and non-deterministic transducers

Lexical transformations in NLP systems

Aligned and unaligned dictionaries

Transducers: quasideterministic and nondeterministic

Building transducers from dictionaries

Comparing quasi- and non-deterministic transducers

Lexical transformations in NLP systems

Aligned and unaligned dictionaries

Transducers: quasideterministic and nondeterministic

Building transducers from dictionaries

Comparing quasi- and non-deterministic transducers

Lexical transformations in NLP systems

Aligned and unaligned dictionaries

Transducers: quasideterministic and nondeterministic

Building transducers from dictionaries

Comparing quasi- and non-deterministic transducers

Lexical transformations in NLP systems

Aligned and unaligned dictionaries

Transducers: quasideterministic and nondeterministic

Building transducers from dictionaries

Comparing quasi- and non-deterministic transducers

Lexical transformations in NLP systems

Aligned and unaligned dictionaries

Transducers: quasideterministic and nondeterministic

Building transducers from dictionaries

Comparing quasi- and non-deterministic transducers

Lexical transformations in NLP systems:

Lexical transformations in NLP systems:

• Morphological analysis: surface form \rightarrow lexical form(s) [lemma + PoS + inflection info.]

Lexical transformations in NLP systems:

- Morphological analysis: surface form \rightarrow lexical form(s) [lemma + PoS + inflection info.]
- Morphological generation: lexical form \rightarrow surface form.

Lexical transformations in NLP systems:

- Morphological analysis: surface form \rightarrow lexical form(s) [lemma + PoS + inflection info.]
- Morphological generation: lexical form \rightarrow surface form.
- Lexical transfer (in MT): source lexical form → target lexical form.

Lexical transformations in NLP systems:

- Morphological analysis: surface form \rightarrow lexical form(s) [lemma + PoS + inflection info.]
- Morphological generation: lexical form \rightarrow surface form.
- Lexical transfer (in MT): source lexical form → target lexical form.

Transformations usually specified in terms of (morphological, bilingual) dictionaries.

Unaligned dictionary: simple list of (input string, output string) pairs.

Unaligned dictionary: simple list of (input string, output string) pairs.

(recordáis, recordar<vblex><pri><2><pl>)

Unaligned dictionary: simple list of (input string, output string) pairs.

(recordáis, recordar<vblex><pri><2><pl>)
(recuerdo, recordar<vblex><pri><1><sg>)

Unaligned dictionary: simple list of (input string, output string) pairs.

(recordáis, recordar<vblex><pri><2><pl>)
(recuerdo, recordar<vblex><pri><1><sg>)
 (recuerdo, recuerdo<n><m><sg>)

Unaligned dictionary: simple list of (input string, output string) pairs.

(recordáis, recordar<vblex><pri><2><pl>)
(recuerdo, recordar<vblex><pri><1><sg>)
 (recuerdo, recuerdo<n><m><sg>)

Aligned dictionary: list of sequences of (input substring, output substring) pairs expressing linguistic regularities.

Unaligned dictionary: simple list of (input string, output string) pairs.

(recordáis, recordar<vblex><pri><2><pl>)
(recuerdo, recordar<vblex><pri><1><sg>)
 (recuerdo, recuerdo<n><m><sg>)

Aligned dictionary: list of sequences of (input substring, output substring) pairs expressing linguistic regularities.

(re,re)(c,c)(o,o)(rd,rd)(áis,ar<vblex><2><pl>)

Unaligned dictionary: simple list of (input string, output string) pairs.

(recordáis, recordar<vblex><pri><2><pl>)
(recuerdo, recordar<vblex><pri><1><sg>)
 (recuerdo, recuerdo<n><m><sg>)

Aligned dictionary: list of sequences of (input substring, output substring) pairs expressing linguistic regularities.

(re,re)(c,c)(o,o)(rd,rd)(áis,ar<vblex><2><pl>)
(re,re)(c,c)(ue,o)(rd,rd)(o,ar<vblex><1><sg>)

Unaligned dictionary: simple list of (input string, output string) pairs.

