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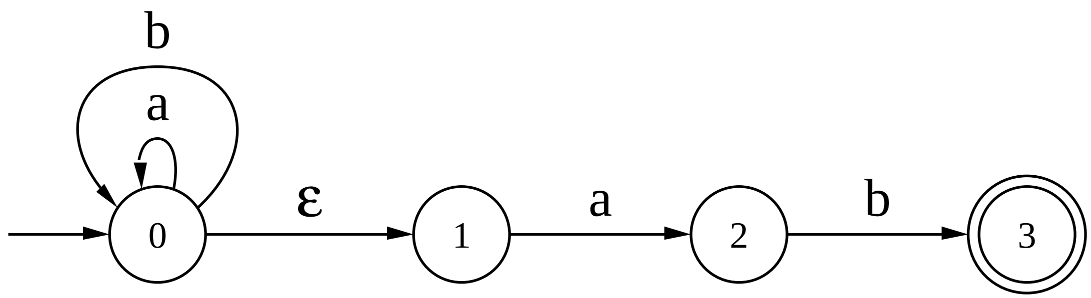
Finite-State Techniques for Speech Recognition

- motivation
- definitions
  - finite-state acceptor (FSA)
  - finite-state transducer (FST)
  - deterministic FSA/FST
  - weighted FSA/FST
- operations
  - closure, union, concatenation
  - intersection, composition
  - epsilon removal, determinization, minimization
- on-the-fly implementation
- FSTs in speech recognition: recognition cascade
- research systems within SLS impacted by FST framework
- conclusion

Motivation

- many speech recognition components/constraints are finite-state
  - language models (e.g., n-grams, on-the-fly CFGs)
  - lexicons
  - phonological rules
  - N-best lists
  - word graphs
  - recognition paths
- should use same representation and algorithms for all
  - consistency
  - make powerful algorithms available at all levels
  - flexibility to combine or factor in unforeseen ways
- AT&T [Pereira, Riley, Ljolje, Mohri, et al.]

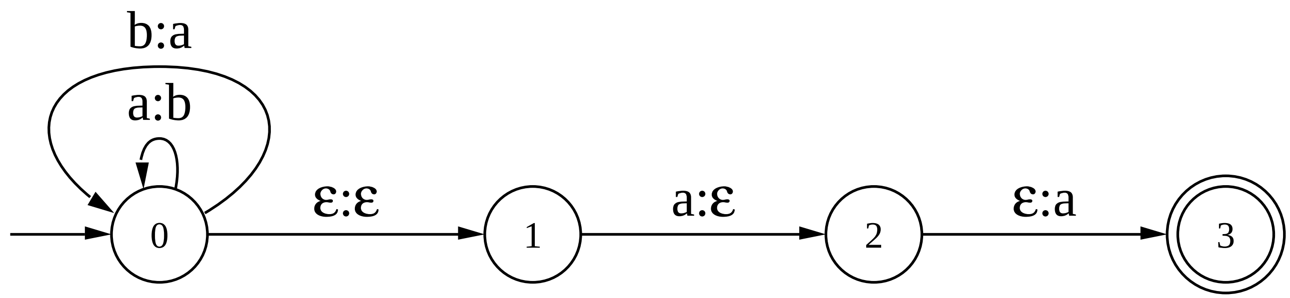
Finite-State Acceptor (FSA)



accepts $(a|b)^*ab$

- definition:
  - finite number of states
  - one initial state
  - at least one final state
  - transition labels:
    - label from alphabet Σ must match input symbol
    - ϵ consumes no input
- accepts a regular language

Finite-State Transducer (FST)

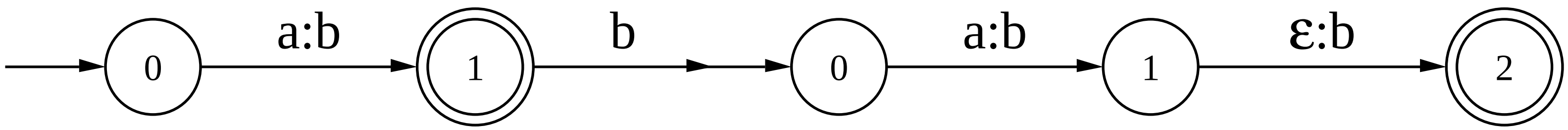


e.g., $(aba)a \to (bab)a$

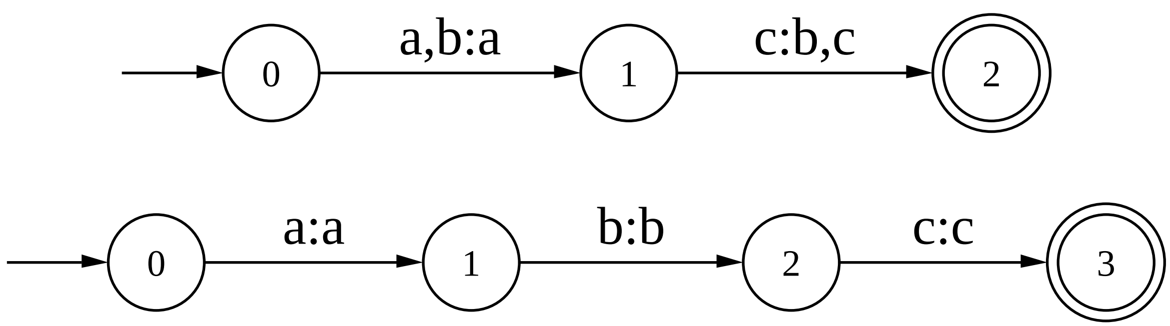
- definition, like FSA except:
  - transition labels:
    - *pairs* of input:output labels
    - ϵ on input consumes no input
    - ϵ on output produces no output
- relates input sequences to output sequences (maybe ambiguous)
- FST with labels x:x is an FSA

Finite-State Transducer (FST)

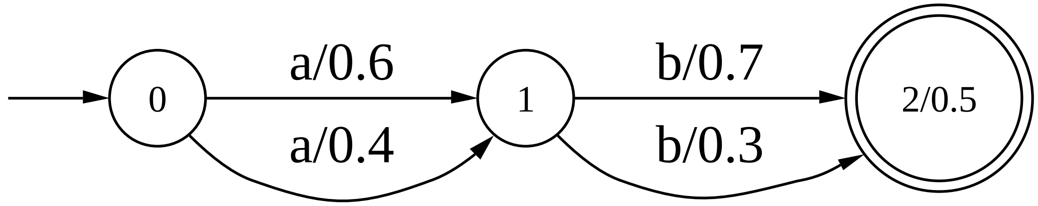
- final states can have outputs, but we use ϵ transitions instead



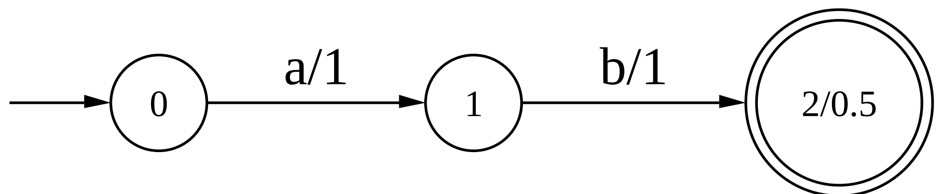
- transitions can have multiple labels, but we split them up



Weights

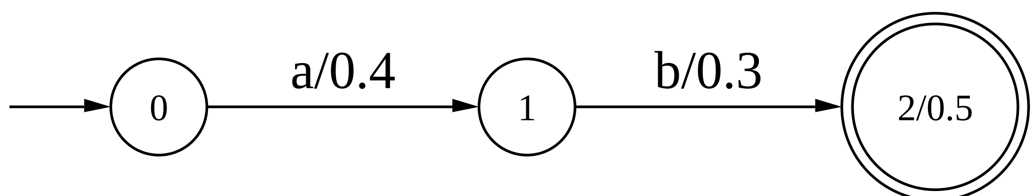


- transitions and final states can have weights (costs or scores)
- weight *semirings* $(\oplus, \otimes, \mathbf{0}, \mathbf{1})$, $\oplus \sim$ parallel, $\otimes \sim$ series:
  - $\mathbf{0} \oplus x = x$, $\mathbf{1} \otimes x = x$, $\mathbf{0} \otimes x = \mathbf{0}$, $\mathbf{0} \otimes \mathbf{1} = \mathbf{0}$
  - $(+, \times, 0, 1) \sim$ probability (sum parallel, multiply series)



