Algorithms for Speech Recognition and Language Processing

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Introduction (1)

Text and speech processing: hard problems

- Theory of automata
- Appropriate level of abstraction
- Well-defined algorithmic problems

Introduction (2)

Three Sections:

- Algorithms for text and speech processing (2h)
- Speech recognition (2h)
- Finite-state methods for language processing (2h)

PART I
Algorithms for Text and Speech Processing

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Definitions: finite automata (1)

$A = (\Sigma, Q, \delta, I, F)$

- Alphabet Σ,
- Finite set of states Q,
- Transition function δ: $Q \times \Sigma \to 2^Q$,
- $I \subseteq Q$ set of initial states,
- $F \subseteq Q$ set of final states.

A recognizes $L(A) = \{w \in \Sigma^* : \delta(I, w) \cap F \neq \emptyset\}$
(Hopcroft and Ullman, 1979; Perrin, 1990)

Theorem 1 *(Kleene, 1965). A set is regular (or rational) iff it can be recognized by a finite automaton.*

Definitions: finite automata (2)

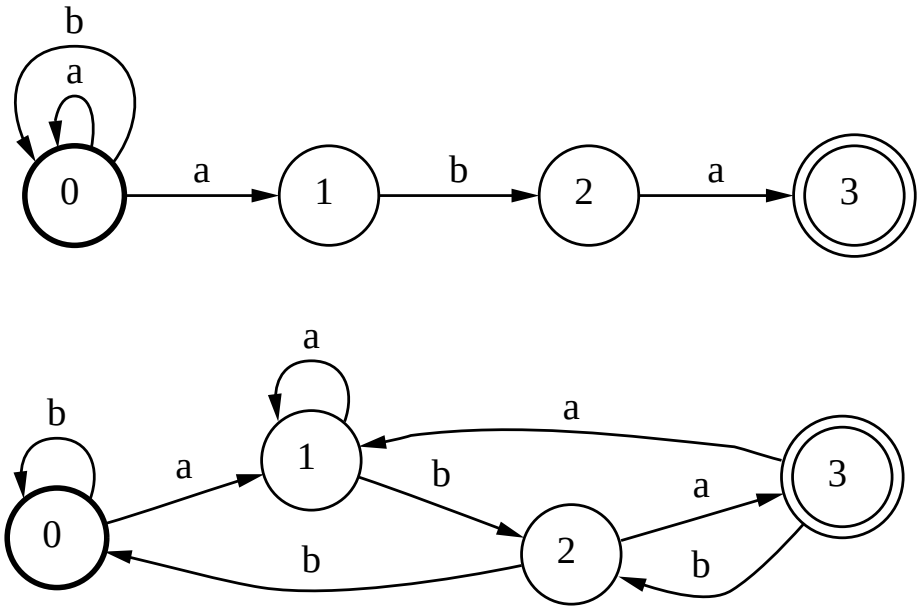

Figure 1: $L(A) = \Sigma^* aba.$

Definitions: weighted automata (1)

$A = (\Sigma, Q, \lambda, \delta, \sigma, \rho, I, F)$

- $(\Sigma, Q, \delta, I, F)$ is an automaton,
- Initial output function λ,
- Output function σ: $Q \times \Sigma \times Q \to K$,
- Final output function ρ,
- Function $f : \Sigma^* \to (K, +, \cdot)$ associated with A:
  $\forall u \in Dom(f), f(u) = \sum_{(i,q) \in I \times (\delta(i,u) \cap F)} (\lambda(i) \cdot \sigma(i, u, q) \cdot \rho(q))$.

Definitions: weighted automata (2)

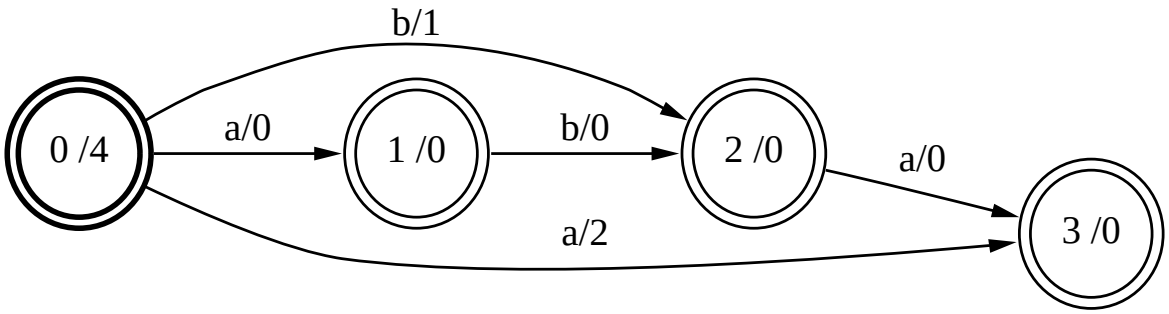

Figure 2: Index of $t = aba$.

Definitions: rational power series

- *Power series*: functions mapping Σ^* to a semiring $(K, +, \cdot)$
  - Notation: $S = \sum_{w \in \Sigma^*} (S, w)w$, (S, w): coefficients
  - Support: $supp(S) = \{w \in \Sigma^* : (S, w) \neq 0\}$
  - Sum: $(S + T, w) = (S, w) + (T, w)$
  - Star: $S^* = \sum_{n \geq 0} S^n$
  - Product: $(ST, w) = \sum_{uv=w \in \Sigma^*} (S, u)(T, v)$
- *Rational power series*: closure under rational operations of polynomials (polynomial power series) (Salomaa and Soittola, 1978; Berstel and Reutenauer, 1988)

Theorem 2 *(Schützenberger, 1961). A power series is rational iff it can be represented by a weighted finite automaton.*

Definitions: transducers (1)

$T = (\Sigma, \Delta, Q, \delta, \sigma, I, F)$

- Finite alphabets Σ and Δ,
- Finite set of states Q,
- Transition function δ: $Q \times \Sigma \to 2^Q$,
- Output function σ: $Q \times \Sigma \times Q \to \Sigma^*$,
- $I \subseteq Q$ set of initial states,
- $F \subseteq Q$ set of final states.

T defines a relation:

$$R(T) = \{(u, v) \in (\Sigma^*)^2 : v \in \bigcup_{q \in (\delta(I,u) \cap F)} \sigma(I, u, q)\}$$

Definitions: transducers (2)

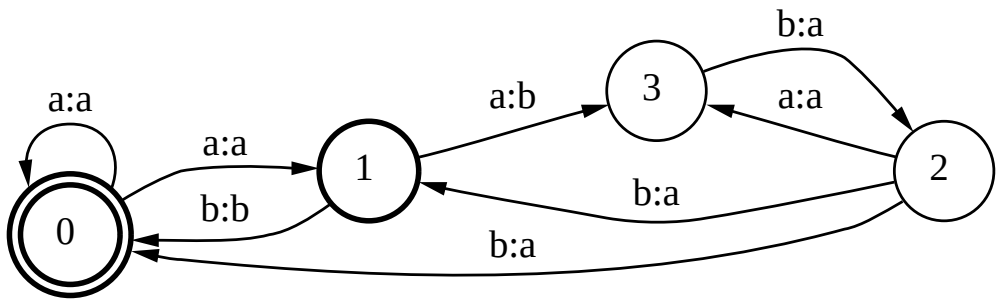

Figure 3: Fibonacci normalizer ($[abb \rightarrow baa] \circ [baa \leftarrow abb]$).

Definitions: weighted transducers

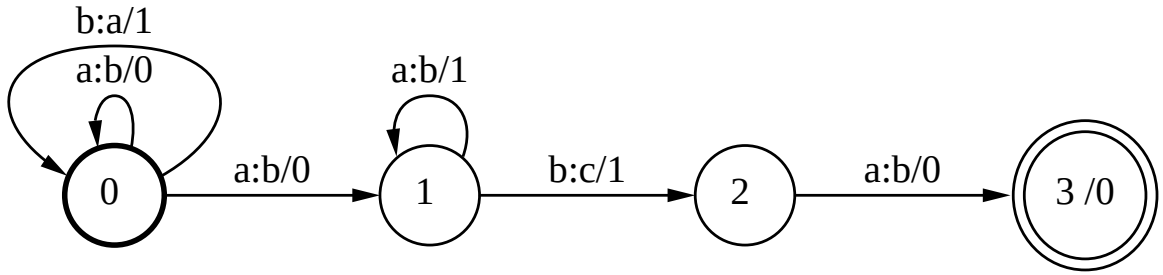

Figure 4: Example, $aaba \rightarrow (bbcb, (0 \odot 0 \odot 1 \odot 0) \oplus (0 \odot 1 \odot 1 \odot 0))$.

$$(\min, +): \quad aaba \rightarrow \min\{1, 2\} = 1$$

$$(+, \cdot): \quad aaba \rightarrow 0 + 0 = 0$$

Composition: Motivation (1)

- Construction of complex sets or functions from more elementary ones
- Modular (modules, distinct linguistic descriptions)
- *On-the-fly* expansion

Composition: Motivation (2)

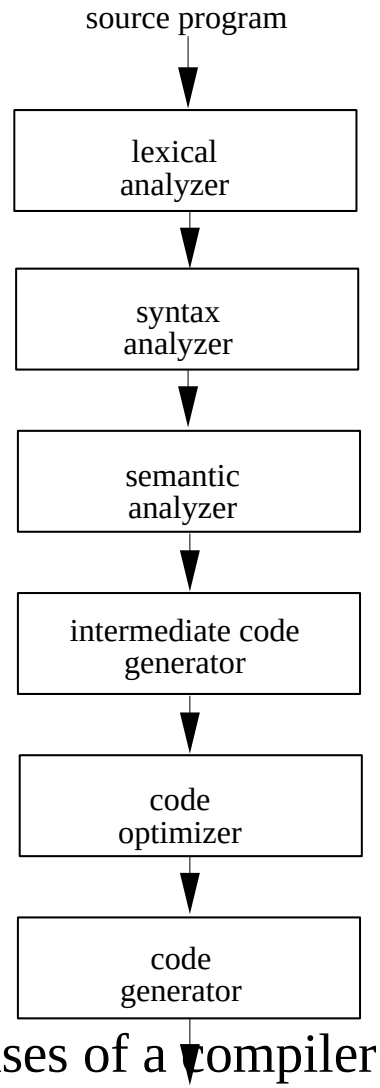

Figure 5: Phases of a compiler (Aho *et al.*, 1986).

Composition: Motivation (3)

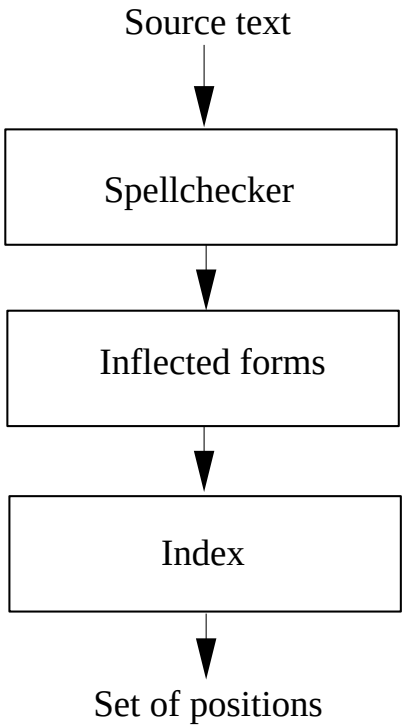

Figure 6: Complex indexation.