(recordáis, recordar<vblex><pri><2><pl>)
(recuerdo, recordar<vblex><pri><1><sg>)
 (recuerdo, recuerdo<n><m><sg>)

Aligned dictionary: list of sequences of (input substring, output substring) pairs expressing linguistic regularities.

(re,re)(c,c)(o,o)(rd,rd)(áis,ar<vblex><2><pl>)
 (re,re)(c,c)(ue,o)(rd,rd)(o,ar<vblex><1><sg>)
 (re,re)(c,c)(ue,ue)(rd,rd)(o,o<n><m><sg>)

Many lexical transformations in Indoeuropean languages may be performed sequentially using transducers:

Many lexical transformations in Indoeuropean languages may be performed sequentially using transducers:

• reading the input left to right;

Many lexical transformations in Indoeuropean languages may be performed sequentially using transducers:

- reading the input left to right;
- incrementally building:

Many lexical transformations in Indoeuropean languages may be performed sequentially using transducers:

- reading the input left to right;
- incrementally building:

- a prefix of the output (deterministic transducers), or

Many lexical transformations in Indoeuropean languages may be performed sequentially using transducers:

- reading the input left to right;
- incrementally building:
 - a prefix of the output (deterministic transducers), or
 - a set of candidate prefixes of the output (nondeterministic transducers).

Many lexical transformations in Indoeuropean languages may be performed sequentially using transducers:

- reading the input left to right;
- incrementally building:
 - a prefix of the output (deterministic transducers), or
 - a set of candidate prefixes of the output (nondeterministic transducers).

Sequential processing possible because inputs sharing a prefix correspond to outputs sharing a nontrivial prefix.

Deterministic, incremental processing: deliver the longest common output prefix corresponding to all inputs sharing the current input prefix.

Deterministic, incremental processing: deliver the longest common output prefix corresponding to all inputs sharing the current input prefix.

In deterministic ("earliest *p*-subsequential" transducers):

Deterministic, incremental processing: deliver the longest common output prefix corresponding to all inputs sharing the current input prefix.

In deterministic ("earliest *p*-subsequential" transducers):

 states represent sets of prefixes sharing a common output behavior;

Deterministic, incremental processing: deliver the longest common output prefix corresponding to all inputs sharing the current input prefix.

In deterministic ("earliest *p*-subsequential" transducers):

- states represent sets of prefixes sharing a common output behavior;
- a single state is reached for each state and input symbol;

Deterministic, incremental processing: deliver the longest common output prefix corresponding to all inputs sharing the current input prefix.

In deterministic ("earliest *p*-subsequential" transducers):

- states represent sets of prefixes sharing a common output behavior;
- a single state is reached for each state and input symbol;
- output is associated to state-to-state transitions: the longest common output prefix is built incrementally.
Deterministic, incremental processing: deliver the longest common output prefix corresponding to all inputs sharing the current input prefix.

In deterministic ("earliest *p*-subsequential" transducers):

- states represent sets of prefixes sharing a common output behavior;
- a single state is reached for each state and input symbol;
- output is associated to state-to-state transitions: the longest common output prefix is built incrementally.

Dictionary alignments ignored: "deterministic alignment" [Details]

Full determinism impossible (hence the name quasideterministic) due to one-to-many (many $\leq p$) correspondences:

Full determinism impossible (hence the name quasideterministic) due to one-to-many (many $\leq p$) correspondences:

• only the longest common output prefix of all outputs (a proper prefix) can be output at the end of the input

Full determinism impossible (hence the name quasideterministic) due to one-to-many (many $\leq p$) correspondences:

• only the longest common output prefix of all outputs (a proper prefix) can be output at the end of the input

 $\tau(\texttt{recuerdo}) = \{\texttt{recordar<\texttt{vblex}}, \texttt{recuerdo<\texttt{n}}, ...\}$ $\mathsf{LCP}(\tau(\texttt{recuerdo})) = \texttt{rec}$

Full determinism impossible (hence the name quasideterministic) due to one-to-many (many $\leq p$) correspondences:

• only the longest common output prefix of all outputs (a proper prefix) can be output at the end of the input

 $\tau(\texttt{recuerdo}) = \{\texttt{recordar<\texttt{vblex}}, \texttt{recuerdo<\texttt{n}}, ...\}$ $\mathsf{LCP}(\tau(\texttt{recuerdo})) = \texttt{rec}$

• (at most *p*) output suffixes have to be appended at acceptance states.