$ab/0.5$

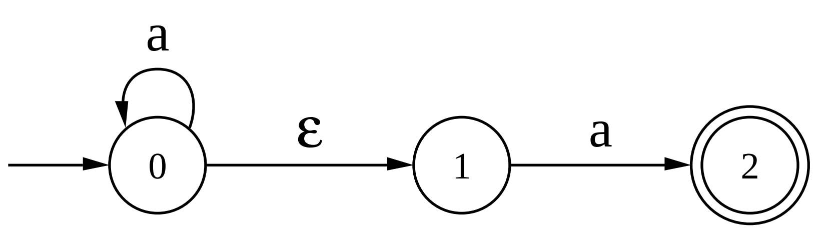
  - $(\min, +, \infty, 0) \sim -\log$ probability (best of parallel, sum series)



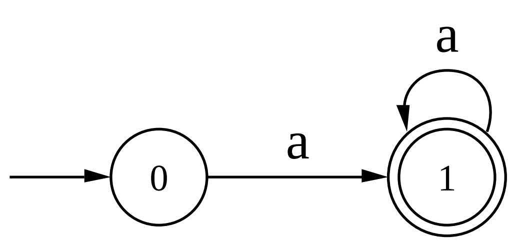
$ab/1.2$

Deterministic FSA or FST

- input sequence uniquely determines state sequence
- no ϵ transitions
- at most one transition per label for all states



non-deterministic (NFA)

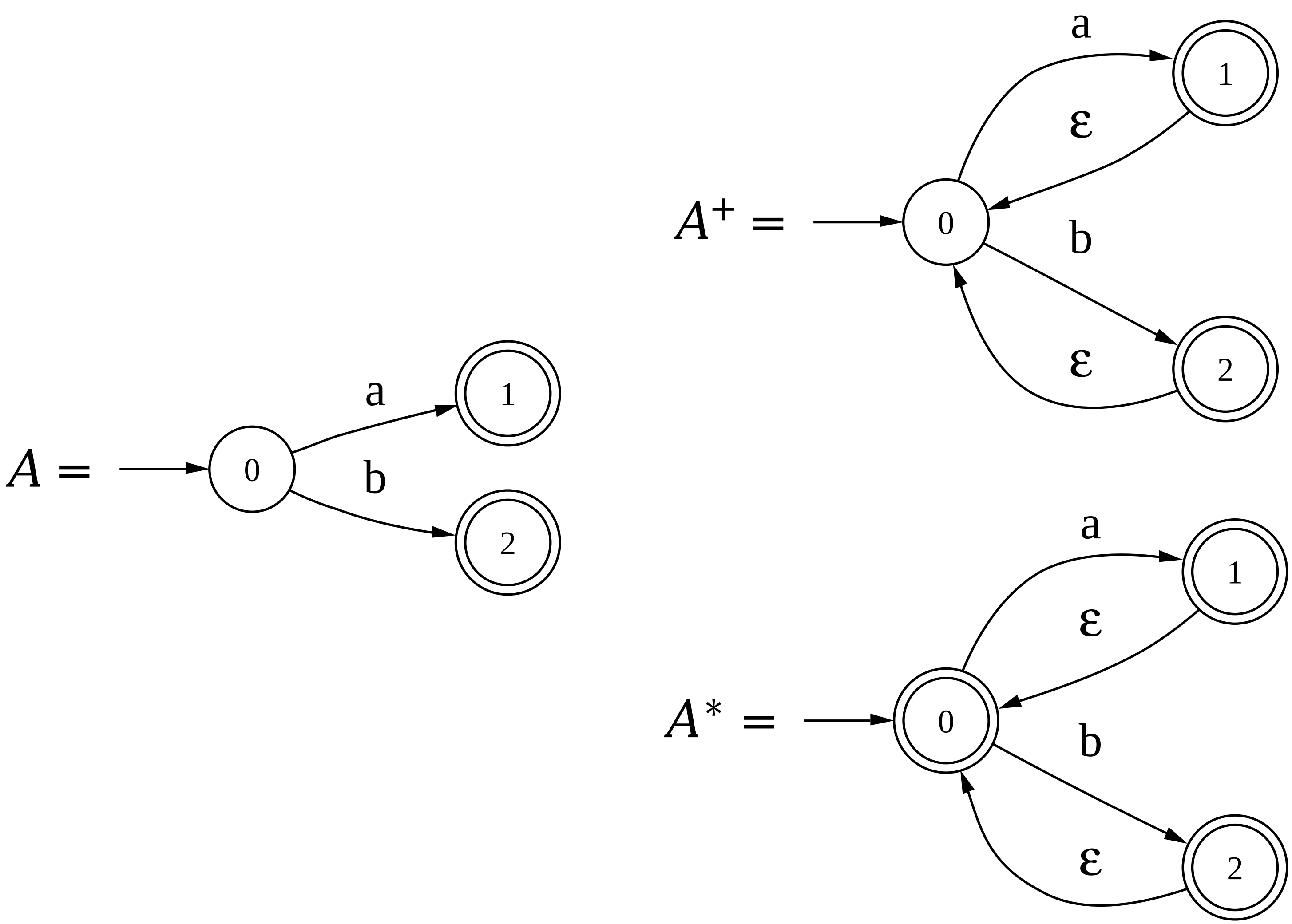


deterministic (DFA)

Operations

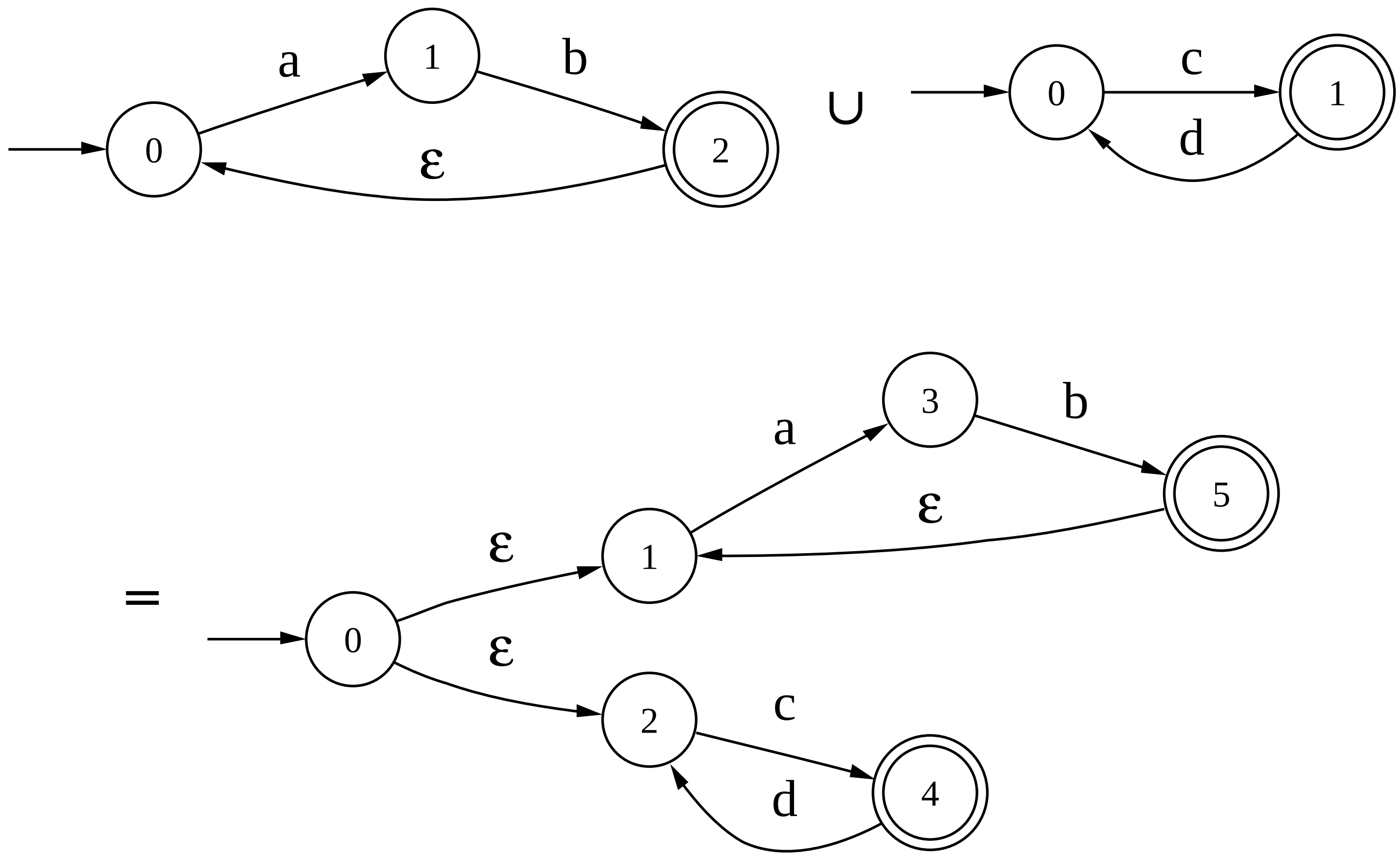
- constructive operations:
  - closure A^* and A^+
  - union $A \cup B$
  - concatenation AB
  - complementation $\overline{A}$ (FSA only)
  - intersection $A \cap B$ (FSA only)
  - composition $A \circ B$ (FST only, FSA $\equiv \cap$)
- identity operations (optimization):
  - epsilon removal
  - determinization
  - minimization