Composition: Example (1)

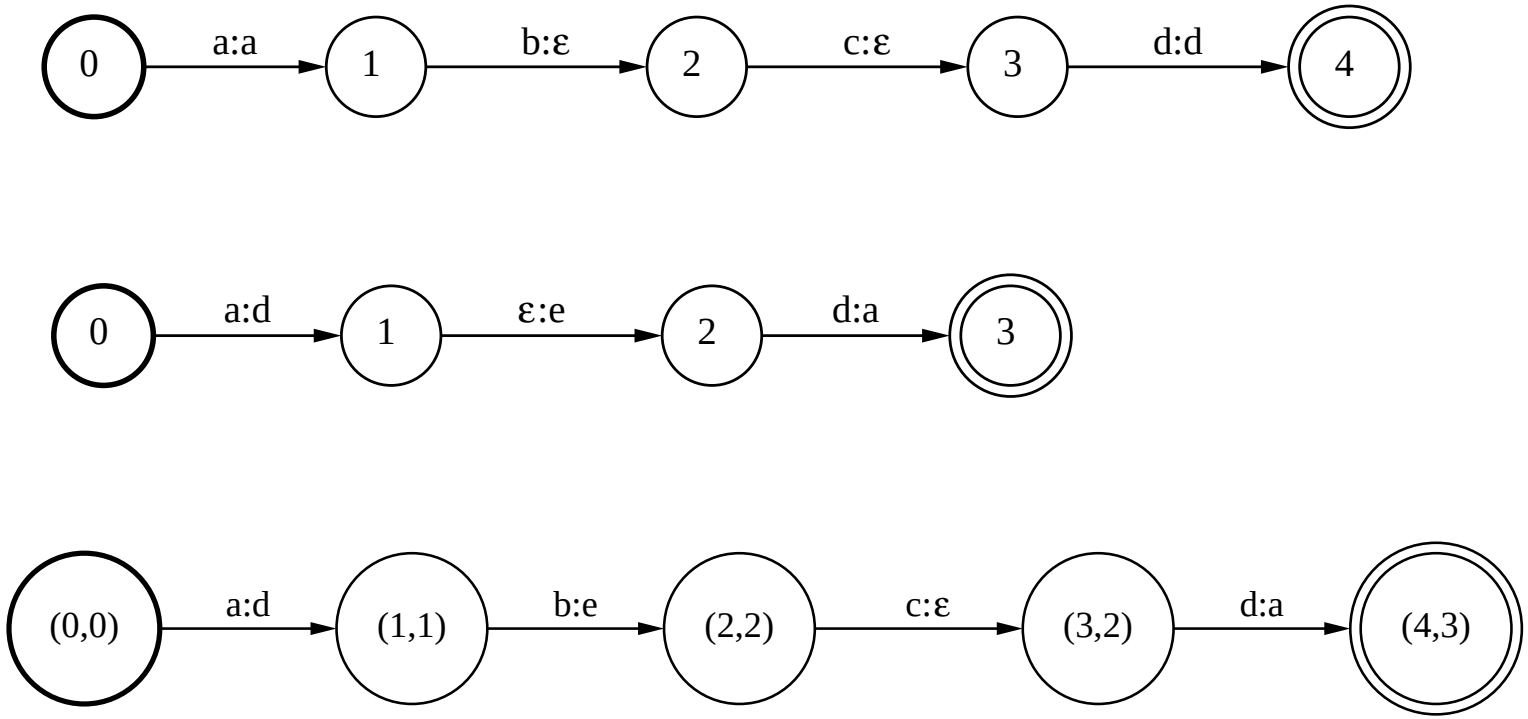

Figure 7: Composition of transducers.

Composition: Example (2)

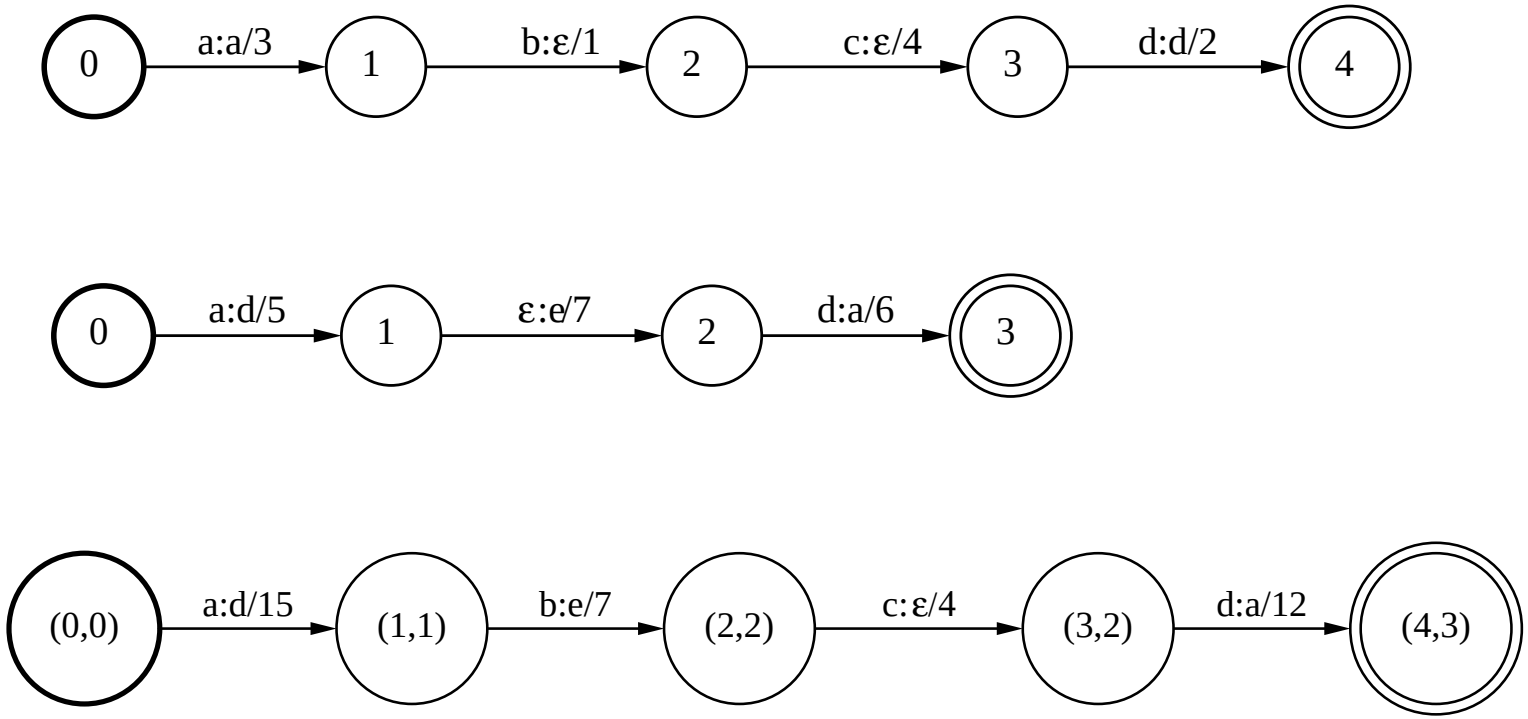

Figure 8: Composition of weighted transducers $(+, \cdot)$.

Composition: Algorithm (1)

- Construction of pairs of states
  - Match: $q_1 \xrightarrow{a:b/w_1} q_1'$ and $q_2 \xrightarrow{b:c/w_2} q_2'$
  - Result: $(q_1, q_2) \xrightarrow{a:c/(w_1 \odot w_2)} (q_1', q_2')$
- Elimination of ϵ-paths redundancy: filter
- Complexity: quadratic
- *On-the-fly* implementation

Composition: Algorithm (2)

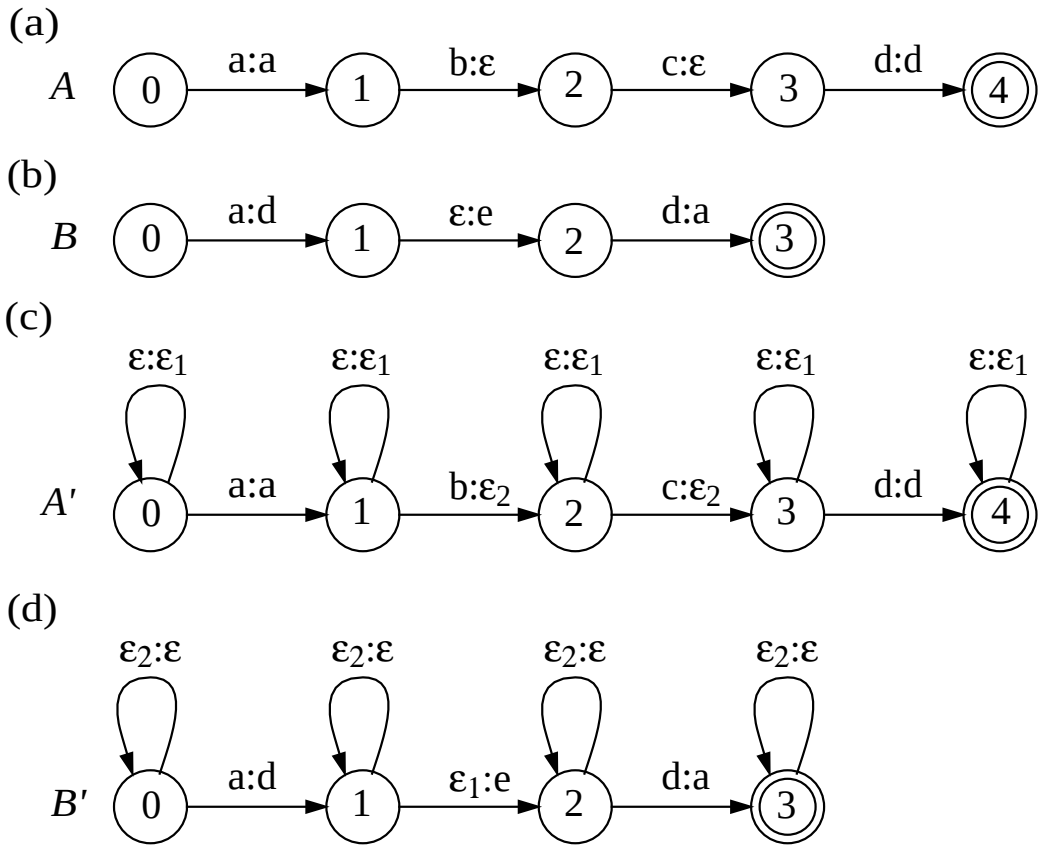

Figure 9: Composition of weighted transducers with ϵ-transitions.

Composition: Algorithm (3)

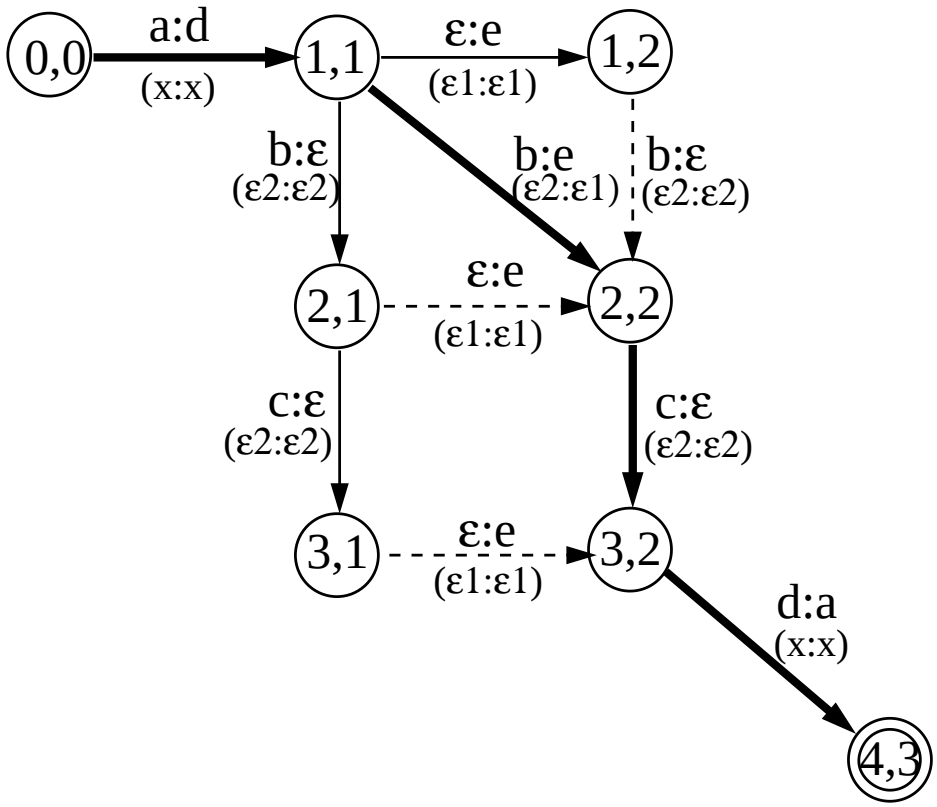

Figure 10: Redundancy of ϵ-paths.

Composition: Algorithm (4)

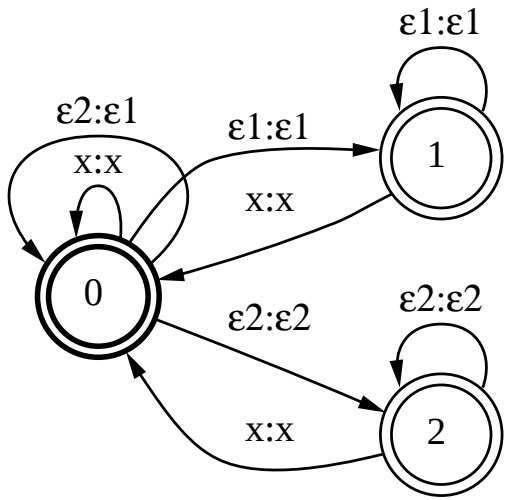

Figure 11: Filter for efficient composition.