Full determinism impossible (hence the name quasideterministic) due to one-to-many (many $\leq p$) correspondences:

• only the longest common output prefix of all outputs (a proper prefix) can be output at the end of the input

 $\tau(\texttt{recuerdo}) = \{\texttt{recordar<\texttt{vblex}}, \texttt{recuerdo<\texttt{n}}, ...\}$ $\mathsf{LCP}(\tau(\texttt{recuerdo})) = \texttt{rec}$

• (at most *p*) output suffixes have to be appended at acceptance states.

 $(rec)^{-1}\tau(recuerdo) = \{ ordar < vblex > ..., uerdo < n > ... \}$

Disadvantages of quasideterministic transducers:

Disadvantages of quasideterministic transducers:

• Any linguistic knowledge encoded in dictionary alignments is thrown away.

Disadvantages of quasideterministic transducers:

- Any linguistic knowledge encoded in dictionary alignments is thrown away.
- For large dictionaries, irregularities may lead to very short longest common output prefixes and very long output suffixes.

Disadvantages of quasideterministic transducers:

- Any linguistic knowledge encoded in dictionary alignments is thrown away.
- For large dictionaries, irregularities may lead to very short longest common output prefixes and very long output suffixes.
- Adding a new dictionary entry may force a complete reconstruction (longest common output prefixes may change)

Nondeterministic transducers avoid this by maintaining several output prefix candidates for each input:

Nondeterministic transducers avoid this by maintaining several output prefix candidates for each input:

 more than one state may be reached for each state and input symbol;

Nondeterministic transducers avoid this by maintaining several output prefix candidates for each input:

- more than one state may be reached for each state and input symbol;
- output is associated to state-to-state transitions so that a set of output prefix candidates is built incrementally by maintaining a set of alive state-output pairs during processing;

Nondeterministic transducers avoid this by maintaining several output prefix candidates for each input:

- more than one state may be reached for each state and input symbol;
- output is associated to state-to-state transitions so that a set of output prefix candidates is built incrementally by main-taining a set of alive state-output pairs during processing;
- output suffixes are no longer necessary.

Advantages of nondeterministic transducers:

Advantages of nondeterministic transducers:

• May be very compact! (when linguists are good at finding regularities to align inputs and outputs) (see later).

Advantages of nondeterministic transducers:

- May be very compact! (when linguists are good at finding regularities to align inputs and outputs) (see later).
- When expressed as finite-state letter transducers (with transitions reading or writing at most one symbol), they may be determinized and minimized similarly to finite automata.

Advantages of nondeterministic transducers:

- May be very compact! (when linguists are good at finding regularities to align inputs and outputs) (see later).
- When expressed as finite-state letter transducers (with transitions reading or writing at most one symbol), they may be determinized and minimized similarly to finite automata.
- New entries may be added and removed without realignment and maintaining minimality (Garrido et al., TMI-2002).



Building quasideterministic transducers from unaligned dictionaries [Details]

1. Build a **trie** for the input strings of the dictionary (each prefix in the input vocabulary is a state)

- 1. Build a **trie** for the input strings of the dictionary (each prefix in the input vocabulary is a state)
- 2. Using the output strings, compute the longest common output prefix (LCOP) for each prefix

- 1. Build a **trie** for the input strings of the dictionary (each prefix in the input vocabulary is a state)
- 2. Using the output strings, compute the longest common output prefix (LCOP) for each prefix
- 3. Associate as output of each transition the suffix necessary to get the arrival state LCOP from the departure state LCOP