Closure: A^+, A^*



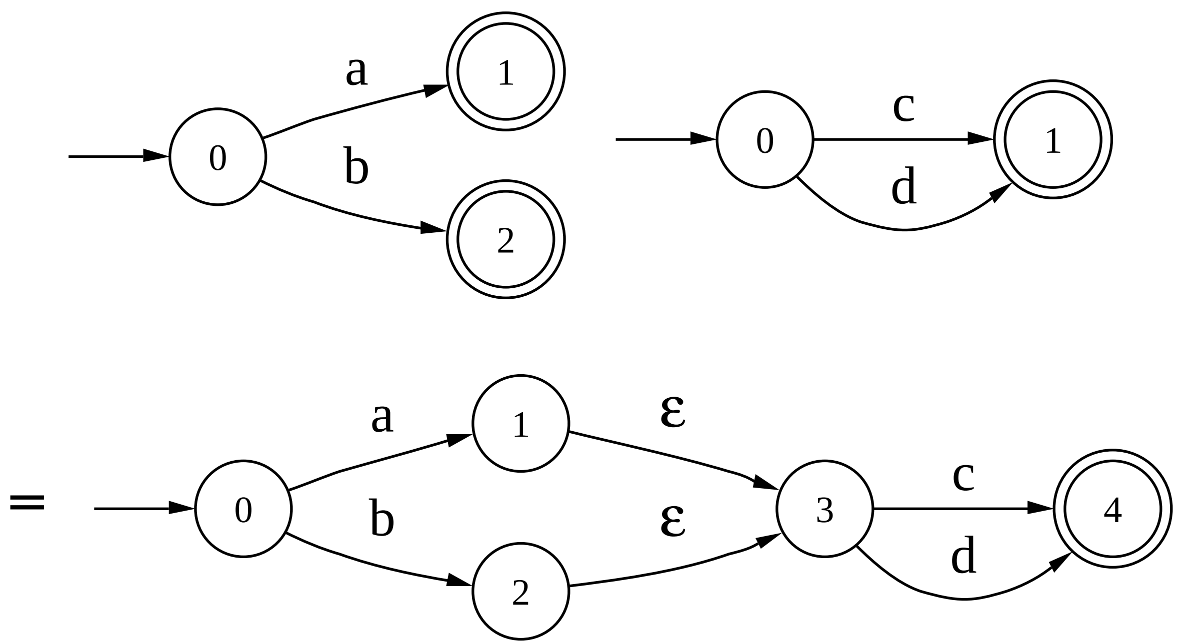
Union: $A \cup B$

parallel combination, e.g.,



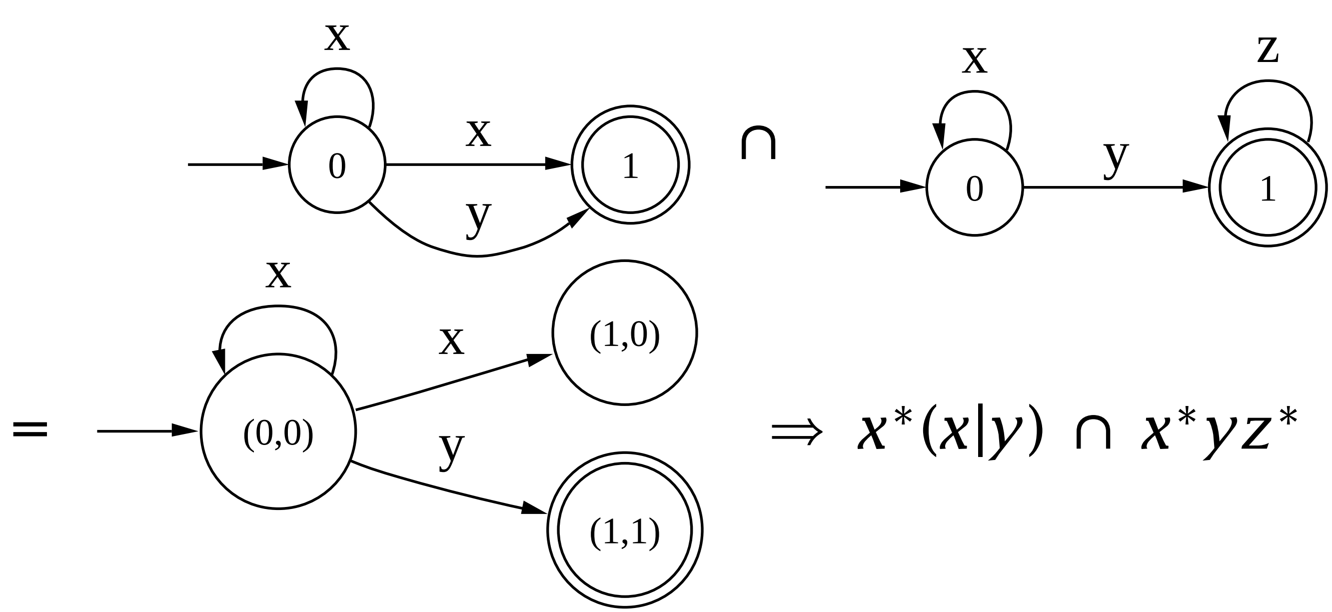
Concatenation: *AB*

serial combination, e.g.,



FSA Intersection: $A \cap B$

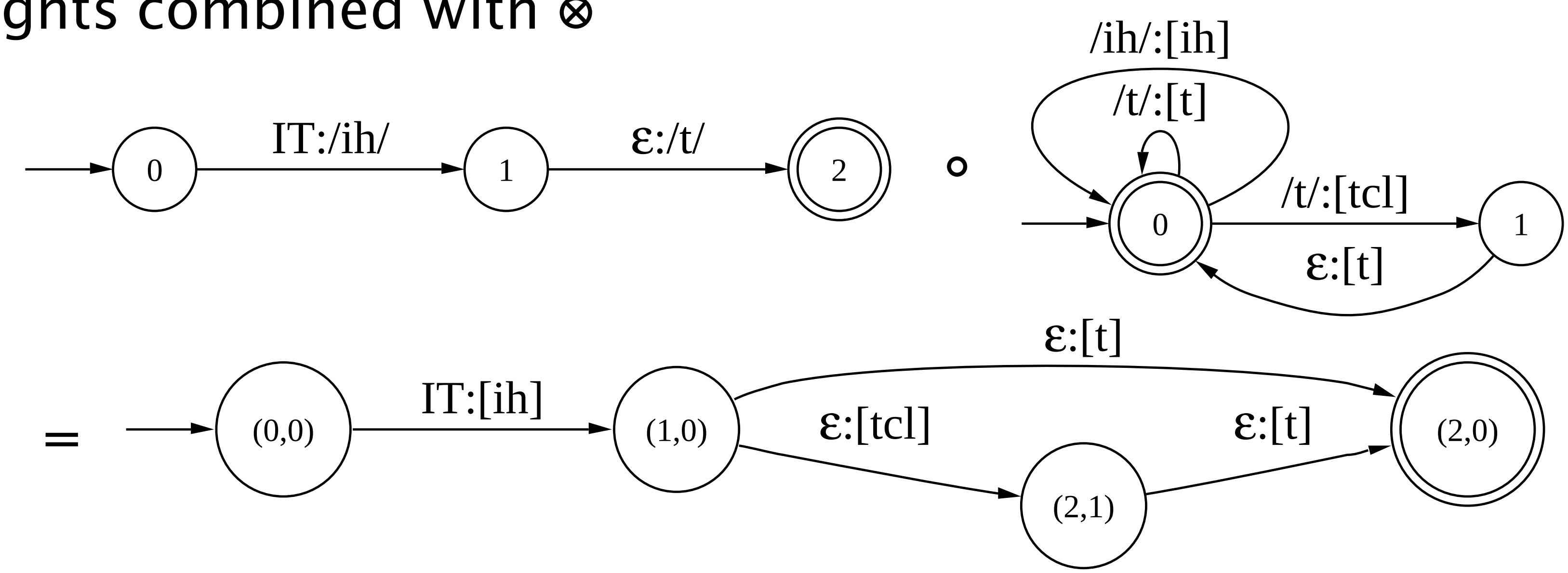
- output states associated with input state pairs (a, b)
- output state is final only if both a and b are final
- transition with label x only if both a and b have x transition
- weights combined with $\otimes$