Composition: Theory

- Transductions (Elgot and Mezei, 1965; Eilenberg, 1974 1976; Berstel, 1979).
- **Theorem 3** *Let τ_1 and τ_2 be two (weighted) (automata + transducers), then $(\tau_1 \circ \tau_2)$ is a (weighted) (automaton + transducer).*
- Efficient composition of weighted transducers (Mohri, Pereira, and Riley, 1996).
- Works with any semiring
- Intersection: composition of automata (weighted).

Intersection: Example

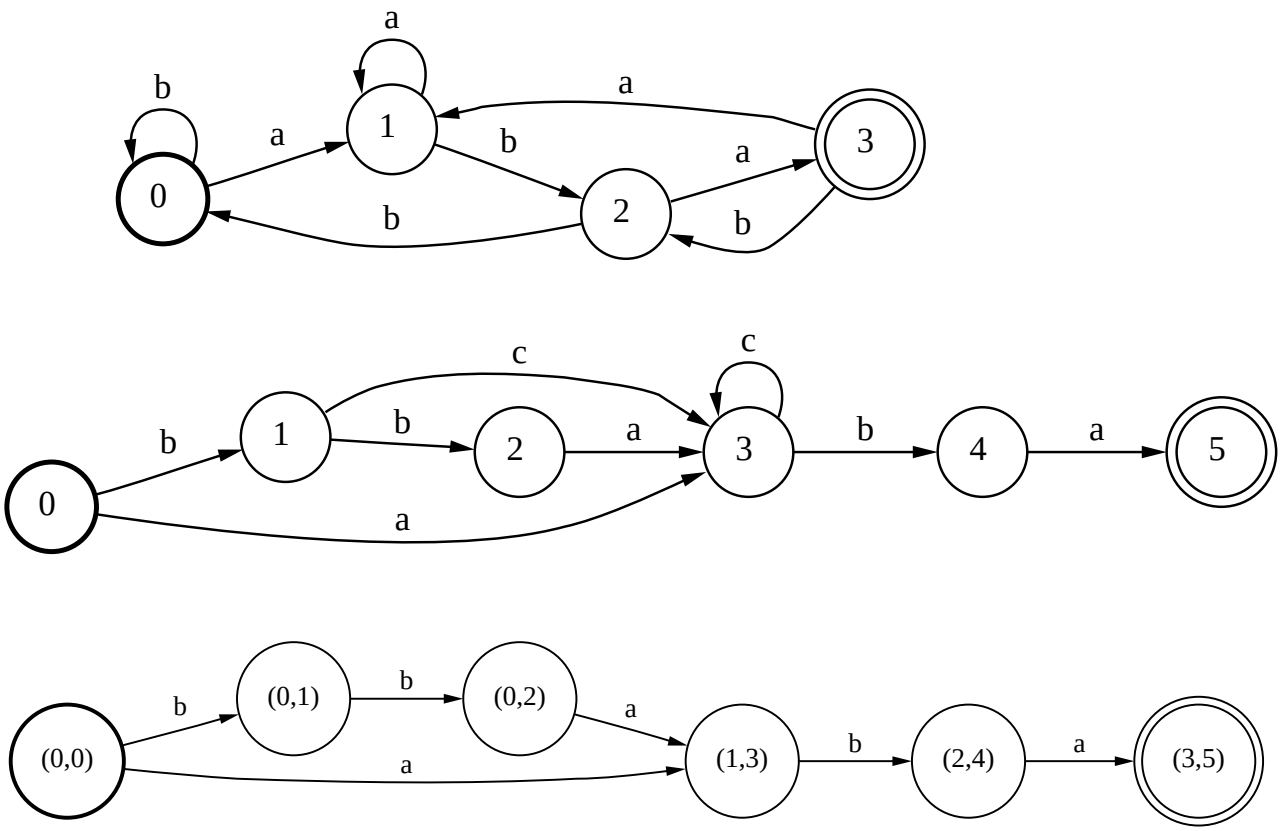

Figure 12: Intersection of automata.

Union: Example

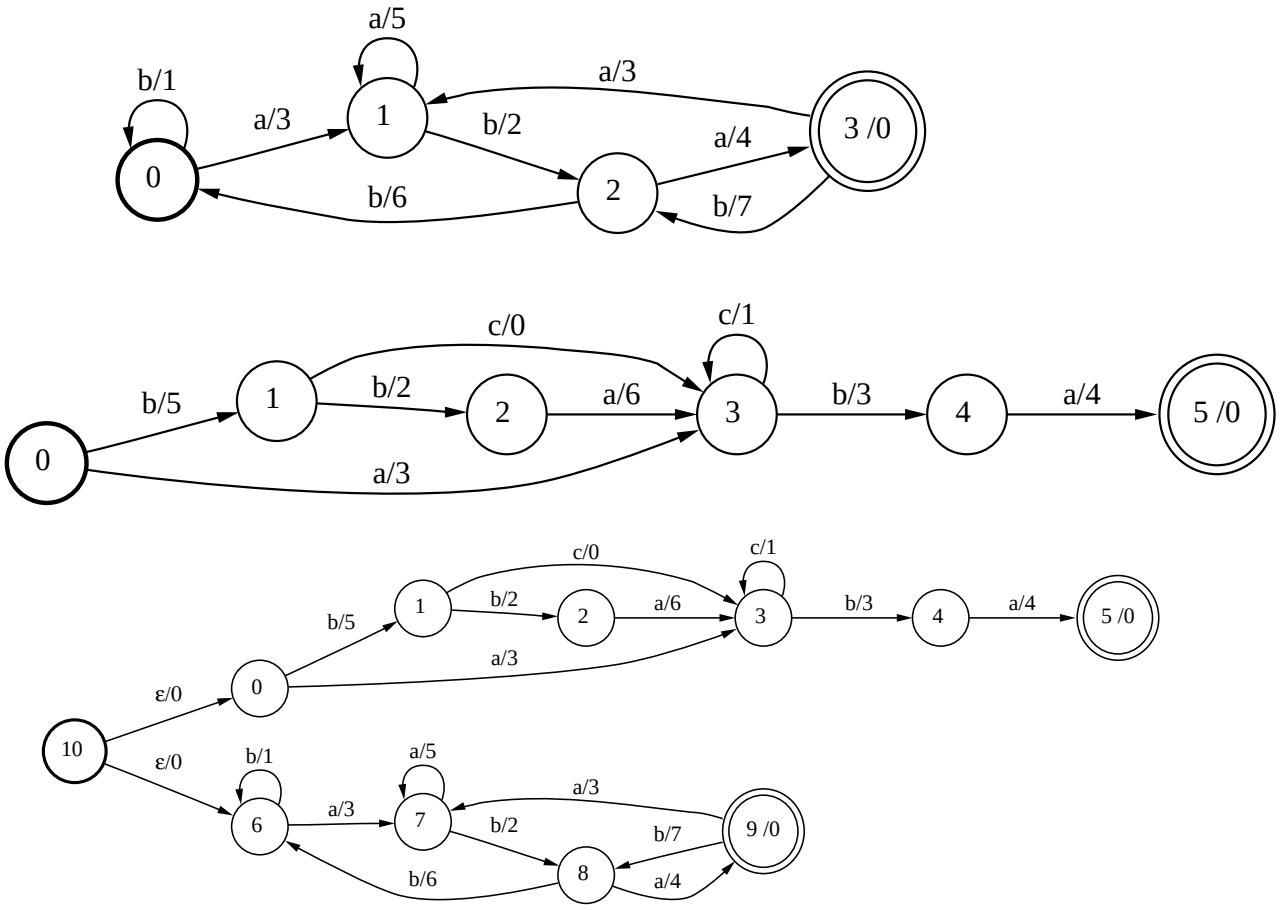

Figure 13: Union of weighted automata (min, +).

Determinization: Motivation (1)

- Efficiency of use (time)
- Elimination of redundancy
- No loss of information ($\neq$ pruning)

Determinization: Motivation (2)

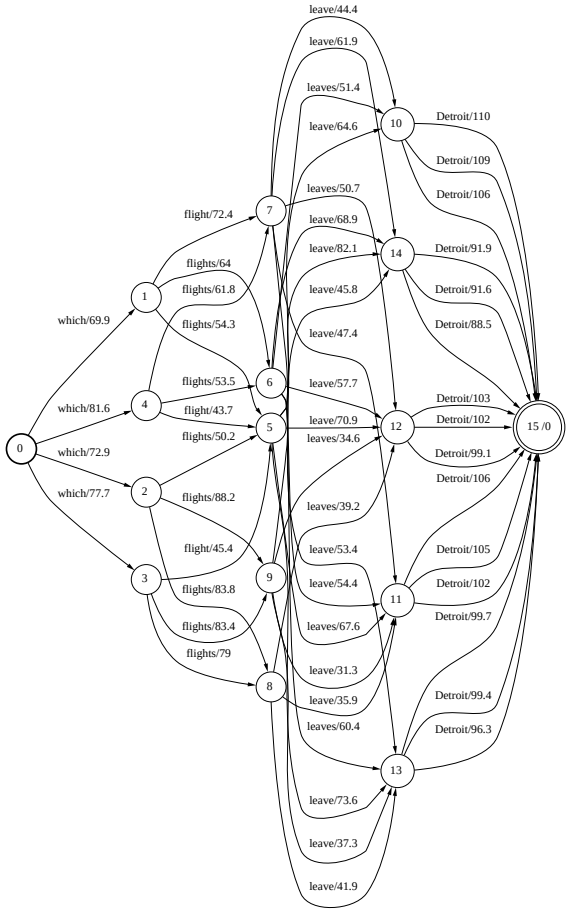

Figure 14: *Toy* language model (16 states, 53 transitions, 162 paths).

Determinization: Motivation (3)

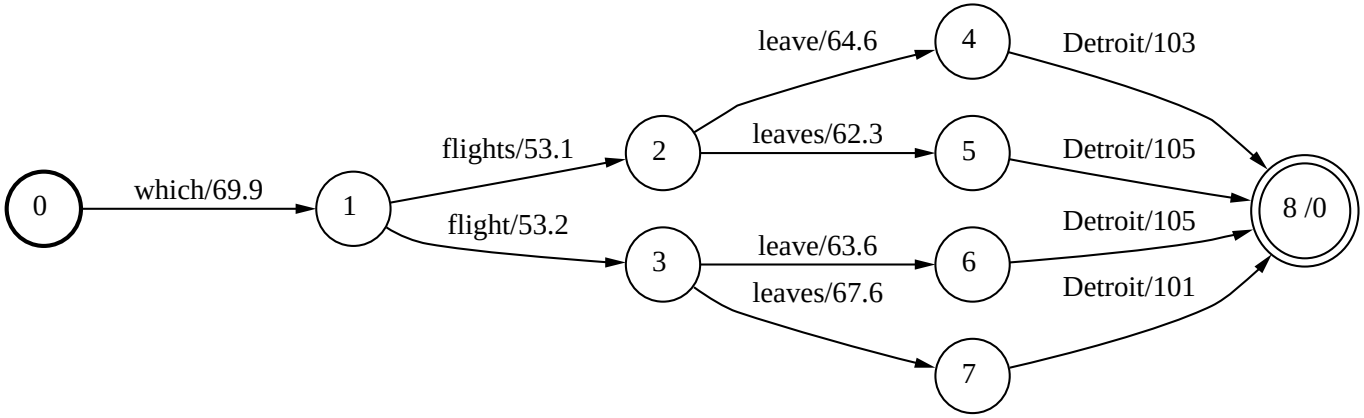

Figure 15: Determinized *language model* (9 states, 11 transitions, 4 paths).

