INTRODUCTIO

COMPUTATIONAL PROPERTIES OF REDUPLICATIO

METHOT

RESULT

DISCUSSIO

REFERENCE

PROBING RNN ENCODER-DECODER GENERALIZATION OF SUBREGULAR FUNCTIONS USING REDUPLICATION

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TALK IN A NUTSHELL

- Formal Languages/Automata:
 - Necessary and sufficient conditions on computable functions
 - ▶ Provide target function classes for generalization/learning
 - transparent, analytical guarantees independent of the machine
- Recurrent Neural Network/ finite-state connections
- What is the generalization capacity of RNN Encoder-Decoders?

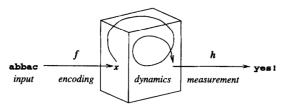
ENCODER-DECODERS AND SUBREGULAR REDUPLICATION

- Reduplication: variable-length subregular copy functions
- Vanilla Encoder-Decoders struggle to capture generalizable reduplication, networks with attention reliably succeed
- Attention weights mirror subregular 2-way FST processing, suggests they are approximating them

RNN AND REGULAR LANGUAGES

Language: Does string w belong to stringset (language) L

• Computed by different classes of grammars (acceptors)

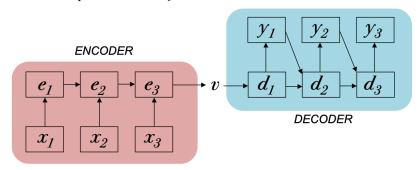


How expressive are RNNs?

Turing complete	infinite precision+time	(Siegelmann, 2012)
\subseteq counter languages	LSTM/ReLU	(Weiss et al., 2018)
Regular	SRNN/GRU	(Weiss et al., 2018)
	asymptotic acceptance	(Merrill, 2019)
Weighted FSA	Linear 2nd Order RNN	(Rabusseau et al., 2019)
Subregular	LSTM problems	(Avcu et al., 2017)
	•	

RNN ENCODER-DECODER AND TRANSDUCERS

- Function: Given string w, generate f(w) = v
 - = accepted pairs of input & output strings
 - ▶ Computed by different classes of grammars (transducers)
- Recurrent encoder maps a sequence to $v \in \mathbb{R}^n$, recurrent decoder language model conditioned on v (Sutskever et al., 2014)
- How expressive are they?



BRIEF TYPOLOGY OF REDUPLICATION

- Reduplication is typologically common¹
- Basic division: partial vs. total reduplication
 - (1) Partial reduplication = bounded copy

a. CV: $guyon \rightarrow gu \sim guyon$

'to jest'→'to jest repeatedly' (Sundanese)

b. Foot: $(gindal)ba \rightarrow gindal \sim gindalba$

'lizard sp.' → 'lizards'

c. Syllable $vam.se \rightarrow vam \sim vamse$

'hurry' → 'hurry (habitual)' (Yaqui)

(2) Total reduplication = unbounded copy

a. wanita→wanita~wanita

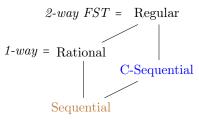
'woman'→'women' (Indonesian)

(Yidin)

¹(Moravcsik, 1978; Rubino, 2013)

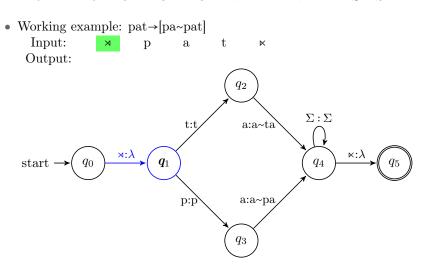
SUBREGULAR COMPUTING OF REDUPLICATION

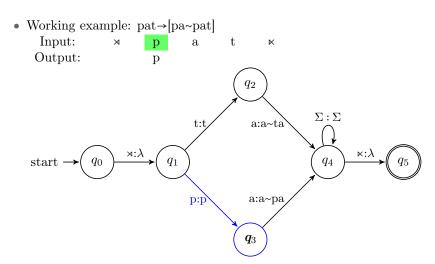
- Why reduplication (RED)?
 - ▶ inhabits **sub**classes of **regular** string-to-string functions
 - computed by restricted types of Finite-State Transducers
- 1. 1-way FST: reads input once in one direction
 - ~ computes Rational functions e.g., Sequential functions like partial RED
- 2. 2-way FST: reads multiple times, moves back and forth
 - ~ computes Regular functions e.g., Concatenated-Sequential functions like partial & total RED