$$\Rightarrow x^*(x|y) \cap x^*yz^* = x^*y$$

FST Composition: $A \circ B$

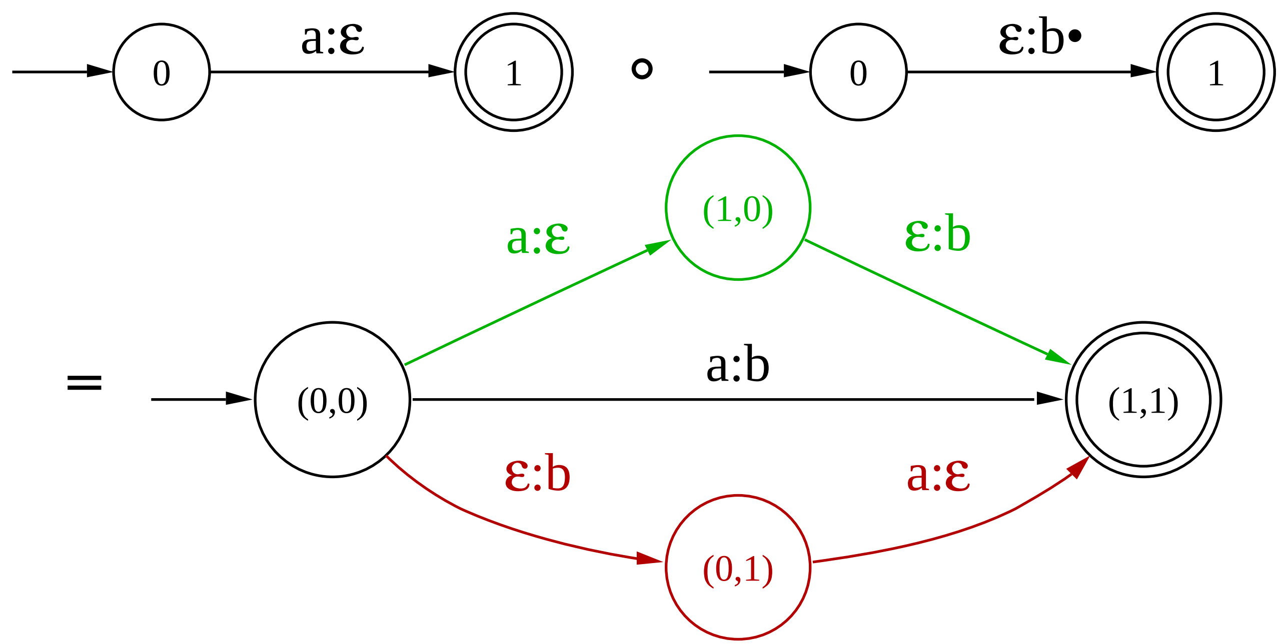
- output states associated with input state pairs (a, b)
- output state is final only if both a and b are final
- transition with label x:y only if a has x:α and b has α:y transition
- weights combined with $\otimes$



- (words → phonemes) ∘ (phonemes → phones) = (words → phones)

FST Composition: ϵ Interaction

- A output ϵ allows B to hold
- B input ϵ allows A to hold



- multiple paths typically filtered (resulting in dead end states)

FST Composition: Parsing

- language model from JSGF grammar compiled into on-the-fly recursive transition network (RTN) transducer G:

```
<top> = <forecast> | <conditions> | ... ;
<forecast> = [what is the] forecast for <city> {FORECAST};
<city> = boston [massachusetts] {BOS}
       | chicago [illinois] {ORD};
```

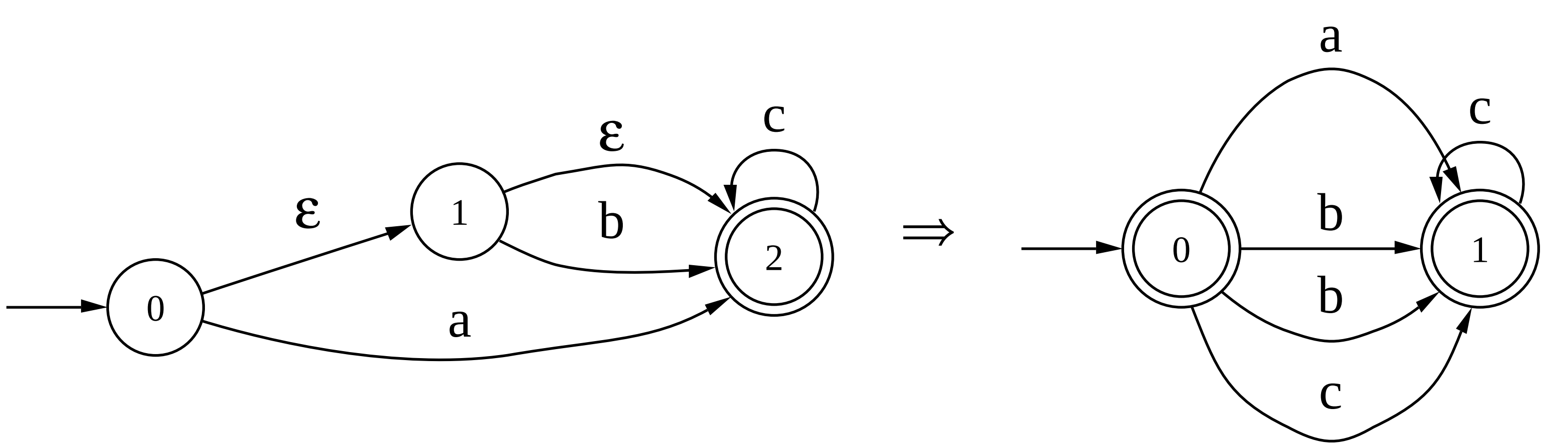
- "what is the forecast for boston" $\circ\ G \ \rightarrow$
  - BOS FORECAST *output tags only*
  - <forecast> what is the forecast for <city> boston </city> </forecast> *bracketed parse*

FST Composition Summary

- very powerful operation
- can implement other operations:
  - intersection
  - application of rules/transformations
  - instantiation
  - dictionary lookup
  - parsing

Epsilon Removal (Identity)

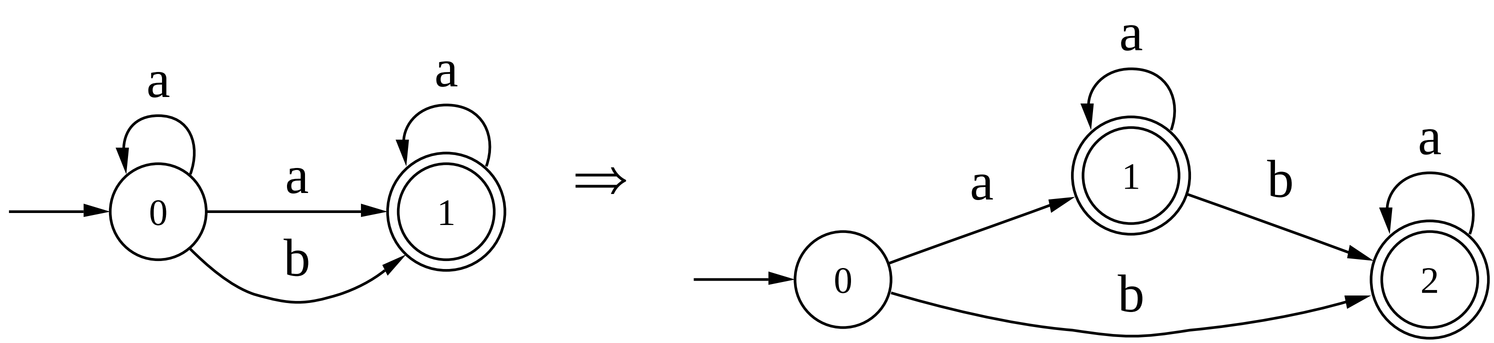
- required for determinization
- compute ϵ-closure for each state: set of states reachable via ϵ^*