Determinization: Example (1)

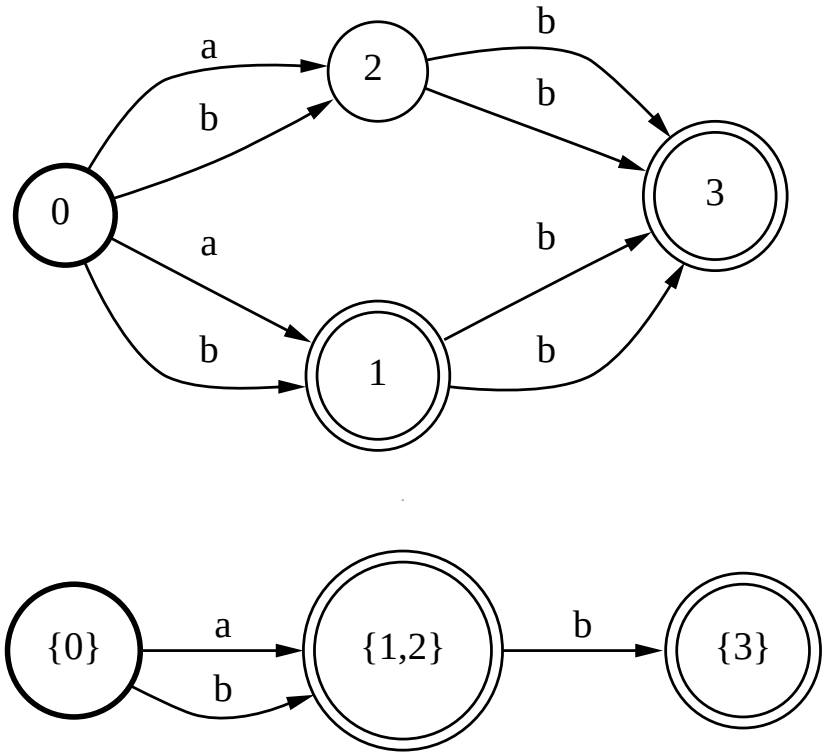

Figure 16: Determinization of automata.

Determinization: Example (2)

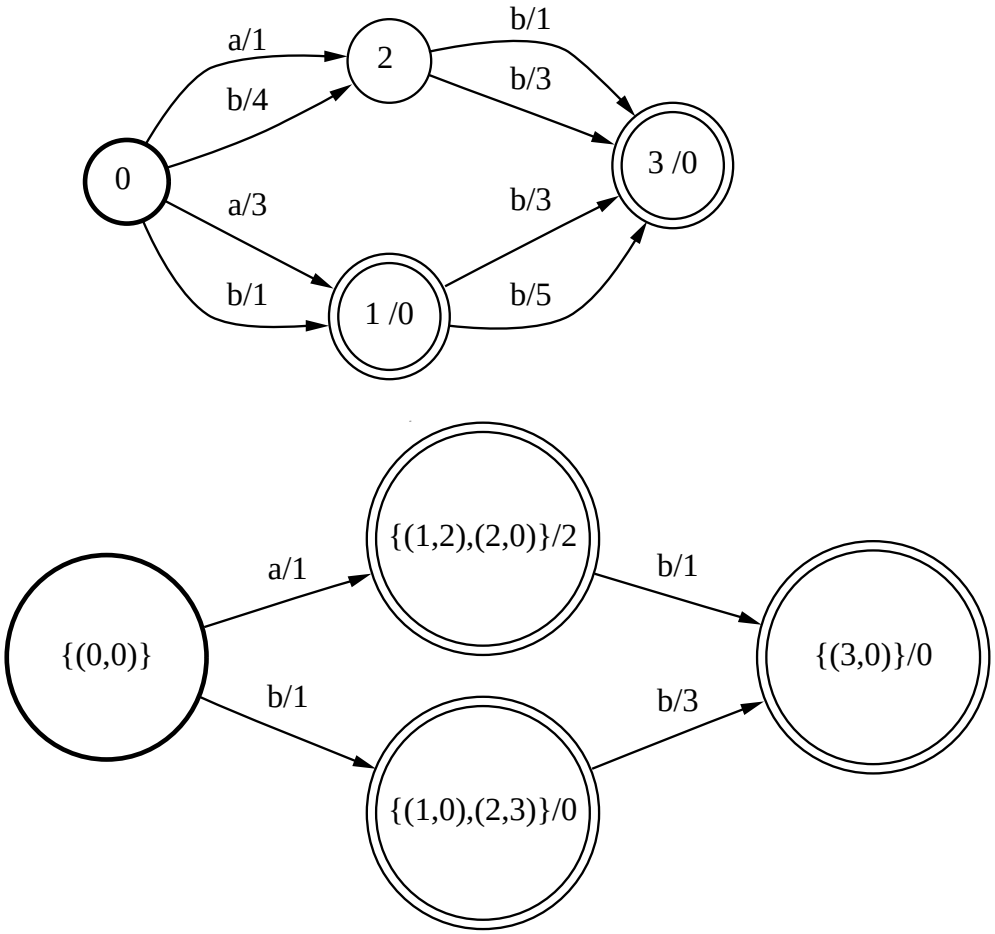

Figure 17: Determinization of weighted automata (min, +).

Determinization: Example (3)

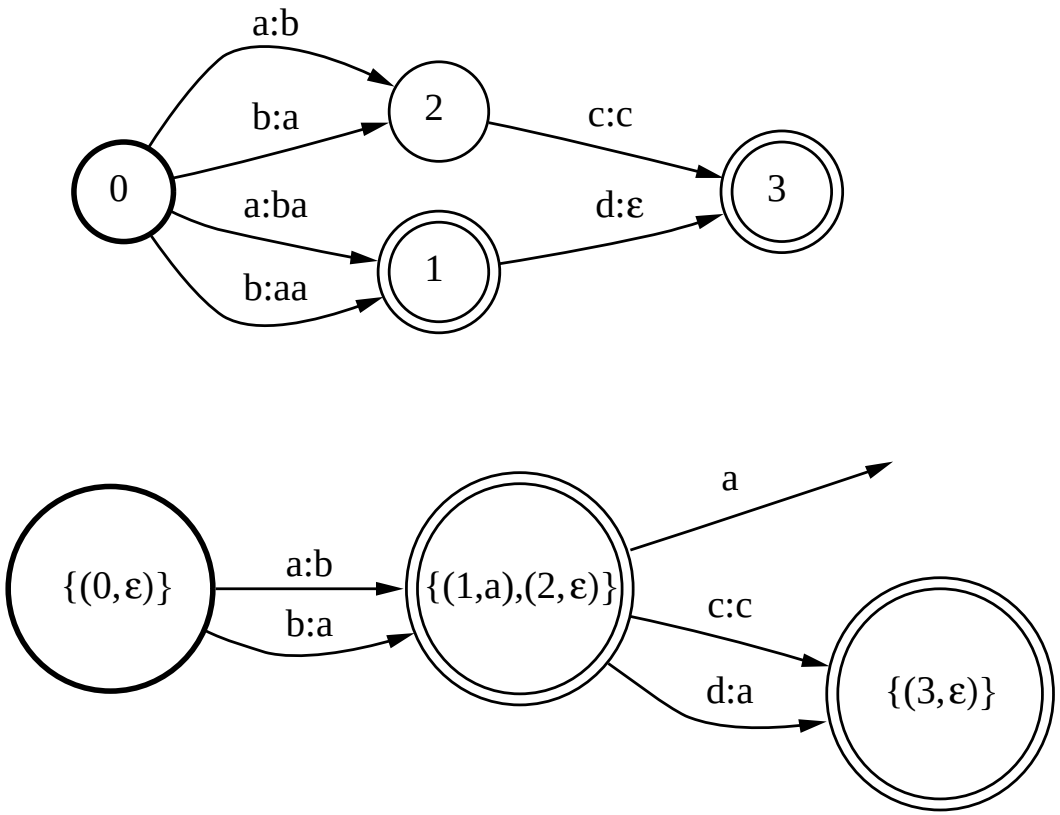

Figure 18: Determinization of transducers.

Determinization: Example (4)

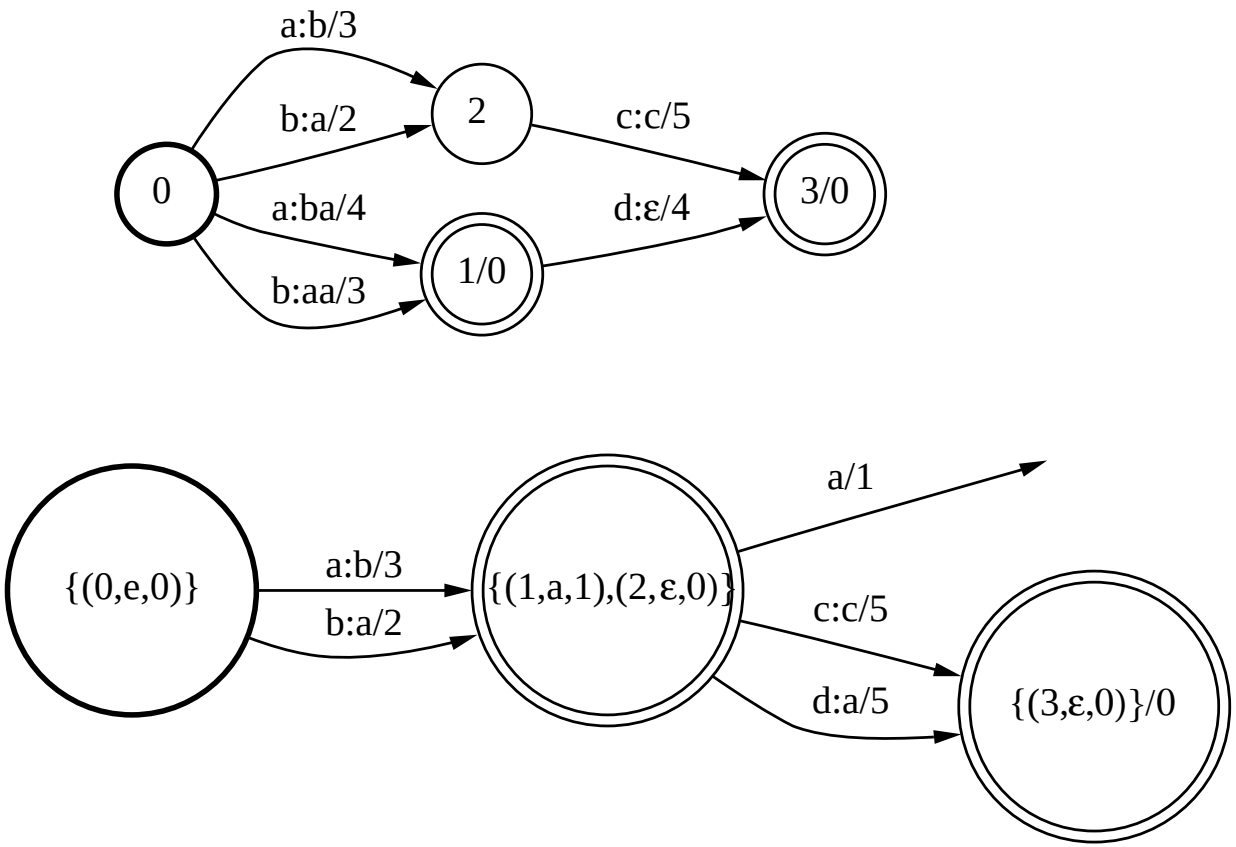

Figure 19: Determinization of weighted transducers (min, +).