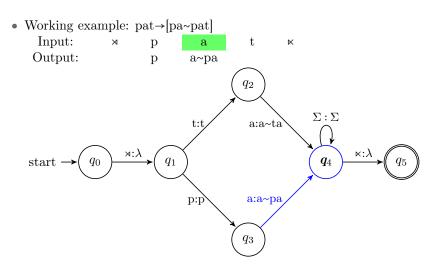


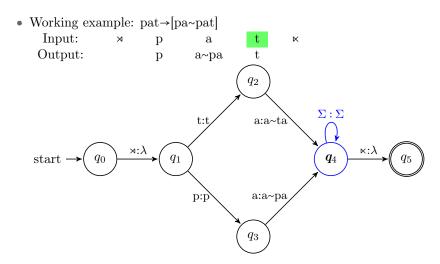
• Working example: $pat \rightarrow [pa \sim pat]$

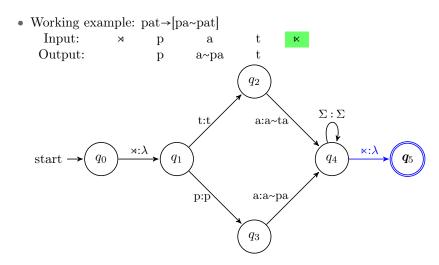
• Working example: pat→[pa~pat] Input: р Output: q_2 $\Sigma:\Sigma$ a:a~ta $\rtimes:\lambda$ **κ**:λ q_4 $start \rightarrow$ p:p a:a~pa q_3

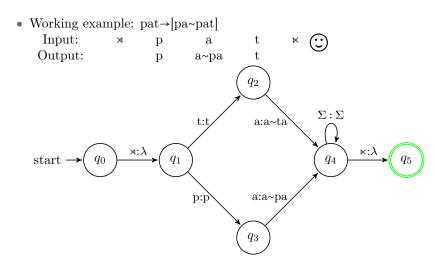












1-WAY FST LIMITATIONS

- How does a 1-way FST handle reduplication?
 - \rightarrow memorizes all possible reduplicants
- Many limitations:

1. State explosion:

- scaling problems as size of reduplicant and alphabet increases
- ▶ unwieldy machines (Roark and Sproat, 2007:54)

2. Limited expressivity:

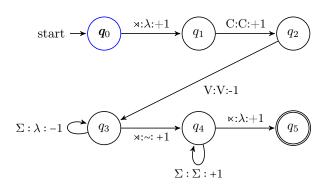
- can do partial reduplication but not total reduplication
- No bound on how big the copies are

3. Segment alignment:

Memorizes, doesn't 'copy'

 \bullet Working example: pat \rightarrow [pa~pat]

Working example: pat→[pa~pat]
 Input: × p a t
 Output:



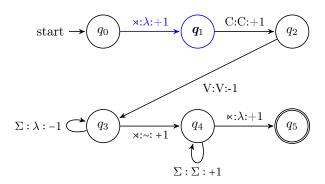
• Working example: pat→[pa~pat]

Input: par par

 \mathbf{a}

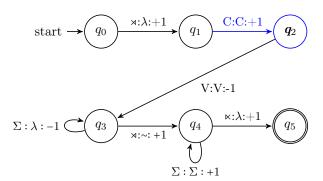
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Output:



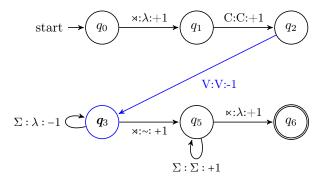
• Working example: pat→[pa~pat]

Input: \rtimes p a t \bowtie Output: p



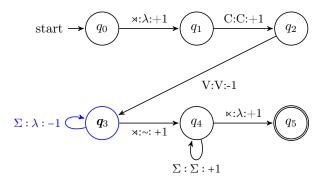
• Working example: $pat \rightarrow [pa \sim pat]$

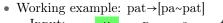
Input: \rtimes p a t \bowtie Output: p a



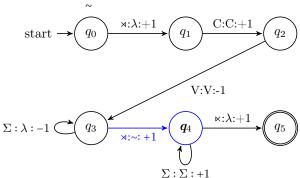
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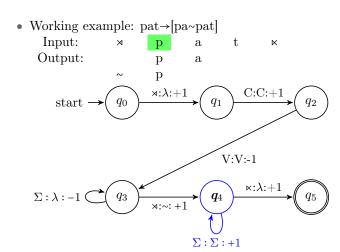
Input: \rtimes p a t \bowtie Output: p a