- 1. Build a **trie** for the input strings of the dictionary (each prefix in the input vocabulary is a state)
- 2. Using the output strings, compute the longest common output prefix (LCOP) for each prefix
- 3. Associate as output of each transition the suffix necessary to get the arrival state LCOP from the departure state LCOP
- 4. Compute the remaining output suffixes necessary to complete the output at each acceptance state from the LCOP of that state

- 1. Build a **trie** for the input strings of the dictionary (each prefix in the input vocabulary is a state)
- 2. Using the output strings, compute the longest common output prefix (LCOP) for each prefix
- 3. Associate as output of each transition the suffix necessary to get the arrival state LCOP from the departure state LCOP
- 4. Compute the remaining output suffixes necessary to complete the output at each acceptance state from the LCOP of that state
- 5. Minimize the resulting transducer

Building nondeterministic transducers from aligned dictionaries [Details]

1. Build a **state path** from the start state to an acceptance state for each aligned pair in the dictionary (with transitions reading or writing zero or one characters)

- 1. Build a **state path** from the start state to an acceptance state for each aligned pair in the dictionary (with transitions reading or writing zero or one characters)
- 2. Determinize as a finite automaton using the input-output pairs as the alphabet

- 1. Build a **state path** from the start state to an acceptance state for each aligned pair in the dictionary (with transitions reading or writing zero or one characters)
- 2. Determinize as a finite automaton using the input-output pairs as the alphabet
- 3. Minimize in the same way

• Build both kinds of transducers from a set of representative dictionaries

- Build both kinds of transducers from a set of representative dictionaries
- Convert quasideterministic transducers also into finite-state letter transducers

- Build both kinds of transducers from a set of representative dictionaries
- Convert quasideterministic transducers also into finite-state letter transducers
 - unfolding transitions with outputs longer than 1
- Build both kinds of transducers from a set of representative dictionaries
- Convert quasideterministic transducers also into finite-state letter transducers
 - unfolding transitions with outputs longer than 1
 - creating letter-by-letter state paths for output suffixes at acceptance states

- Build both kinds of transducers from a set of representative dictionaries
- Convert quasideterministic transducers also into finite-state letter transducers
 - unfolding transitions with outputs longer than 1
 - creating letter-by-letter state paths for output suffixes at acceptance states
- Determinize and minimize the resulting letter transducers

- Build both kinds of transducers from a set of representative dictionaries
- Convert quasideterministic transducers also into finite-state letter transducers
 - unfolding transitions with outputs longer than 1
 - creating letter-by-letter state paths for output suffixes at acceptance states
- Determinize and minimize the resulting letter transducers
- Compare (unfair without conversion: LTs are more "rudimentary")

Results:

Results:

• Without conversion, both kinds of transducers have roughly the same number of states (comparison unfair to LT)

Results:

- Without conversion, both kinds of transducers have roughly the same number of states (comparison unfair to LT)
- After conversion, nondeterministic transducers are consistently 2.5 times more compact than quasideterministic transducers

Results:

- Without conversion, both kinds of transducers have roughly the same number of states (comparison unfair to LT)
- After conversion, nondeterministic transducers are consistently 2.5 times more compact than quasideterministic transducers
- Observed nondeterminism (average number of ASOPs) is of the order of corpus-computed ambiguity in dictionaries: quasidet., 1.3; nondet., 1.5–1.9 (slightly worse)

For lexical transformations, nondeterministic transducers are a viable alternative to quasideterministic transducers:

For lexical transformations, nondeterministic transducers are a viable alternative to quasideterministic transducers:

• they are compact

For lexical transformations, nondeterministic transducers are a viable alternative to quasideterministic transducers:

- they are compact
- their nondeterminism is limited

For lexical transformations, nondeterministic transducers are a viable alternative to quasideterministic transducers:

- they are compact
- their nondeterminism is limited
- they are easily maintained

For lexical transformations, nondeterministic transducers are a viable alternative to quasideterministic transducers:

- they are compact
- their nondeterminism is limited
- they are easily maintained

Nondeterministic letter transducers are in use in www.interNOSTRUM.com (a Spanish-Catalan MT system)