Determinization: Algorithm (1)

- Generalization of the classical algorithm for automata
  - Powerset construction
  - Subsets made of (state, weight) or (state, string, weight)
- Applies to subsequentiable weighted automata and transducers
- Time and space complexity: exponential (polynomial w.r.t. size of the result)
- *On-the-fly* implementation

Determinization: Algorithm (2)

Conditions of applications

- *Twin* states: q and q' are twin states iff:
  - If: they can be reached from the initial states by the same input string u
  - Then: cycles at q and q' with the same input string v have the same output value
- **Theorem 4** *(Choffrut, 1978; Mohri, 1996a) Let τ be an unambiguous weighted automaton (transducer, weighted transducer), then τ can be determinized iff it has the twin property.*
- **Theorem 5** *(Mohri, 1996a) The twin property can be tested in polynomial time.*

Determinization: Theory

- Determinization of automata
  - General case (Aho, Sethi, and Ullman, 1986)
  - Specific case of $\Sigma^* \alpha$: failure functions (Mohri, 1995)
- Determinization of transducers, weighted automata, and weighted transducers
  - General description, theory and analysis (Mohri, 1996a; Mohri, 1996b)
  - Conditions of application and test algorithm
  - Acyclic weighted transducers or transducers admit determinization
- Can be used with other semirings (ex: $(\mathcal{R}, +, \cdot)$)

Local determinization: Motivation

- Time efficiency
- Reduction of redundancy
- Control of the resulting size (flexibility)
- Equivalent function (or equal set)
- No loss of information

Local determinization: Example

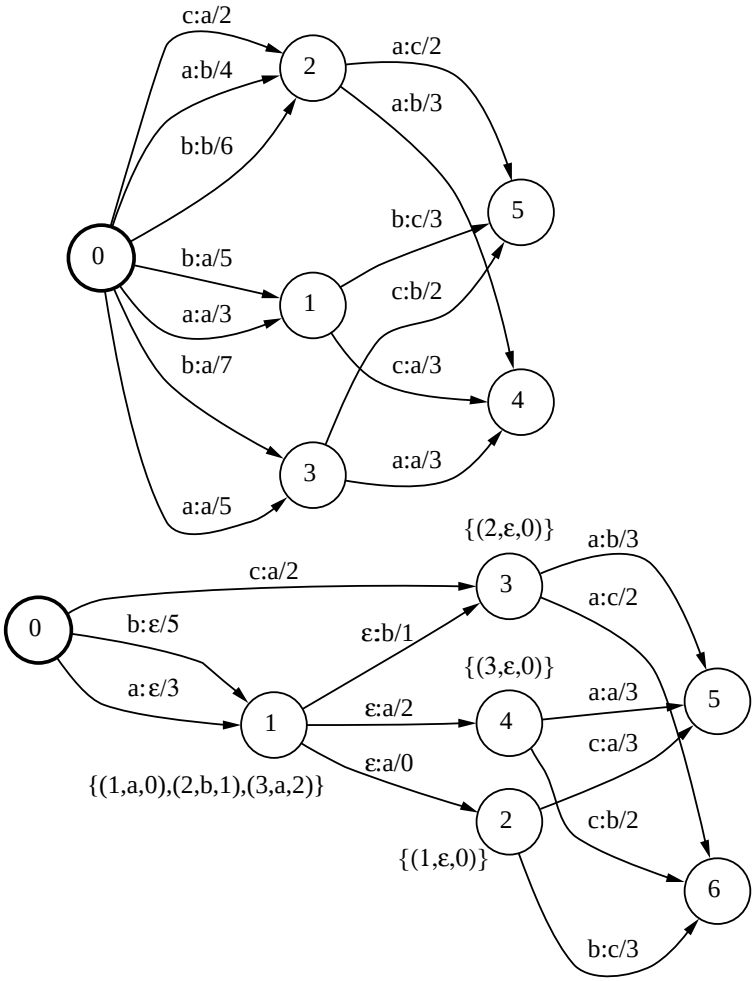

Figure 20: Local determinization of weighted transducers (min, +).

Local determinization: Algorithm

- Predicate, ex: (P) $(out - degree(q) > k)$
- k: threshold parameter
- Local: $Dom(det) = \{q : P(q)\}$
- *Determinization* only for $q \in Dom(det)$
- *On-the-fly* implementation
- Complexity $O(|Dom(det)| \cdot \max_{q \in Q}(out - degree(q)))$

Local determinization: theory

- Various choices of predicate (constraint: local)
- Definition of parameters
- Applies to all automata, weighted automata, transducers, and weighted transducers
- Can be used with other semirings (ex: $(\mathcal{R}, +, \cdot)$)

Minimization: Motivation

- Space efficiency
- Equivalent function (or equal set)
- No loss of information ($\neq$ pruning)

Minimization: Motivation (2)

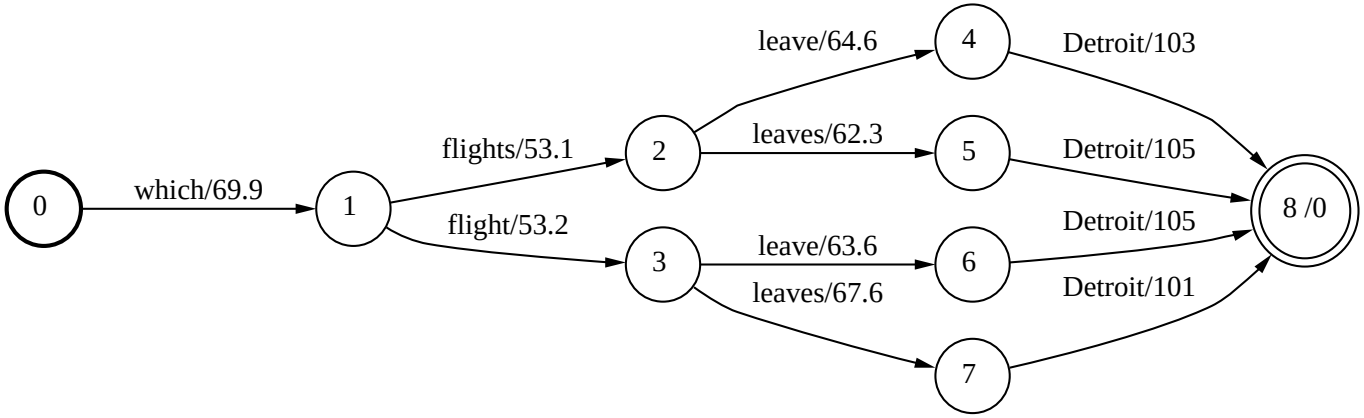

Figure 21: Determinized *language model*.

Minimization: Motivation (3)

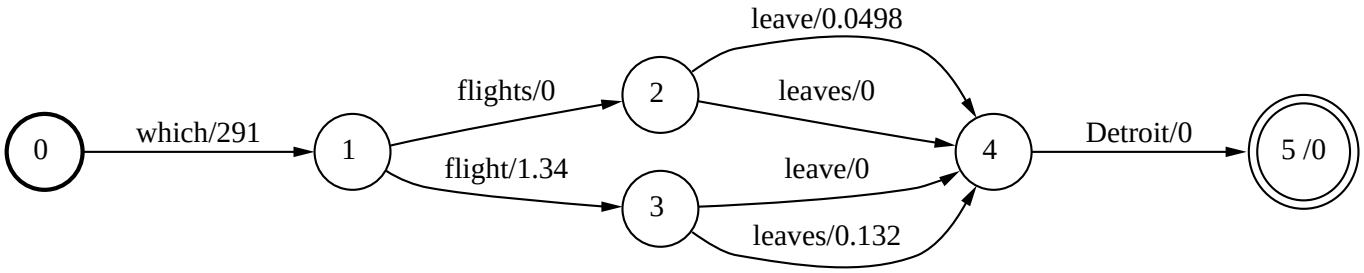

Figure 22: Minimized *language model*.

Minimization: Example (1)

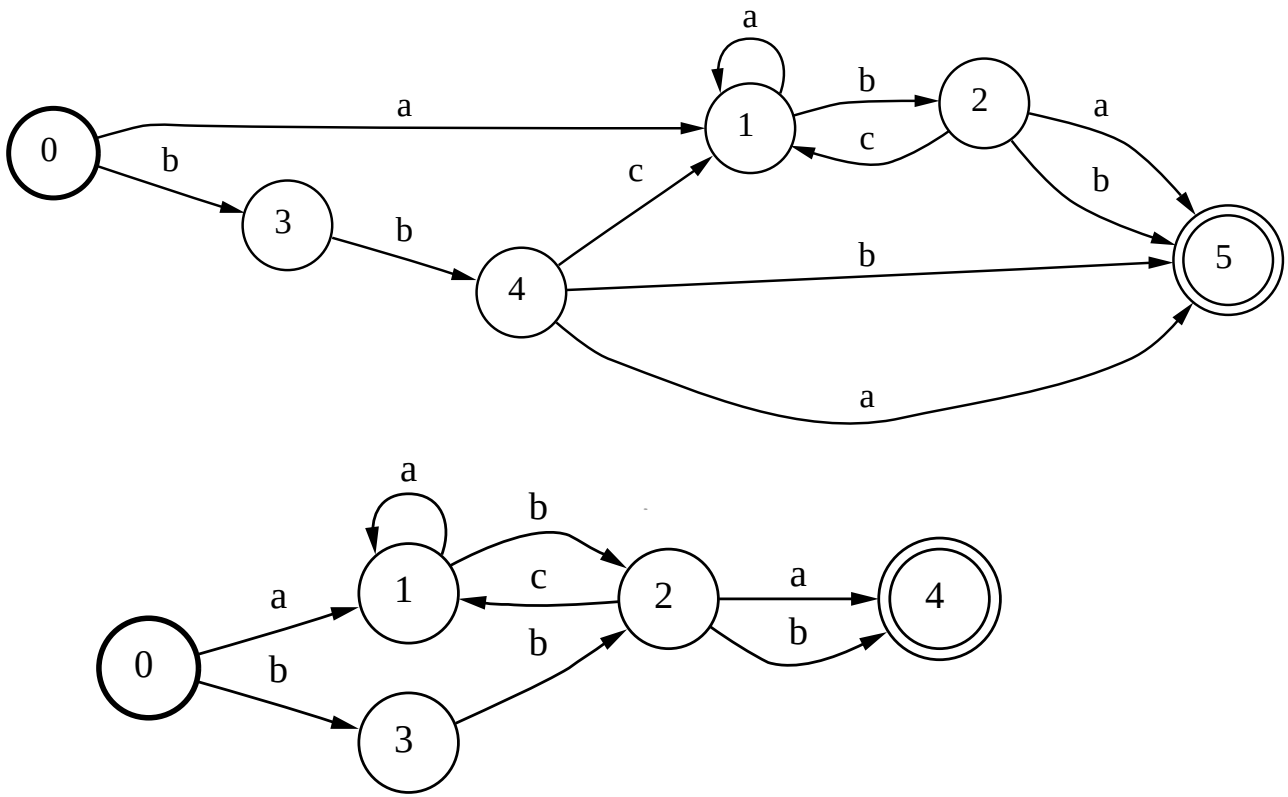

Figure 23: Minimization of automata.

Minimization: Example (2)

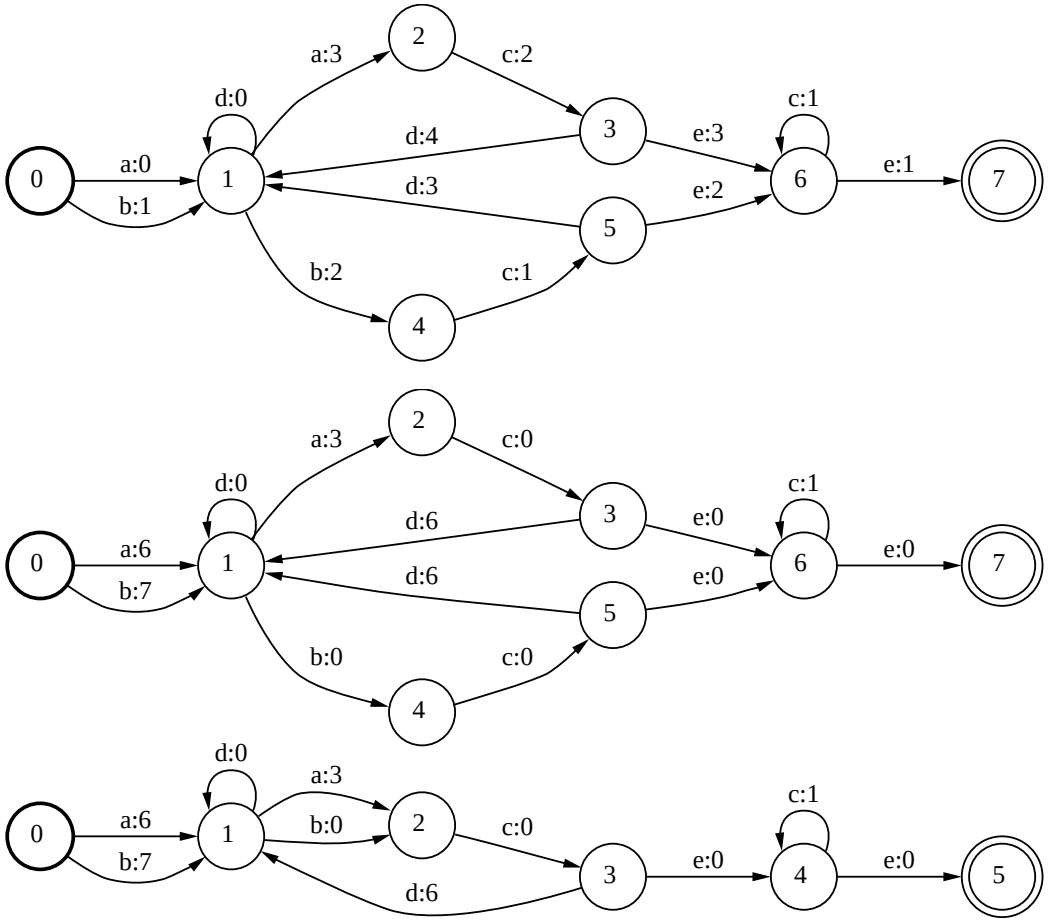

Figure 24: Minimization of weighted automata $(\min, +)$.