- can dramatically increase number of transitions (copies)

FSA Determinization (Identity)

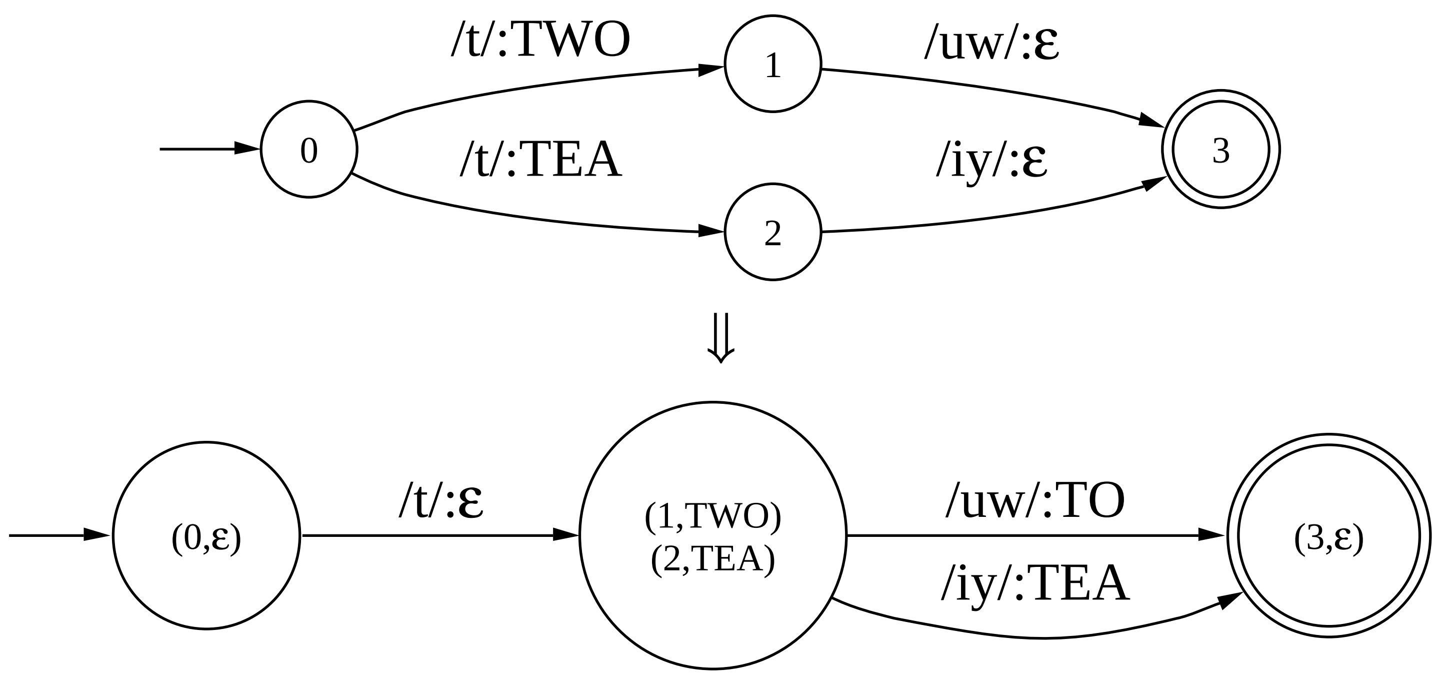
- subset construction
  - output states associated with *subsets* of input states
  - treat a subset as a superposition of its states
- worst case is exponential (2^N)
- locally optimal: each state has at most $|\Sigma|$ transitions



- weights: subsets of (state, weight)
  - weights might be delayed
  - transition weight is ⊕ subset weights
  - worst case is infinite (not common)

FST Determinization (Identity)

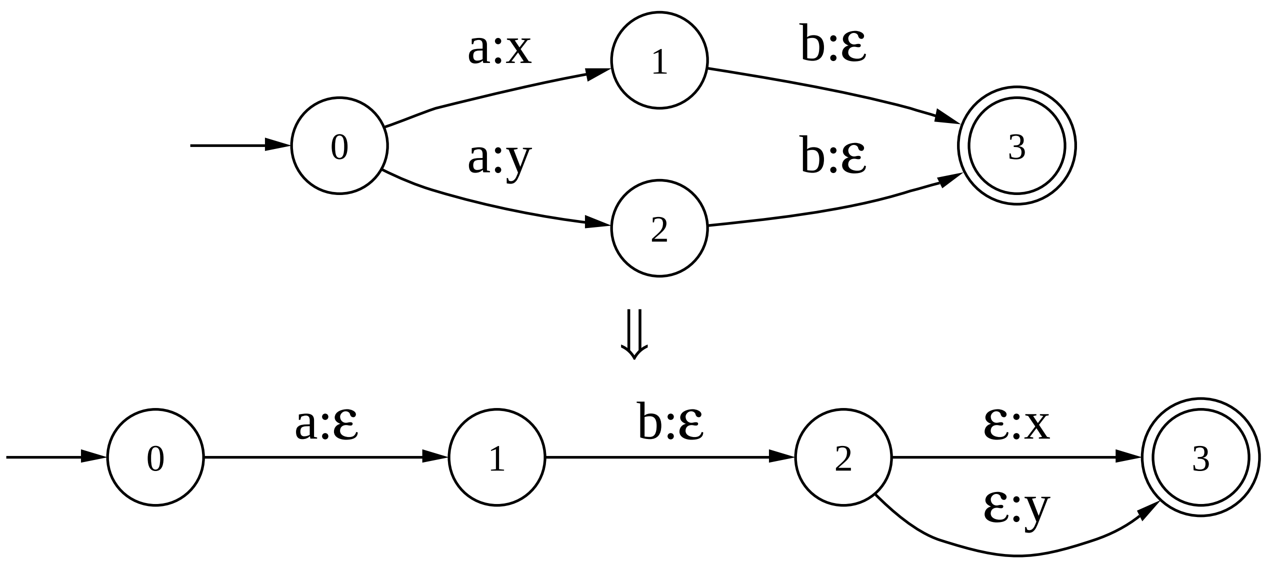
- subsets of (state, output*, weight)
- outputs and weights might be delayed
- transition output is least common prefix of subset outputs



- worst case is infinite (not uncommon due to ambiguity)

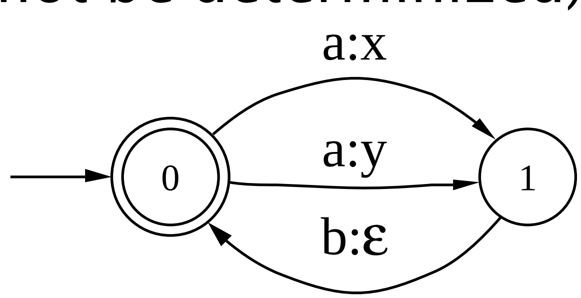
FST Ambiguity

- input sequence maps to more than one output (e.g., homophones)
- finite ambiguity (delayed to output states):

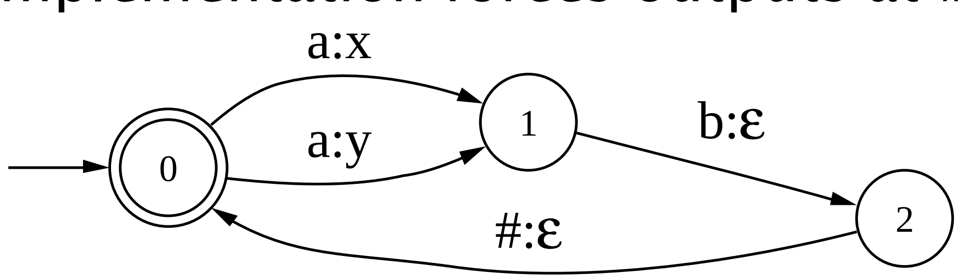


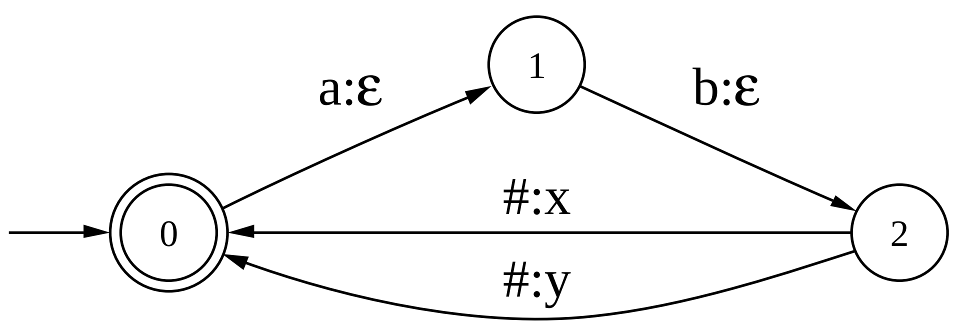
FST Ambiguity

- cycles (e.g., closure) can produce infinite ambiguity
- infinite ambiguity (cannot be determinized):