A (nondeterministic) finite-state letter transducer is

 $T = (Q, L, \delta, q_I, F),$

A (nondeterministic) finite-state letter transducer is

 $T = (Q, L, \delta, q_I, F),$

• Q: finite set of states

A (nondeterministic) finite-state letter transducer is

$$T = (Q, L, \delta, q_I, F),$$

- Q: finite set of states
- L = (Σ ∪ {θ}) × (Γ ∪ {θ}): label alphabet (Σ: input alphabet, Γ: output alphabet, θ: "empty symbol")

A (nondeterministic) finite-state letter transducer is

$$T = (Q, L, \delta, q_I, F),$$

- Q: finite set of states
- L = (Σ ∪ {θ}) × (Γ ∪ {θ}): label alphabet (Σ: input alphabet, Γ: output alphabet, θ: "empty symbol")
- $\delta: Q \times L \to 2^Q$: transition function

A (nondeterministic) finite-state letter transducer is

$$T = (Q, L, \delta, q_I, F),$$

- Q: finite set of states
- L = (Σ ∪ {θ}) × (Γ ∪ {θ}): label alphabet (Σ: input alphabet, Γ: output alphabet, θ: "empty symbol")
- $\delta: Q \times L \to 2^Q$: transition function
- $q_I \in Q$: initial state

A (nondeterministic) finite-state letter transducer is

$$T = (Q, L, \delta, q_I, F),$$

- Q: finite set of states
- L = (Σ ∪ {θ}) × (Γ ∪ {θ}): label alphabet (Σ: input alphabet, Γ: output alphabet, θ: "empty symbol")
- $\delta: Q \times L \rightarrow 2^Q$: transition function
- $q_I \in Q$: initial state
- $F \subseteq Q$: acceptance states

State-to-state arrows have input-output labels (σ, γ) :

State-to-state arrows have input-output labels (σ, γ) :

• Input σ can be an input symbol from Σ or nothing (θ)

State-to-state arrows have input-output labels (σ, γ) :

- Input σ can be an input symbol from Σ or nothing (θ)
- Output γ can be an output symbol from Γ or nothing (θ)

State-to-state arrows have input-output labels (σ, γ) :

- Input σ can be an input symbol from Σ or nothing (θ)
- Output γ can be an output symbol from Γ or nothing (θ)

Clearly, (θ, θ) arrows do nothing may be avoided.

Using FSLT: keep a set of alive state–output pairs (SASOP), updated after reading each input symbol from $w = \sigma[1]\sigma[2] \dots \sigma[|w|]$.

Using FSLT: keep a set of alive state–output pairs (SASOP), updated after reading each input symbol from $w = \sigma[1]\sigma[2] \dots \sigma[|w|]$.

t = 0, initial SASOP: $\mathcal{V}^{[0]} = \{(q, z) : q \in \delta^*(q_I, (\epsilon, z))\}$, where δ^* is the extension of δ to input-output string pairs

Using FSLT: keep a set of alive state–output pairs (SASOP), updated after reading each input symbol from $w = \sigma[1]\sigma[2] \dots \sigma[|w|]$.

t = 0, initial SASOP: $\mathcal{V}^{[0]} = \{(q, z) : q \in \delta^*(q_I, (\epsilon, z))\}$, where δ^* is the extension of δ to input-output string pairs

 $t \rightarrow t + 1$ (after reading $\sigma[t]$):

 $\mathcal{V}^{[t]} = \{ (q, z\gamma) : q \in \delta^*(q', (\sigma[t], \gamma)) \land (q', z) \in \mathcal{V}^{[t-1]} \}$

Using FSLT: keep a set of alive state–output pairs (SASOP), updated after reading each input symbol from $w = \sigma[1]\sigma[2] \dots \sigma[|w|]$.

t = 0, initial SASOP: $\mathcal{V}^{[0]} = \{(q, z) : q \in \delta^*(q_I, (\epsilon, z))\}$, where δ^* is the extension of δ to input-output string pairs