Minimization: Example (3)

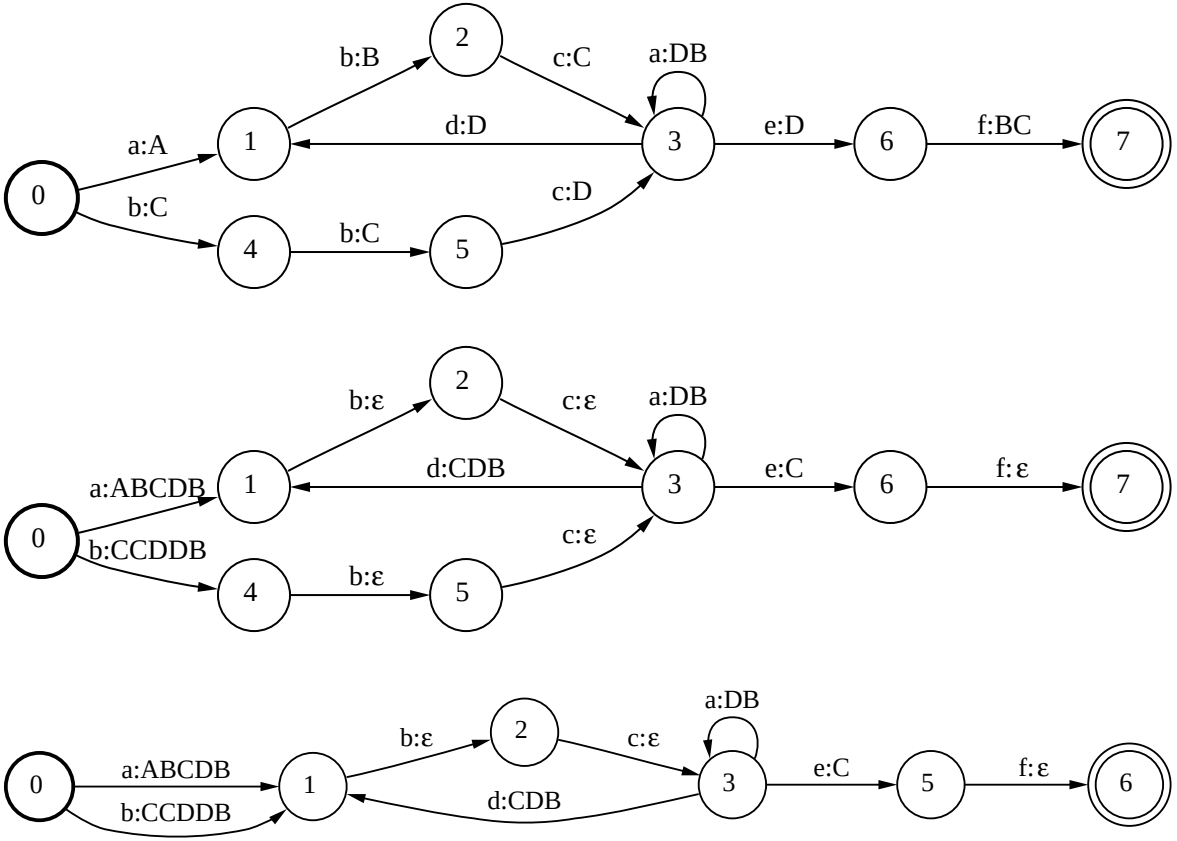

Figure 25: Minimization of transducers.

Minimization: Example (4)

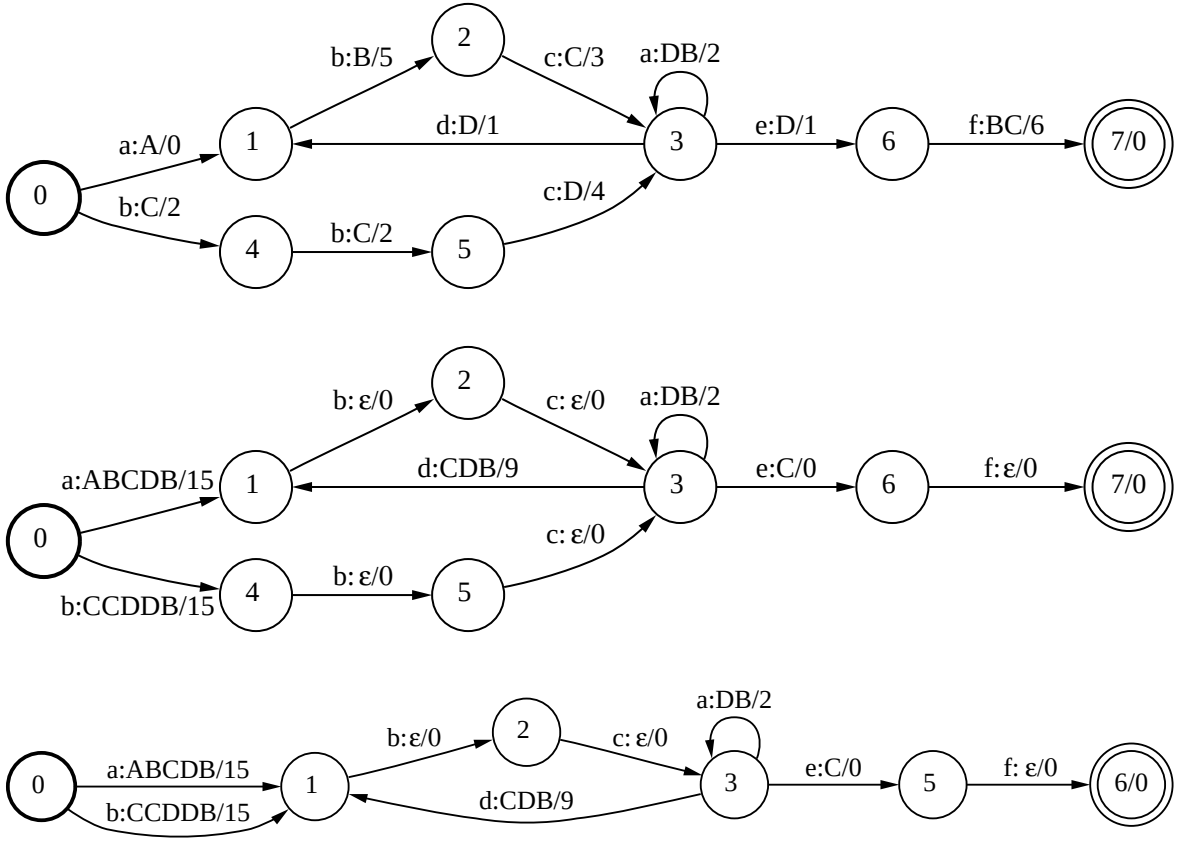

Figure 26: Minimization of weighted transducers (min, +).

Minimization: Algorithm (1)

- Two steps
  - *Pushing* or *extraction* of strings or weights towards initial state
  - Classical minimization of automata, (input,ouput) considered as a single label
- Algorithm for the first step
  - Transducers: specific algorithm
  - Weighted automata: shortest-paths algorithms

Minimization: Algorithm (2)

- Complexity
  - E: set of transitions
  - S: sum of the lengths of output strings
  - the longest of the longest common prefixes of the output paths leaving each state

Type	General	Acyclic
Automata	$O(\|E\| \cdot \log(\|Q\|))$	$O(\|Q\| + \|E\|)$
Weighted automata	$O(\|E\| \cdot \log(\|Q\|))$	$O(\|Q\| + \|E\|)$
Transducers	$O(\|Q\| + \|E\| \cdot (\log \|Q\| + \|P_{max}\|))$	$O(S + \|E\| + \|Q\| + (\|E\| - (\|Q\| - \|F\|)) \cdot \|P_{max}\|)$

Minimization: Theory

- Minimization of automata (Aho, Hopcroft, and Ullman, 1974; Revuz, 1991)
- Minimization of transducers (Mohri, 1994)
- Minimization of weighted automata (Mohri, 1996a)
  - Minimal number of transitions
  - Test of equivalence
- Standardization of power series (Schützenberger, 1961)
  - Works only with fields
  - Creates too many transitions

Conclusion (1)

- Theory
  - Rational power series
  - Weighted automata and transducers
- Algorithms
  - General (various semirings)
  - Efficiency (used in practice, large sizes)

Conclusion (2)

- Applications
  - Text processing
    (spelling checkers, pattern-matching, indexation, OCR)
  - Language processing
    (morphology, phonology, syntax, language modeling)
  - Speech processing (speech recognition, text-to-speech synthesis)
  - Computational biology (matching with errors)
  - Many other applications

PART II
Speech Recognition

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August 3rd, 1996

Overview

- The speech recognition problem
- Acoustic, lexical and grammatical models
- Finite-state automata in speech recognition
- Search in finite-state automata

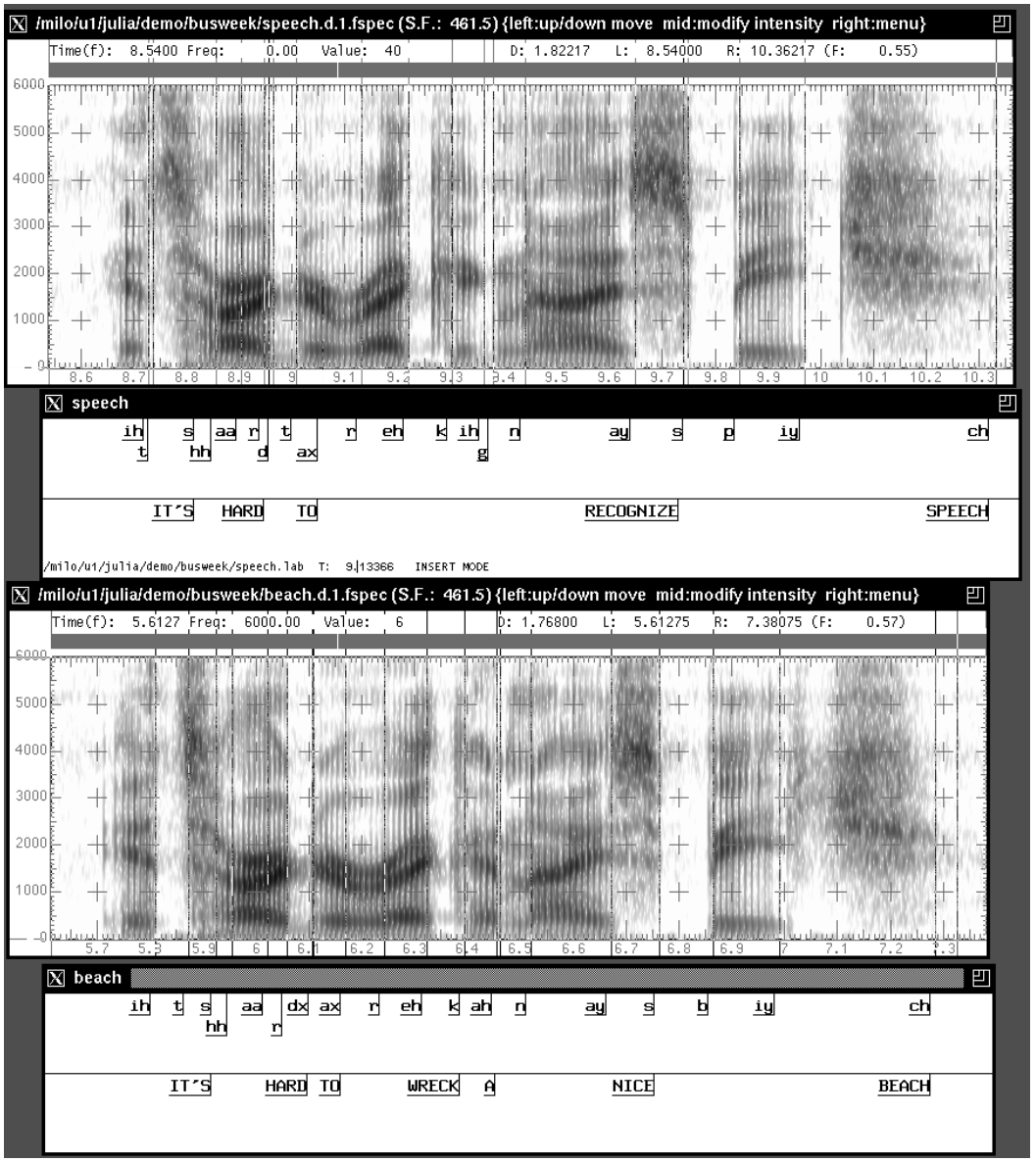
Speech Recognition

Given an utterance, find its most likely written transcription.