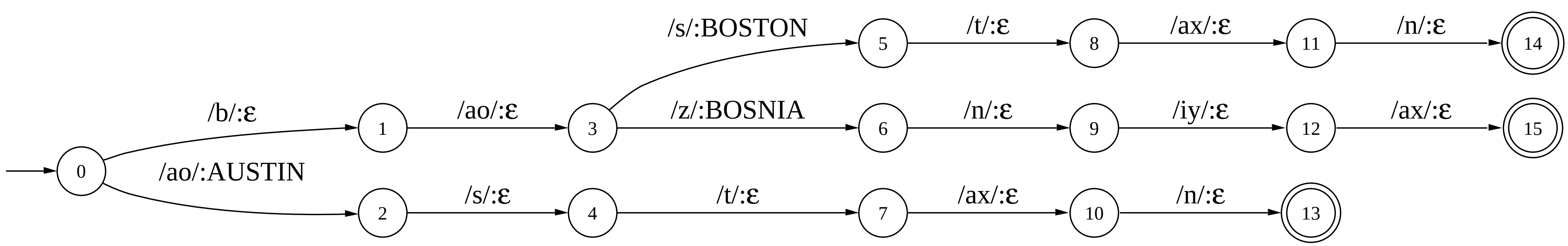
- a solution: our implementation forces outputs at #, a special ϵ

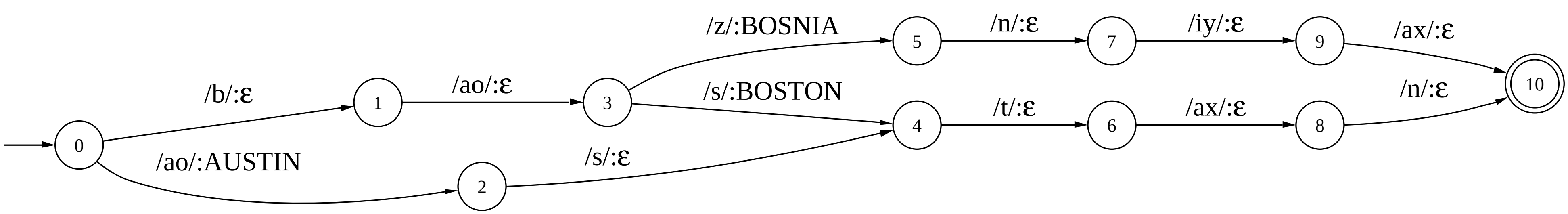




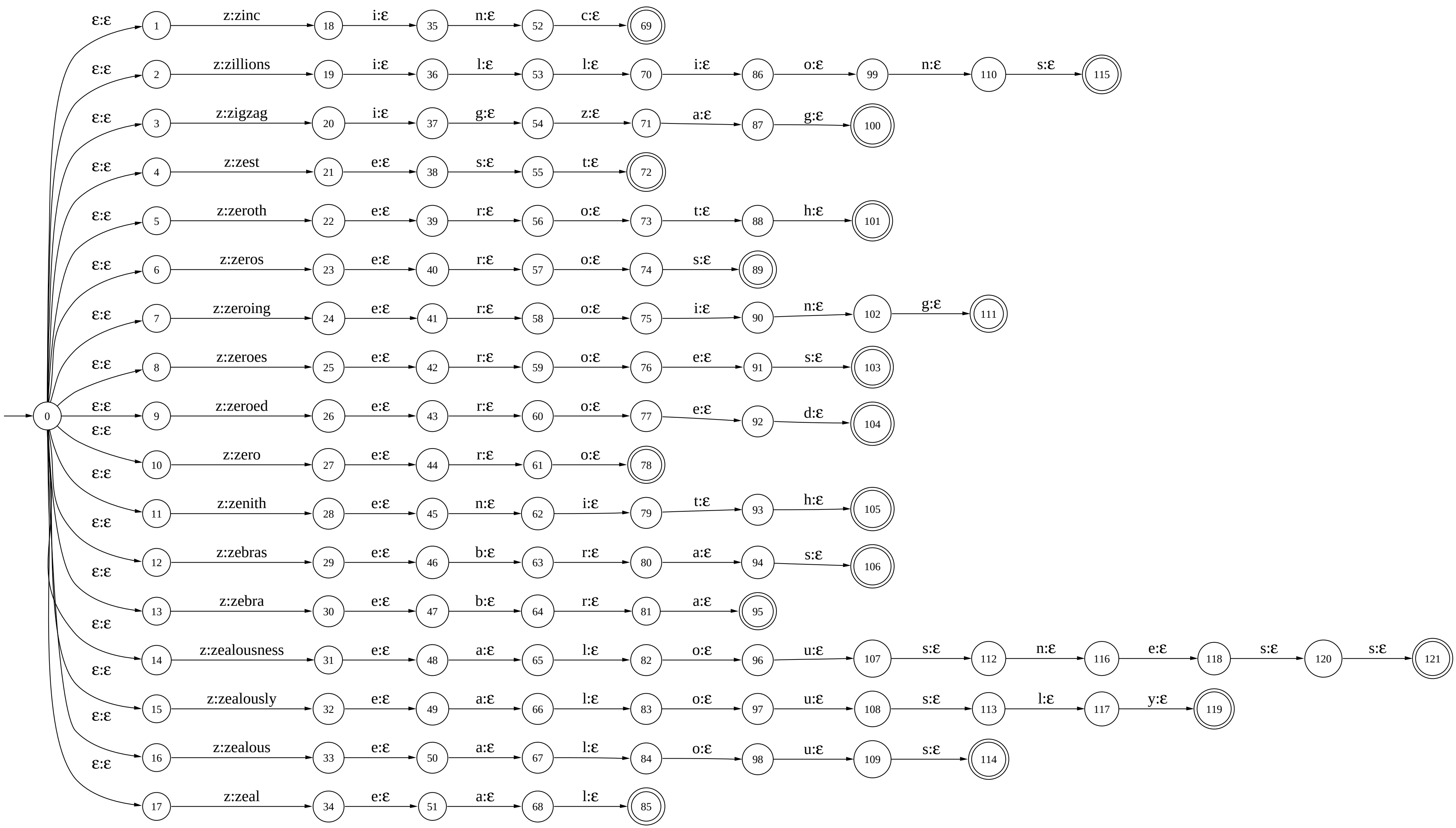
Minimization (Identity)

- minimal $\not\equiv$ minimal number of states
- minimal $\equiv$ deterministic with minimal number of states
- merge *equivalent* states, will not increase size
- cyclic $O(N \log N)$, acyclic $O(N)$