 $t \to t+1$ (after reading $\sigma[t]$): $\mathcal{V}^{[t]} = \{(q, z\gamma) : q \in \delta^*(q', (\sigma[t], \gamma)) \land (q', z) \in \mathcal{V}^{[t-1]}\}$

t = |w| (at the end of w): $\tau(w) = \{z : (q, z) \in \mathcal{V}^{[|w|]} \land q \in F\}.$

Longest common output prefix

The longest common output prefix for input \boldsymbol{w} is

$$\mathsf{LCOP}(w) = \mathsf{LCP}(\tau(ww^{-1}E))$$

where

- $E \subset \Sigma^*$ is the vocabulary of inputs,
- $\tau: E \to 2^{\Gamma^*}$ is the transformation function, and
- $ww^{-1}E = \{x \in E : w \in \Pr(x)\}.$

Build a *p*-subsequential transducer $T = (Q, \Sigma, \Gamma, \delta, \lambda, q_I, \psi)$:

Build a *p*-subsequential transducer $T = (Q, \Sigma, \Gamma, \delta, \lambda, q_I, \psi)$:

With a trie structure: Q = Pr(E) ∪ {⊥} (⊥ is the absorption state), q_I = ε, and

$$\delta(x,\sigma) = \begin{cases} x\sigma & \text{if } x, x\sigma \in \Pr(E) \\ \bot & \text{otherwise} \end{cases}$$

Build a *p*-subsequential transducer $T = (Q, \Sigma, \Gamma, \delta, \lambda, q_I, \psi)$:

With a trie structure: Q = Pr(E) ∪ {⊥} (⊥ is the absorption state), q_I = ε, and

$$\delta(x,\sigma) = \begin{cases} x\sigma & \text{if } x, x\sigma \in \Pr(E) \\ \bot & \text{otherwise} \end{cases}$$

• With transition outputs $\lambda(x,\sigma) = (LCOP(x))^{-1}LCOP(x\sigma)$ for $x, x\sigma \in Pr(E)$, and undefined otherwise.
Build a *p*-subsequential transducer $T = (Q, \Sigma, \Gamma, \delta, \lambda, q_I, \psi)$:

With a trie structure: Q = Pr(E) ∪ {⊥} (⊥ is the absorption state), q_I = ε, and

$$\delta(x,\sigma) = \begin{cases} x\sigma & \text{if } x, x\sigma \in \Pr(E) \\ \bot & \text{otherwise} \end{cases}$$

- With transition outputs $\lambda(x, \sigma) = (LCOP(x))^{-1}LCOP(x\sigma)$ for $x, x\sigma \in Pr(E)$, and undefined otherwise.
- With output suffix sets $\psi(w) = (LCOP(w))^{-1}\tau(w)$.

Build a *p*-subsequential transducer $T = (Q, \Sigma, \Gamma, \delta, \lambda, q_I, \psi)$:

With a trie structure: Q = Pr(E) ∪ {⊥} (⊥ is the absorption state), q_I = ε, and

$$\delta(x,\sigma) = \begin{cases} x\sigma & \text{if } x, x\sigma \in \Pr(E) \\ \bot & \text{otherwise} \end{cases}$$

- With transition outputs $\lambda(x, \sigma) = (LCOP(x))^{-1}LCOP(x\sigma)$ for $x, x\sigma \in Pr(E)$, and undefined otherwise.
- With output suffix sets $\psi(w) = (LCOP(w))^{-1}\tau(w)$.

The resulting transducer is minimized using the equivalence class algorithm (which iteratively refines a partition of Q).

Two different states \boldsymbol{q} and \boldsymbol{r} are not equivalent if

- $\psi(q) \neq \psi(r)$
- for some σ , $\delta(q,\sigma)$ not in the same class as $\delta(r,\sigma)$
- for some σ , $\lambda(q, \sigma) \neq \lambda(r, \sigma)$.