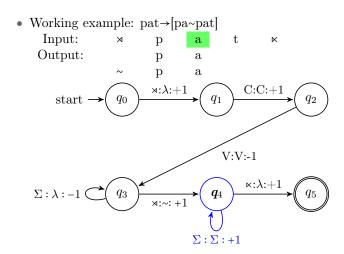


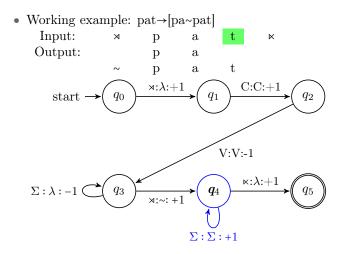


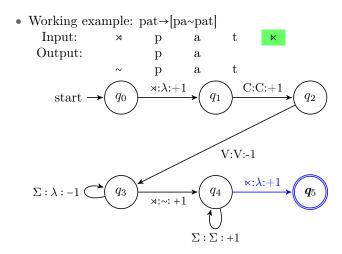
Input: p a t
Output: p a











• Working example: pat→[pa~pat] Input: \mathbf{a} Output: t р a C:C:+1 $\rtimes: \lambda: +1$ V:V:-1 $\kappa:\lambda:+1$ $\Sigma:\lambda:-1$ q_3 ×:~: +1 $\Sigma : \Sigma : +1$

REDUPLICATION WITH 2-WAY FSTS

- How does 2-way FST handle reduplication?
 - \rightarrow look *back* at the input to generate copies
- Increased expressivity, removes limitations...

1. Compact:

no state explosion

2. Expressive:

can do partial and total reduplication

3. Segment alignment:

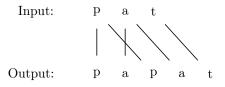
- Output segments are aligned with the 'right' input segments
- Formally, look at origin semantics of how input-output segments align (Bojańczyk, 2014)

SEGMENT ALIGNMENT WITH FSTS

- Origin information: origin of output symbols in the input
- 1-way FSTs remember what to repeat, they don't actively copy



• But linguistic theory says "copy" like a 2-way FST!



LEARNING REDUPLICATION

Reduplication is *provably* learnable in polynomial time and data (Chandlee et al., 2015; Dolatian and Heinz, 2018)

RNNs with segmental inputs cannot be trained as reduplication acceptors (Gasser, 1993; Marcus et al., 1999)

• Recognizing reduplication requires the comparison of static subsequences - difficult for an RNN to store

Encoder-Decoders learn reduplication with a fixed-size reduplicant in a small toy language (Prickett et al., 2018)

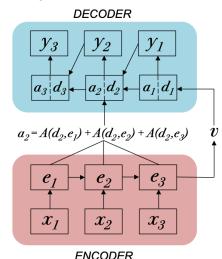
- Generalizable to novel segments and sequences
- Generalization to novel lengths not tested, computable by 1-way FST that uses featural representations

RECURRENCE

- Recurrence relation: The function relating hidden states in the encoder and decoder RNNs - affects practical expressivity of network
- Two types of recurrence tested:
 - ▶ **sRNN** t^{th} state is a nonlinear function of the t^{th} input and state t-1 (Elman, 1990)
 - ▶ **GRU** t^{th} state is a linear function of three functions (gates) of the t^{th} input and state t-1 (Cho et al., 2014)
- Saturating nonlinearities (tanh) sRNNs and GRUs cannot count with finite precision (Weiss et al., 2018)
- LSTM is supra-regular, we are testing necessary properties of RNN and GRU, which are finite-state (Merrill, 2019)

ATTENTION

- In standard ED, the encoded representation is the only link between the encoder and decoder
- Global attention allows the decoder to selectively pull information from hidden states of the encoder (Bahdanau et al., 2014)
- **FLT Analog**: 2-way FST has full access to the input by moving back and forth



Test data

• Input-output mappings generated with 2-way FSTs from RedTyp database²

Initial-CV tasgati→ta~tasgati
 Fixed-size reduplicant
 Initial two-syllable (C*VC*V) tasgati→tasga*tasgati
 Onset maximizing, fixed over vowels
 Total tasgati→tasgati~tasgati
 Variably sized reduplicant

- 10,000 generated for each language, 70/30 train/test split
- Minimum string length 3 maximum string length varied
- Alphabet of 10, 16, or 26 characters
- Boundary symbols (~) are not present