Fundamental ideas:

- Utterances are built from sequences of units
- Acoustic correlates of a unit are affected by surrounding units
- Units combine into units at a higher level — phones $\rightarrow$ syllables $\rightarrow$ words
- Relationships between levels can be modeled by weighted graphs — we use *weighted finite-state transducers*
- *Recognition: find the best path in a suitable product graph*

Levels of Speech Representation



Maximum A Posteriori Decoding

Overall analysis [4, 57]:

- *Acoustic observations:* parameter vectors derived by local spectral analysis of the speech waveform at regular (e.g. 10msec) intervals
- Observation sequence **o**
- Transcriptions **w**
- Probability $P(\mathbf{o}|\mathbf{w})$ of observing **o** when **w** is uttered
- *Maximum a posteriori decoding*:

$$\begin{aligned}\hat{\mathbf{w}} &= \operatorname*{argmax}_{\mathbf{w}} P(\mathbf{w}|\mathbf{o}) = \operatorname*{argmax}_{\mathbf{w}} \frac{P(\mathbf{o}|\mathbf{w})P(\mathbf{w})}{P(\mathbf{o})} \\ &= \operatorname*{argmax}_{\mathbf{w}} \underbrace{P(\mathbf{o}|\mathbf{w})}_{\substack{\text{generative} \\ \text{model}}} \underbrace{P(\mathbf{w})}_{\substack{\text{language} \\ \text{model}}}\end{aligned}$$

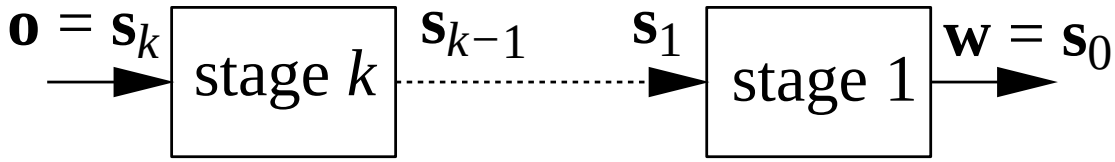
Generative Models of Speech

Typical decomposition of $P(\mathbf{o}|\mathbf{w})$ into conditionally-independent mappings between levels:

- Acoustic model $P(\mathbf{o}|\mathbf{p})$: phone sequences $\rightarrow$ observation sequences. Detailed model:
  - $P(o|d)$: distributions $\rightarrow$ observation vectors — *symbolic* $\rightarrow$ *quantitative*
  - $P(\mathbf{d}|m)$: context-dependent phone models $\rightarrow$ distribution sequences
  - $P(\mathbf{m}|\mathbf{p})$: phone sequences $\rightarrow$ model sequences
- Pronunciation model $P(\mathbf{p}|\mathbf{w})$: word sequences $\rightarrow$ phone sequences
- Language model $P(\mathbf{w})$: word sequences

Recognition Cascades: General Form

- Multistage cascade:



Find $\mathbf{s}_0$ maximizing

$$P(\mathbf{s}_0, \mathbf{s}_k) = P(\mathbf{s}_k|\mathbf{s}_0)P(\mathbf{s}_0) = P(\mathbf{s}_0) \sum_{\mathbf{s}_1,\ldots,\mathbf{s}_{k-1}} \prod_{1 \le j \le k} P(\mathbf{s}_j|\mathbf{s}_{j-1})$$

- "Viterbi" approximation:

$$\begin{aligned} \text{Cost}(\mathbf{s}_0, \mathbf{s}_k) &= \text{Cost}(\mathbf{s}_k|\mathbf{s}_0) + \text{Cost}(\mathbf{s}_0) \\ \text{Cost}(\mathbf{s}_k|\mathbf{s}_0) &\approx \min_{\mathbf{s}_1,\ldots,\mathbf{s}_{k-1}} \sum_{1 \le j \le k} \text{Cost}(\mathbf{s}_j|\mathbf{s}_{j-1}) \end{aligned}$$

where $\text{Cost}(\ldots) = -\log P(\ldots)$.

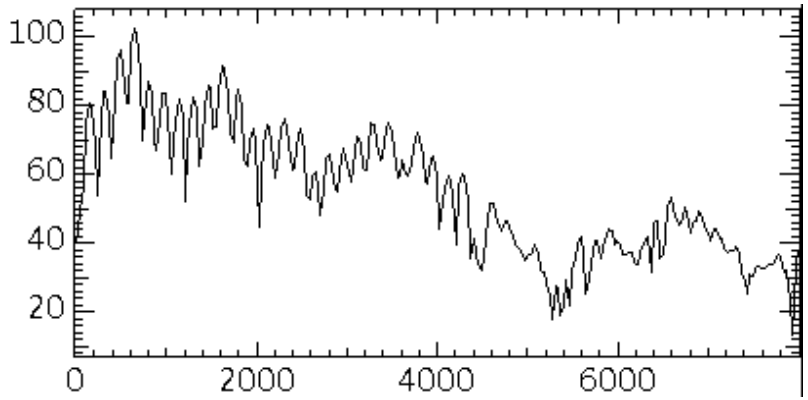
Speech Recognition Problems

- *Modeling:* how to describe accurately the relations between levels $\Rightarrow$ *modeling errors*
- *Search:* how to find the best interpretation of the observations according to the given models $\Rightarrow$ *search errors*

Acoustic Modeling – Feature Selection I

- Short-time spectral analysis:

$$\log \left| \int g(\tau) x(t+\tau) e^{-i2\pi f \tau} \, d\tau \right|$$



Short-time (25 msec. Hamming window) spectrum of /ae/ – Hz. vs. Db.

- Scale selection:
  - Cepstral smoothing
  - Parameter sampling (13 parameters)

Acoustic Modeling – Feature Selection II [40, 38]

- Refinements
  - Time derivatives – 1st and 2nd order
  - non-Fourier analysis (e.g., Mel scale)
  - speaker/channel adaptation
    - mean cepstral subtraction
    - vocal tract normalization
    - linear transformations
- Result: 39 dimensional feature vector (13 cepstra, 13 delta cepstra, 13 delta-delta cepstra) every 10 milliseconds

Acoustic Modeling – Stochastic Distributions [4, 61, 39, 5]

- Vector quantization – find codebook of prototypes
- Full covariance multivariate Gaussians:

$$P[\mathbf{y}] = \frac{1}{(2\pi)^{N/2}|\mathbf{S}|^{1/2}} e^{-\frac{1}{2}(\mathbf{y}^T - \mu^T)\mathbf{S}^{-1}(\mathbf{y}-\mu)}$$

- Diagonal covariance Gaussian mixtures
- Semi-continuous, tied mixtures

Acoustic Modeling – Units and Training [61, 36]

- Units
  - Phonetic (*sub-word*) units – e.g., cat –> /k ae t/
  - Context-dependent units – $ae_{k,t}$
  - Multiple distributions (*states*) per phone – left, middle, right
- Training
  - *Given a segmentation*, training straight-forward
  - Obtain segmentation by *transcription*
  - Iterate until convergence

Generating Lexicons – Two Steps

- Orthography → Phonemes

  “had” → /hh ae d/

  “your” → /y uw r/

  – complex, context-independent mapping
  – usually small number of alternatives
  – determined by spelling constraints; lexical “facts”
  – large online dictionaries available

- Phonemes → Phones

  /hh ae d y uw r/ → [hh ae dcl jh axr] (60% prob)

  /hh ae d y uw r/ → [hh ae dcl d y axr] (40% prob)

  – complex, context-dependent mapping
  – many possible alternatives
  – determined by phonological and phonetic constraints

Decision Trees: Overview [9]

- **Description/Use:** Simple structure – binary tree of decisions, terminal nodes determine prediction *(cf. "Game of Twenty Questions").* If dependent variable is categorical (e.g., `red, yellow, green`), called "classification tree", if continuous, called "regression tree".

- **Creation/Estimation:** Creating a binary decision tree for classification or regression involves three steps *(Breiman, et al)*:

  1. *Splitting Rules:* Which split to take at a node?
  2. *Stopping Rules:* When to declare a node terminal?
  3. *Node Assignment:* Which class/value to assign to a terminal node?

1. Decision Tree Splitting Rules

Which split to take at a node?

- **Candidate splits considered.**
  - *Binary cuts*: For **continuous** $-\infty \leq x < \infty$, consider splits of form:

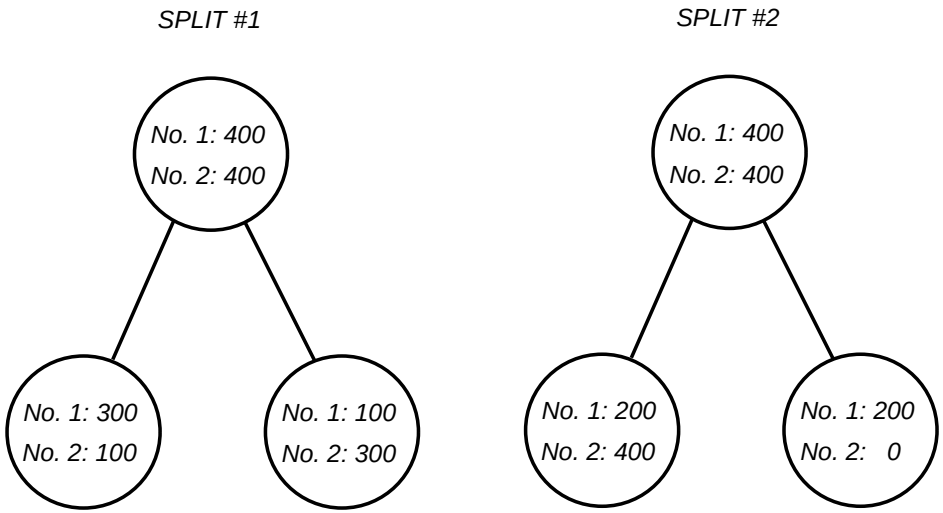
$$x \leq k \quad \text{vs.} \quad x > k, \quad \forall k.$$

  - *Binary partitions*: For **categorical** $x \in \{1, 2, ..., n\} = X$, consider splits of form:

$$x \in A \quad \text{vs.} \quad x \in X - A, \quad \forall A \subset X.$$

1. Decision Tree Splitting Rules – Continued

- **Choosing best candidate split.**
  - *Method 1*: Choose k (continuous) or A (categorical) that minimizes estimated classification (regression) error after split.
  - *Method 2 (for classification)*: Choose k or A that minimizes estimated entropy after that split.



2. Decision Tree Stopping Rules

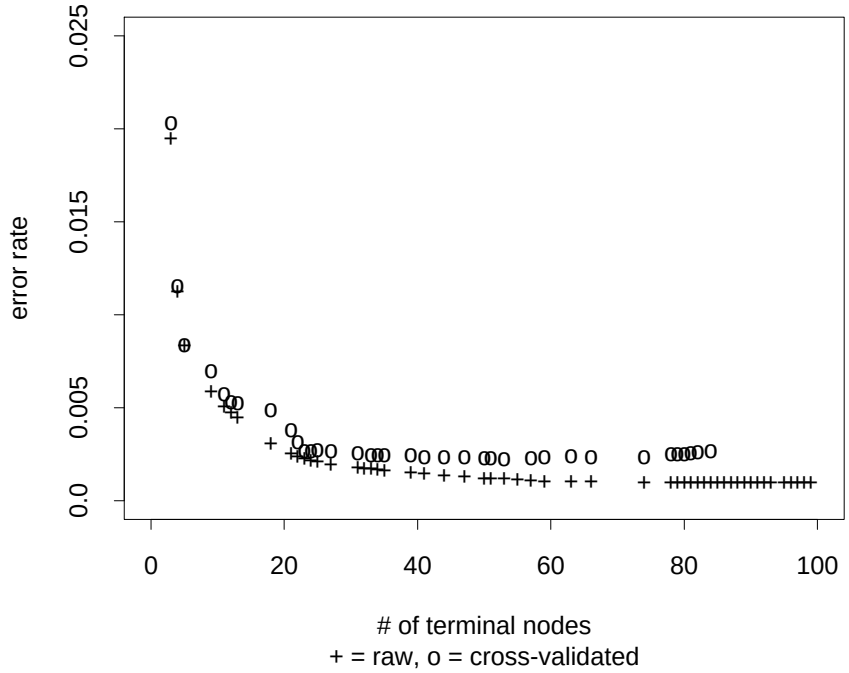
When to declare a node terminal?

- Strategy (*Cost-Complexity pruning*):
  1. Grow over-large tree.
  2. Form sequence of subtrees, $T_0, \ldots, T_n$ ranging from full tree to just the root node.
  3. Estimate "honest" error rate for each subtree.
  4. Choose tree size with mininum "honest" error rate.
- To form sequence of subtrees, vary α from 0 (for full tree) to ∞ (for just root node) in:

$$\min_T \left[R(T) + \alpha |T| \right].$$

- To estimate "honest" error rate, test on data different from training data, e.g., grow tree on $9/10$ of available data and test on $1/10$ of data repeating 10 times and averaging (*cross-validation)*.