For each dictionary entry $(a_1, b_1)(a_2, b_2) \dots (a_N, b_N) \dots$

For each dictionary entry $(a_1, b_1)(a_2, b_2) \dots (a_N, b_N) \dots$

... build a path $q_I \xrightarrow{(a_1,b_1)} s_1 \xrightarrow{(a_2,b_2)} s_2 \dots \xrightarrow{(a_N,b_N)} q_F \dots$

For each dictionary entry $(a_1, b_1)(a_2, b_2) \dots (a_N, b_N) \dots$

... build a path
$$q_I \xrightarrow{(a_1,b_1)} s_1 \xrightarrow{(a_2,b_2)} s_2 \dots \xrightarrow{(a_N,b_N)} q_F \dots$$

... from initial state q_I to acceptance state q_F .

For each dictionary entry $(a_1, b_1)(a_2, b_2) \dots (a_N, b_N) \dots$

... build a path
$$q_I \xrightarrow{(a_1,b_1)} s_1 \xrightarrow{(a_2,b_2)} s_2 \dots \xrightarrow{(a_N,b_N)} q_F \dots$$

... from initial state q_I to acceptance state q_F .

For example, (haces, haz<n><m><pl>)...

For each dictionary entry $(a_1, b_1)(a_2, b_2) \dots (a_N, b_N) \dots$

... build a path
$$q_I \xrightarrow{(a_1,b_1)} s_1 \xrightarrow{(a_2,b_2)} s_2 \dots \xrightarrow{(a_N,b_N)} q_F \dots$$

... from initial state q_I to acceptance state q_F .

For example, (haces, haz<n><m><pl>)...

... may be aligned as $(h,h)(a,a)(c,z)(\theta, <n>)(\theta, <m>)(e,\theta)(s, <pl>).$ [back]





The resulting transducer is determinized and minimized.

• Transitions $q \xrightarrow{(\sigma, \gamma_1 \gamma_2 \dots \gamma_n)} q'$ with $n > 1 \dots$

• Transitions $q \xrightarrow{(\sigma, \gamma_1 \gamma_2 \dots \gamma_n)} q'$ with $n > 1 \dots$

... are unfolded into state paths $q \xrightarrow{(\sigma,\gamma_1)} s_1 \xrightarrow{(\theta,\gamma_2)} s_2 \dots \xrightarrow{(\theta,\gamma_n)} q'$

• Transitions
$$q \xrightarrow{(\sigma, \gamma_1 \gamma_2 \dots \gamma_n)} q'$$
 with $n > 1 \dots$

... are unfolded into state paths $q \xrightarrow{(\sigma,\gamma_1)} s_1 \xrightarrow{(\theta,\gamma_2)} s_2 \dots \xrightarrow{(\theta,\gamma_n)} q'$

• For each state q and for each tail $\gamma_1 \gamma_2 \dots \gamma_n \in \psi(q), \dots$

• Transitions
$$q \xrightarrow{(\sigma, \gamma_1 \gamma_2 \dots \gamma_n)} q'$$
 with $n > 1 \dots$

... are unfolded into state paths $q \xrightarrow{(\sigma,\gamma_1)} s_1 \xrightarrow{(\theta,\gamma_2)} s_2 \dots \xrightarrow{(\theta,\gamma_n)} q'$

• For each state q and for each tail $\gamma_1 \gamma_2 \dots \gamma_n \in \psi(q), \dots$ Idots build an inputless state path $q \xrightarrow{(\theta, \gamma_1)} s_1 \xrightarrow{(\theta, \gamma_2)} s_2 \dots \xrightarrow{(\theta, \gamma_n)} q_F$

• Transitions
$$q \xrightarrow{(\sigma, \gamma_1 \gamma_2 \dots \gamma_n)} q'$$
 with $n > 1 \dots$

... are unfolded into state paths $q \xrightarrow{(\sigma,\gamma_1)} s_1 \xrightarrow{(\theta,\gamma_2)} s_2 \dots \xrightarrow{(\theta,\gamma_n)} q'$

• For each state q and for each tail $\gamma_1 \gamma_2 \dots \gamma_n \in \psi(q), \dots$ Idots build an inputless state path $q \xrightarrow{(\theta, \gamma_1)} s_1 \xrightarrow{(\theta, \gamma_2)} s_2 \dots \xrightarrow{(\theta, \gamma_n)} q_F$ (the only source of input nondeterminism).