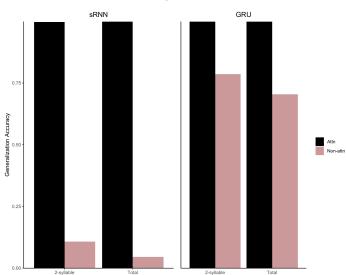
²Dolatian and Heinz (2019); also available on GitHub

EXPERIMENT 1

- Interaction between reduplication type, recurrence, and attention
 - ▶ Total and partial (two-syllable) reduplication
 - sRNN and GRU with and without attention
- Max string length: 9
- 10 symbols alphabet

Attention should improve function generalization across reduplication types and recurrence relations

EXPERIMENT 1

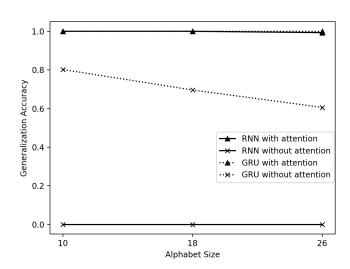


EXPERIMENT 2

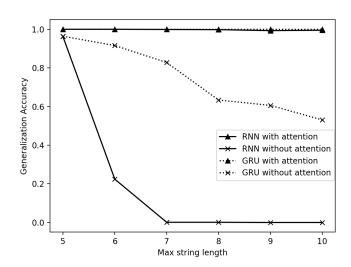
- Effects of alphabet size and range of permitted string lengths
- CV reduplication only
- sRNN/GRU × attention/non-attention × 3 alphabet sizes × 7 length ranges

Network generalization while learning a general reduplication function should be invariant to language composition

EXPERIMENT 2



EXPERIMENT 2

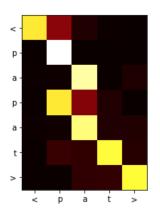


DISCUSSION

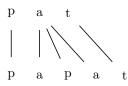
- Networks with global attention learn and generalize all types of reduplication and seem robust to string length and alphabet size
- sRNNs without attention show slightly better generalization of partial reduplication than total reduplication
 - Confound with less attested reduplicant lengths or a bias preferring the regular pattern?
- GRUs perform better than sRNNs across all conditions
 - Without attention not robust to length/alphabet likely learning heuristics that capture most data rather than a general function

Networks that cannot see material in the input multiple times cannot learn generalizable reduplication

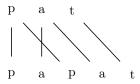
ATTENTION AND ORIGIN SEMANTICS

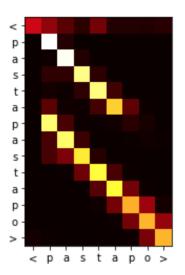


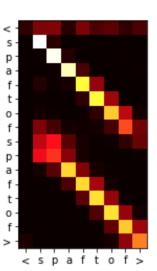
1-Way:



2-Way:







SUMMARY

1. Why use reduplication functions?

- properties define fine-grained subregular function classes
- Allows us to test the generalization capacity of neural nets

2. Expressivity of attention

 Attention is necessary and sufficient for robustly learning and generalizing reduplication functions using Encoder-Decoders

3. FST approximations

- Non-attention networks are limited to a single input pass, approximating 1-way FST
- Attention networks can read the input again during decoding, approximating 2-way FST,

4. Attention weights and origin information

- Evidence for approximation comes from attention weights
- ▶ IO correspondence relations mirror origin semantics of 2-way FST
- 5. Next step: trying more copying and non-copying functions

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Guide to Appendix

- Reduplication across FSTs and RNNs [25]
- Harmony Extensions [26]
- Finite-State Automata & Representation Learning [27]
- Learning Reduplication [28]
- Problems with 1-way FSTs for Total Reduplication [29]
- Total reduplication with 2-way FSTs [31]

REDUPLICATION ACROSS FSTS AND RNNS

1-way and 2-way FSTs compute reduplicative functions differently

	1-way	2-way
Strategy?		
How does it reduplicate?	Memorize	Look back
Scaling?		
Is there state explosion	√ ②	X 🙂
Expressive?		
Can it do total reduplication?	X 😊	√ ©
Alignment?		
Does origin information match theory?	X 😊	√ ②
v	T. Control of the Con	

- Strategy creates all additional properties
- Link to RNNs:
 - attention-less EDs compute like 1-way FSTs!
 - ▶ attention-based EDs compute like 2-way FSTs