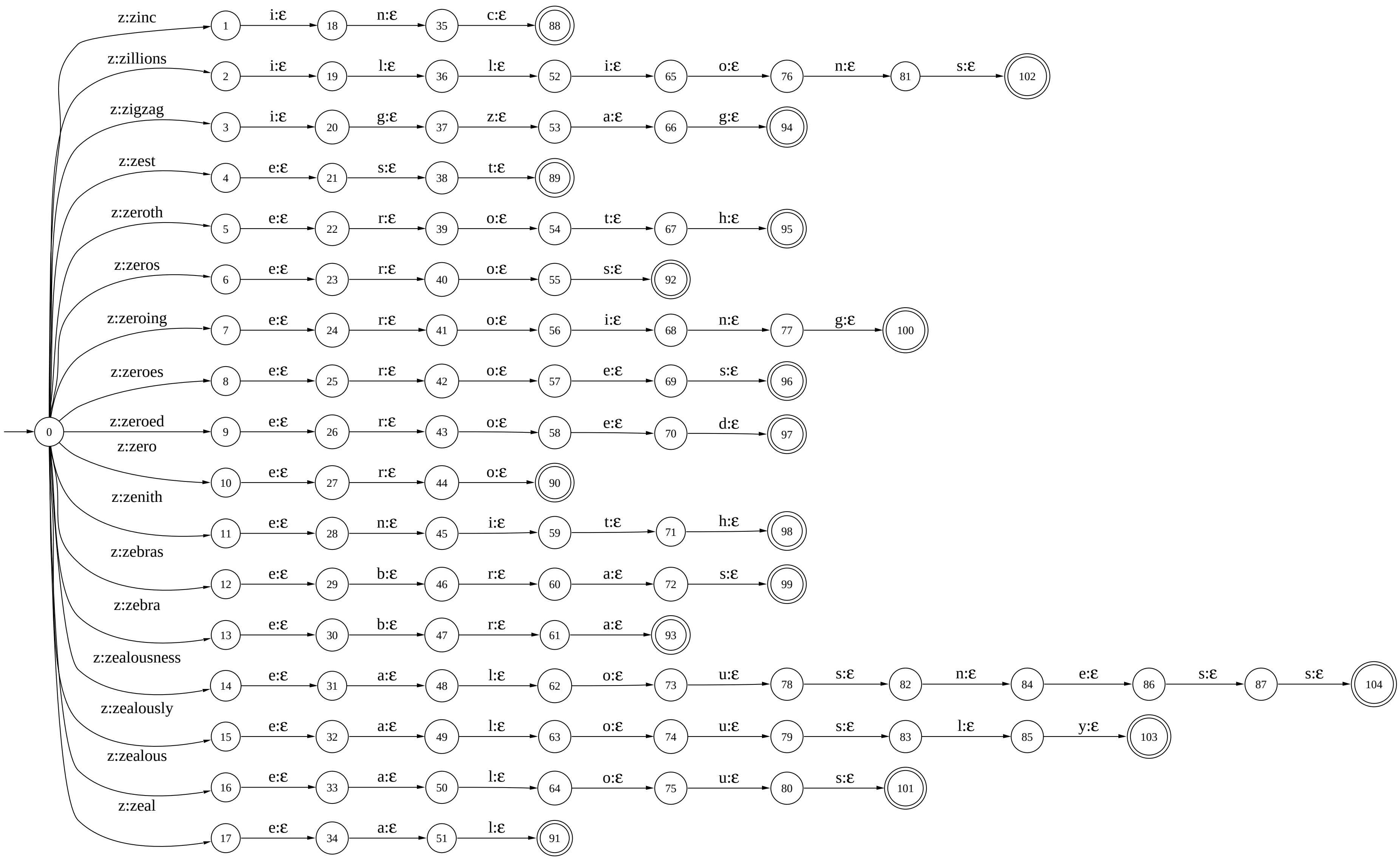




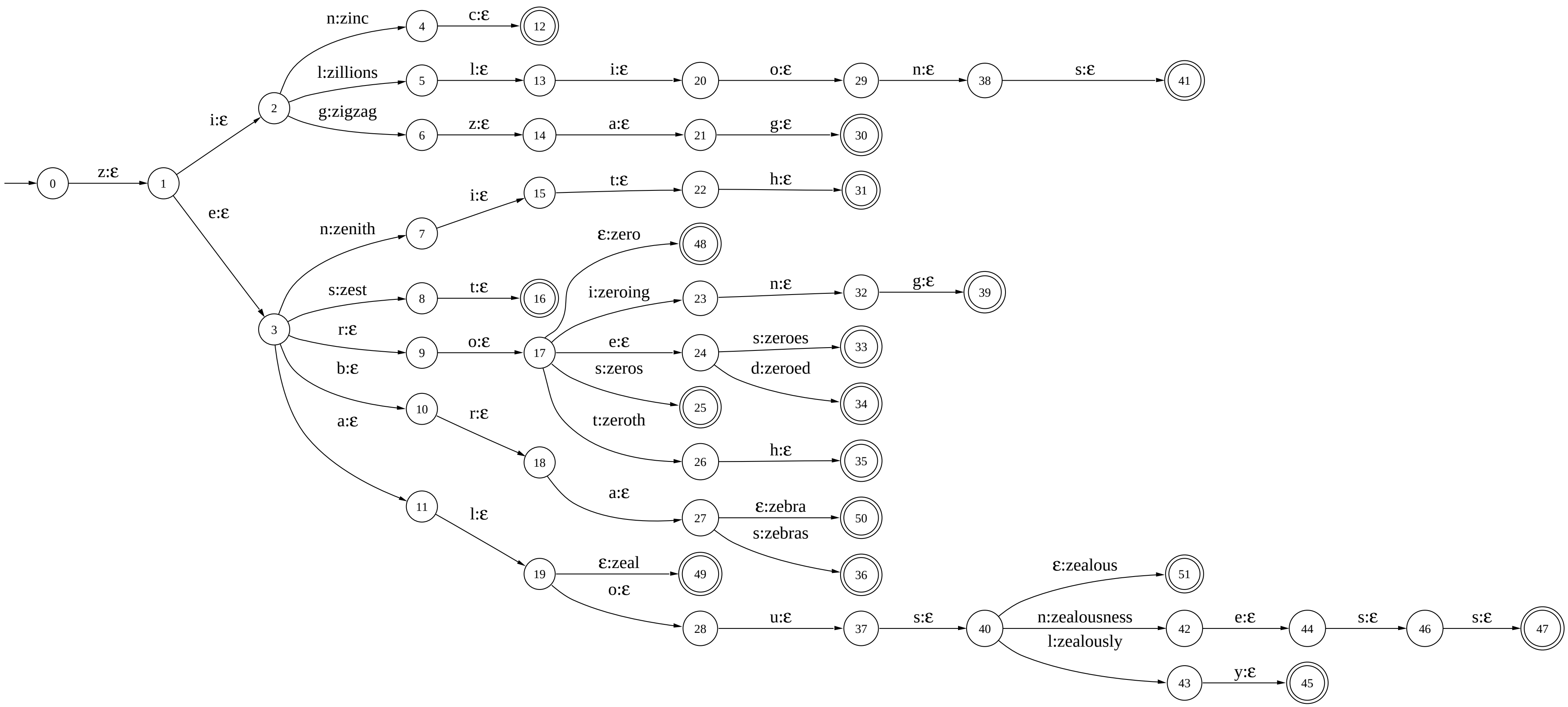
Example Lexicon



Example Lexicon: ϵ Removed

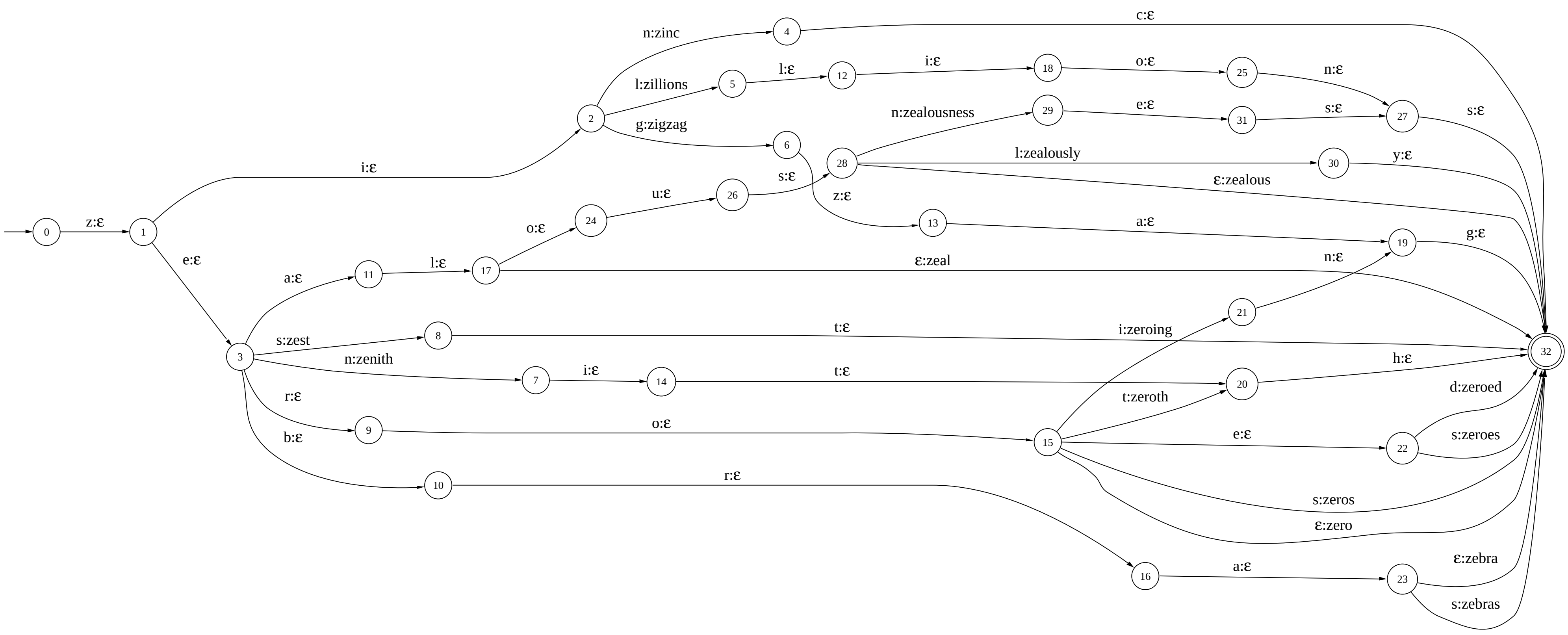


Example Lexicon: Determinized



- lexical tree
- sharing at beginning of words: can prune many words at once

Example Lexicon: Minimized



- sharing at the end of words

On-The-Fly Implementation

- lazy evaluation: generate only relevant states/transitions
- enables use of infinite-state machines (e.g., CFG)
- on-the-fly:
  - composition, intersection
  - union, concatenation, closure
  - ϵ removal, determinization
- not on-the-fly:
  - trimming dead states
  - minimization
  - reverse

FSTs in Speech Recognition

- cascade of FSTs:

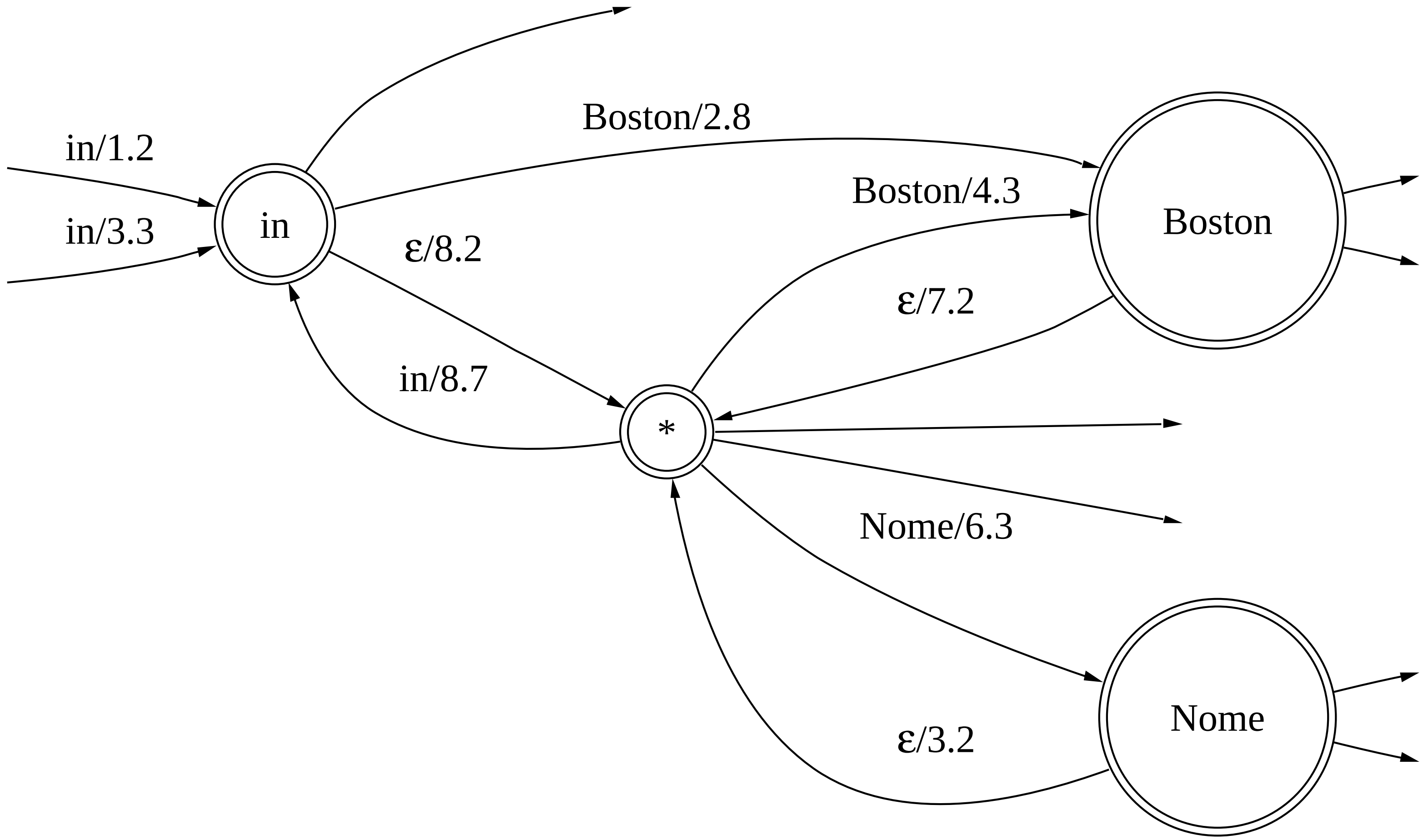
$$(S \circ A) \circ \underbrace{(C \circ P \circ L \circ G)}_{R}$$

  - S: acoustic segmentation*
  - A: application of acoustic models*
  - C: context-dependent relabeling (e.g., diphones, triphones)
  - P: phonological rules
  - L: lexicon
  - G: grammar/language model (e.g., n-gram, finite-state, RTN)

FSTs in Speech Recognition

- in practice:
  - $S \circ A$ is acoustic segmentation with on-demand model scoring
  - $C \circ P \circ L \circ G$: precomputed and optimized or expanded on the fly
  - composition $S \circ A$ with $C \circ P \circ L \circ G$ computed on demand during forward Viterbi search
  - might use multiple passes, perhaps with different G
- advantages:
  - forward search sees a *single* FST $R = C \circ P \circ L \circ G$, doesn't need special code for language models, lexical tree copying, etc...
  - can be very fast
  - easy to do cross-word context-dependent models

N-gram Language Model (G): Bigram



- each distinct word history has its own state
- direct transitions for each existing n-gram
- ϵ transitions to back-off state (*),
  ϵ removal undesirable

Phonological Rules (P)

- segmental system needs to match explicit segments
- ordered rules of the form:

```
{V SV}  b  {V l r w}  =>  bcl [b] ;
{m}     b  {}         =>  [bcl] b ;
{}      b  {}         =>  bcl b   ;

{s}     s  {}         =>  [s]     ;
{}      s  {}         =>  s       ;
```

- rule selection deterministic, rule replacement may be ambiguous
- compile rules into transducer $P = P_l \circ P_r$
  - P_l applied left-to-right
  - P_r applied right-to-left

EM Training of FST Weights

- FSA A_x given set of examples x
  - straightforward application of EM to train $P(x)$
  - our tools can also train an RTN (CFG)
- FST $T_{x:y}$ given set of example pairs $x : y$
  - straightforward application of EM to train $T_{x,y} \Rightarrow P(x, y)$
  - $T_{x|y} = T_{x,y} \circ [\det(T_y)]^{-1} \Rightarrow P(x|y)$ [Bayes' Rule]
- FST $T_{x|y}$ within cascade $S_{v|x} \circ T_{x|y} \circ U_z$ given $v : z$
  - $x = v \circ S$
  - $y = U \circ z$
  - train $T_{x|y}$ given $x : y$
- We have used these techniques to train P, L, and $(P \circ L)$.

Conclusion

- introduced FSTs and their basic operations
- use of FSTs throughout system adds consistency and flexibility
- consistency enables powerful algorithms everywhere
  (write algorithms once)
- flexibility enables new and unforeseen capabilities
  (but enables you to hang yourself too)
- SUMMIT (Jupiter) 25% faster when converted to FST framework,
  yet much more flexible

References

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- M. Mohri, M. Riley, D. Hindle, A. Ljolje, F. Pereira, “Full expansion of context-dependent networks in large vocabulary speech recognition”, in Proc. ICASSP, Seattle, 1998.