NEXT: ATTENTION, 2-WAY, AND DETERMINISM

The subregular hierarchy is more subtle

2-way
$$DFT = 2$$
-way $fNFT =$ Regular functions

1-way $fNFT =$ Rational functions

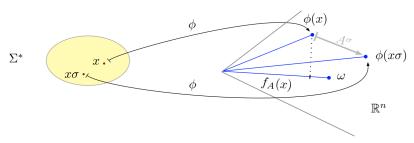
C-Sequential

1-way $DFT =$ Sequential

C-OSL

- Does attention enable non-regularity? Non-determinism?
 - What about $w \to w^3$, $w \to ww^r$, $w \to w^w$, ...
- Idea: Use Harmony processes (Heinz and Lai, 2013)
 - harmony spans subregular hierarchy
 - unattested non-regular harmony (ex. Majority Rules)

FINITE-STATE AUTOMATA & REPRESENTATION LEARNING



- An FSA induces a mapping $\phi: \Sigma^* \to \mathbb{R}$
- The mapping ϕ is compositional
- The output $f_A(x) = \phi(x), \omega$ is linear in $\phi(x)$

LEARNING REDUPLICATION

- Reduplication is *provably* learnable in polynomial time and data (Chandlee et al., 2015; Dolatian and Heinz, 2018)
- RNNs with segmental inputs cannot be trained as reduplication acceptors (Gasser, 1993; Marcus et al., 1999)
 - Recognizing reduplication requires the comparison of static subsequences - difficult for an RNN to store
- Encoder-Decoders learn reduplication with a fixed-size reduplicant in a small toy language (Prickett et al., 2018)
 - Generalizable to novel segments and sequences
 - Generalization to novel lengths not tested, computable by 1-way FST that uses featural representations

PROBLEMS WITH 1-WAY FSTS FOR TOTAL

- 1-way FSTs can do Partial RED inelegantly
- Total reduplication **cannot** be modeled at all.
- Why?
 - copied portion has unbounded size
 - ▶ 1-way FST can't do that!
 - ▶ needs an infinite # of states

PROBLEMS WITH 1-WAY FSTS FOR TOTAL

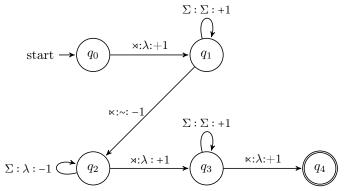
- Total reduplication **cannot** be modeled at all.
- Can you approximate?
 - some finite-state approximations exist...³
 - But: they impose un-linguistic restrictions (e.g. a finite bound on word size,...) so don't directly capture reduplication
- Give up on finite-state?
 - ► MCFGs, HPSG, pushdown accepters with queues⁴
 - ▶ But... those are recognizers not transducers

³Hulden (2009); Beesley and Karttunen (2003); Walther (2000)

⁴Albro (2005); Crysmann (2017); Savitch (1989)

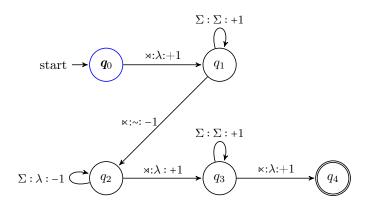
- Total reduplication copies an unbounded size
 - (3) wanita→wanita~wanita 'woman'→'women' (Indo.)

- Total reduplication copies an unbounded size
 - (4) wanita→wanita 'woman'→'women' (Indo.)
- This 2-way FST reads the input left to right (+1), goes back (-1), and reads the input again (+1)



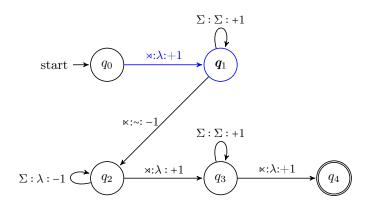
- Indonesian example: wanita-wanita
- Working example: by \rightarrow ?

- Indonesian example: wanita-wanita
- Working example: bye→bye~bye



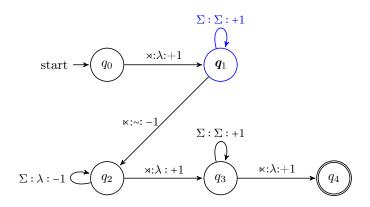
- \bullet Indonesian example: wanita \rightarrow wanita
- Working example: bye→bye~bye

Input: b y e ×
Output:



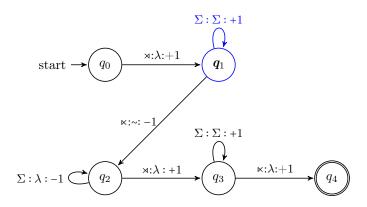
- Working example: bye→bye~bye

Input: × b y e × Output: b



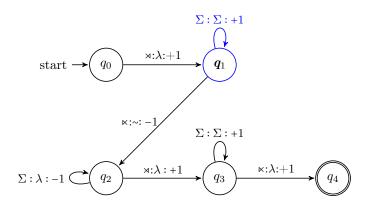
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Input: × b y e × Output: b y



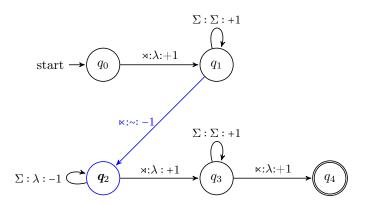
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- Working example: bye→bye~bye

Input: \times b y e \times Output: b y e



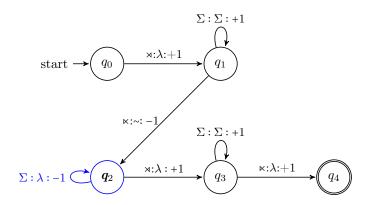
- Indonesian example: wanita-wanita
- Working example: bye→bye~bye

Input: \times b y e \sim Output: b y e \sim



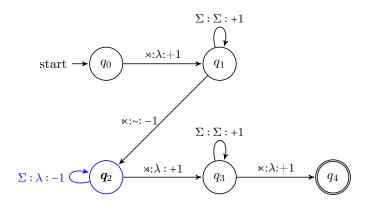
- \bullet Indonesian example: wanita \rightarrow wanita
- Working example: bye→bye~bye

Input: \times b y e \times Output: b y e



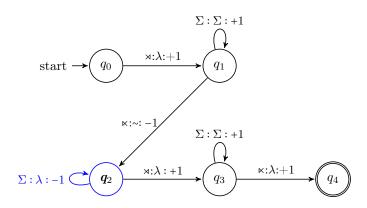
- Indonesian example: wanita-wanita
- Working example: bye→bye~bye

Input: \times b y e \times Output: b y e \sim



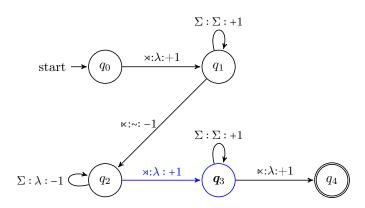
- \bullet Indonesian example: wanita \rightarrow wanita
- Working example: bye→bye~bye

Input: \times b y e \times Output: b y e \sim

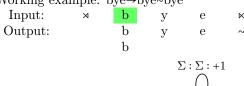


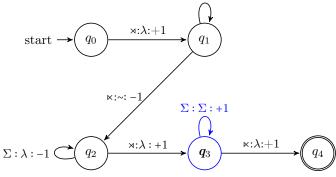
- \bullet Indonesian example: wanita \rightarrow wanita
- Working example: bye→bye~bye

Input: \nearrow b y e \nearrow Output: b y e \sim

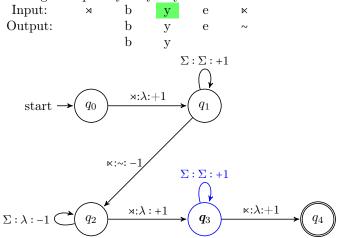


- Indonesian example: wanita-wanita
- Working example: bye→bye~bye

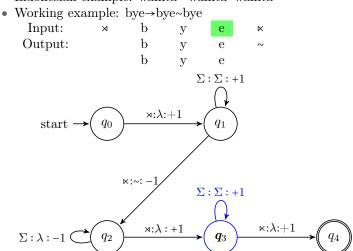




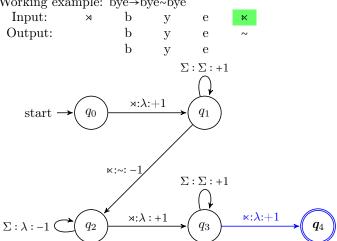
- Indonesian example: wanita-wanita
- Working example: bye→bye~bye



• Indonesian example: wanita-wanita



- Indonesian example: wanita-wanita
- Working example: bye→bye~bye



- Indonesian example: wanita-wanita
- Working example: bye→bye~bye