End of Declarative Sentence Prediction: Pruning Sequence



3. Decision Tree Node Assignment

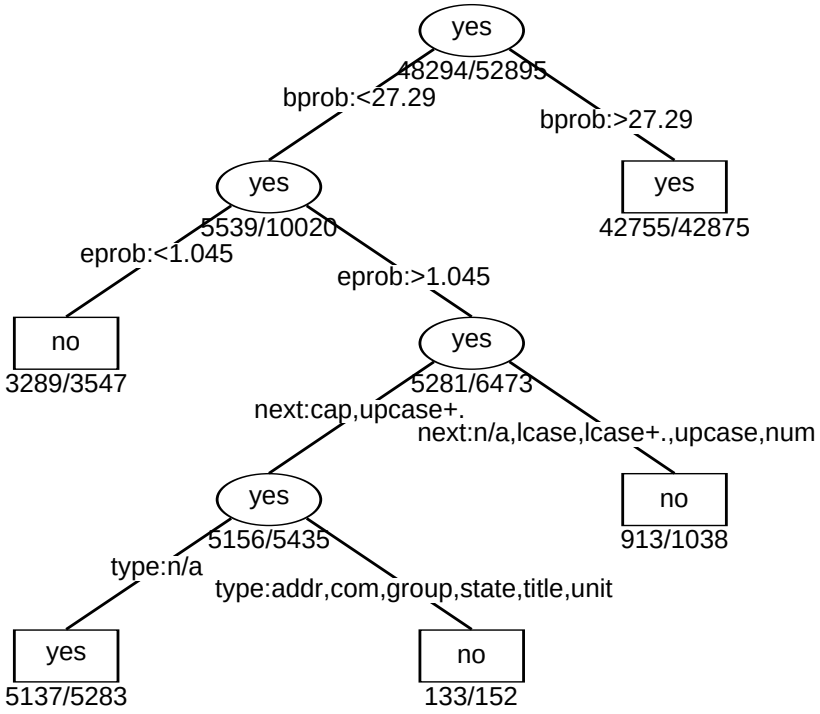
Which class/value to assign to a terminal node?

- *Plurality vote*: Choose most frequent class at that node for classification; choose mean value for regression.

End-of-Declarative-Sentence Prediction: Features [65]

- Prob[word with "." occurs at end of sentence]
- Prob[word after "." occurs at beginning of sentence]
- Length of word with "."
- Length of word after "."
- Case of word with ".": Upper, Lower, Cap, Numbers
- Case of word after ".": Upper, Lower, Cap, Numbers
- Punctuation after "." (if any)
- Abbreviation class of word with ".": – e.g., month name, unit-of-measure, title, address name, etc.

End of Declarative Sentence?



Phoneme-to-Phone Alignment

PHONEME	PHONE	WORD
p	p	purpose
er	er	
p	pcl	
-	p	
ax	ix	
s	s	
ae	ax	and
n	n	
d	-	
r	r	respect
ih	ix	
s	s	
p	pcl	
-	p	
eh	eh	
k	kcl	
t	t	

Phoneme-to-Phone Realization: Features [66, 10, 62]

- Phonemic Context:
  - Phoneme to predict
  - Three phonemes to left
  - Three phonemes to right
- Stress (0, 1, 2)
- Lexical Position:
  - Phoneme count from start of word
  - Phoneme count from end of word

Phoneme-to-Phone Realization: Prediction Example

Tree splits for /t/ in ‘‘your pretty red’’:

PHONE	COUNT	SPLIT
ix	182499	
n	87283	cm0: vstp,ustp,vfri,ufri,vaff,uaff,nas
kcl+k	38942	cm0: vstp,ustp,vaff,uaff
tcl+t	21852	cp0: alv,pal
tcl+t	11928	cm0: ustp
tcl+t	5918	vm1: mono,rvow,wdi,ydi
dx	3639	cm-1: ustp,rho,n/a
dx	2454	rstr: n/a,no

Phoneme-to-Phone Realization: Network Example

Phonetic network for ‘‘Don had your pretty...’’:

PHONEME	PHONE1	PHONE2	PHONE3	CONTEXT
d	0.91 d			
aa	0.92 aa			
n	0.98 n			
hh	0.74 hh	0.15 hv		
ae	0.73 ae	0.19 eh		
d	0.51 dcl jh	0.37 dcl d		
y	0.90 y			(if d→dcl d)
	0.84 -	0.16 y		(if d→dcl jh)
uw	0.48 axr	0.29 er		
r	0.99 -			
p	0.99 pcl p			
r	0.99 r			
ih	0.86 ih			
t	0.73 dx	0.11 tcl t		
iy	0.90 iy			

Acoustic Model Context Selection [92, 39]

- Statistical *regression* trees used to predict contexts based on distribution variance
- One tree per context-independent phone and state (left, middle, right)
- The trees were grown until the data criterion of 500 frames per distribution was met
- Trees pruned using cost-complexity pruning and cross-validation to select best contexts
- About 44000 context-dependent phone models
- About 16000 distributions

N-Grams: Basics

- **'Chain Rule' and Joint/Conditional Probabilities:**

$$P[x_1 x_2 \ldots x_N] = P[x_N | x_1 \ldots x_{N-1}] P[x_{N-1} | x_1 \ldots x_{N-2}] \ldots P[x_2 | x_1] P[x_1]$$

where, e.g.,

$$P[x_N | x_1 \ldots x_{N-1}] = \frac{P[x_1 \ldots x_N]}{P[x_1 \ldots x_{N-1}]}$$

- **(First–Order) Markov assumption:**

$$P[x_k | x_1 \ldots x_{k-1}] = P[x_k | x_{k-1}] = \frac{P[x_{k-1} x_k]}{P[x_{k-1}]}$$

- **nth–Order Markov assumption:**

$$P[x_k | x_1 \ldots x_{k-1}] = P[x_k | x_{k-n} \ldots x_{k-1}] = \frac{P[x_{k-n} \ldots x_k]}{P[x_{k-n} \ldots x_{k-1}]}$$

N-Grams: Maximum Likelihood Estimation

Let N be total number of n-grams observed in a corpus and $c(x_1 \ldots x_n)$ be the number of times the n-gram $x_1 \ldots x_n$ occurred. Then

$$P[x_1 \ldots x_n] = \frac{c(x_1 \ldots x_n)}{N}$$

is the maximum likelihood estimate of that n-gram probability.

For conditional probabilities,

$$P[x_n | x_1 \ldots x_{n-1}] = \frac{c(x_1 \ldots x_n)}{c(x_1 \ldots x_{n-1})}.$$

is the maximum likelihood estimate.

With this method, an n-gram that does not occur in the corpus is assigned **zero** probability.

N-Grams: Good-Turing-Katz Estimation [29, 16]

Let n_r be the number of n-grams that occurred r times. Then

$$P[x_1 \ldots x_n] = \frac{c^*(x_1 \ldots x_n)}{N}$$

is the Good-Turing estimate of that n-gram probability, where $c^*(x) = (c(x)+1)\frac{n_{c(x)+1}}{n_{c(x)}}$.

For conditional probabilities,

$$P[x_n|x_1 \ldots x_{n-1}] = \frac{c^*(x_1 \ldots x_n)}{c(x_1 \ldots x_{n-1})}, \qquad c(x_1 \ldots x_n) > 0$$

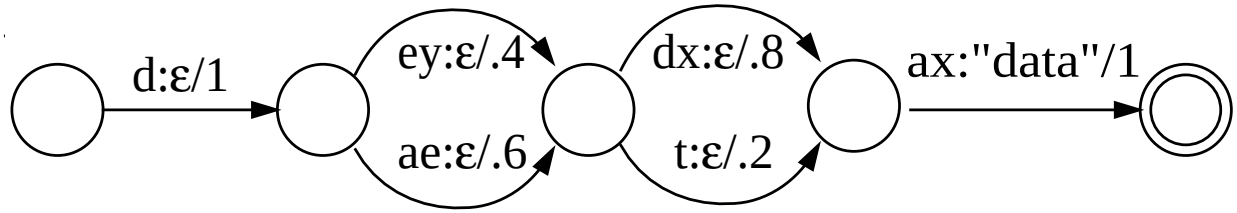
is Katz's extension of the Good-Turing estimate.

With this method, an n-gram that does not occur in the corpus is assigned the backoff probability $P[x_n|x_1 \ldots x_{n-1}] = \alpha P[x_n|x_2 \ldots x_{n-1}]$, where α is a normalizing constant.

Finite-State Modeling [57]

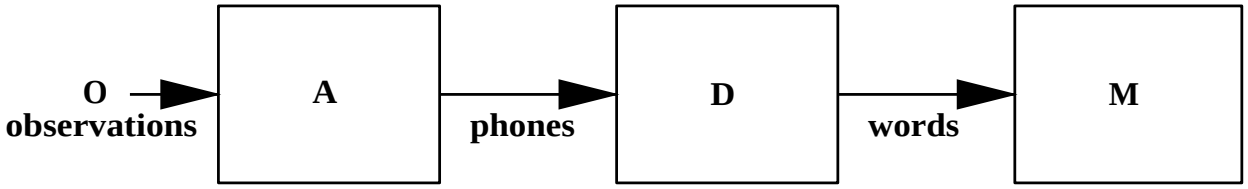
Our view of recognition cascades: represent mappings between levels, observation sequences and language uniformly with *weighted* finite-state machines:

- Probabilistic mapping $P(\mathbf{x}|\mathbf{y})$: *weighted finite-state transducer*. Example — word pronunciation transducer:



- Language model $P(\mathbf{w})$: *weighted finite-state acceptor*

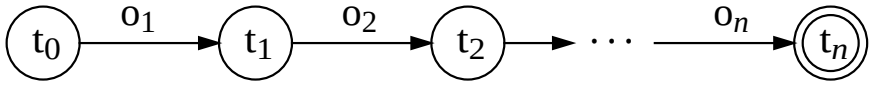
Example of Recognition Cascade



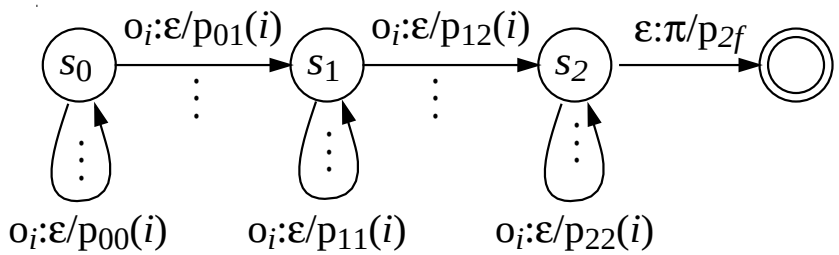
- Recognition from observations **o** by composition:
  - *Observations:* $O(\mathbf{s}, \mathbf{s}) = \begin{cases} 1 & \text{if } \mathbf{s} = \mathbf{o} \\ 0 & \text{otherwise} \end{cases}$
  - *Acoustic-phone transducer:* $A(\mathbf{a}, \mathbf{p}) = P(\mathbf{a}|\mathbf{p})$
  - *Pronunciation dictionary:* $D(\mathbf{p}, \mathbf{w}) = P(\mathbf{p}|\mathbf{w})$
  - *Language model:* $M(\mathbf{w}, \mathbf{w}) = P(\mathbf{w})$
- *Recognition:* $\hat{\mathbf{w}} = \underset{\mathbf{w}}{\text{argmax}}(O \circ A \circ D \circ M)(\mathbf{o}, \mathbf{w})$

Speech Models as Weighted Automata

- Quantized observations:

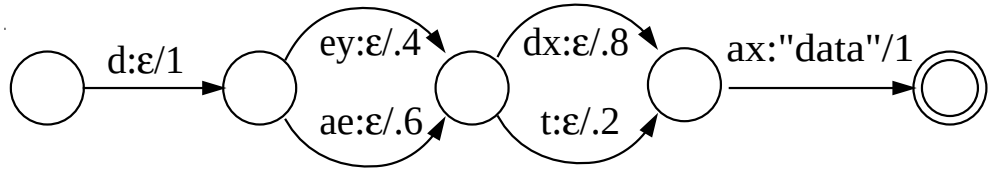


- Phone model A_π : observations $\rightarrow$ phones



Acoustic transducer: $A = \left(\sum_\pi A_\pi\right)^*$

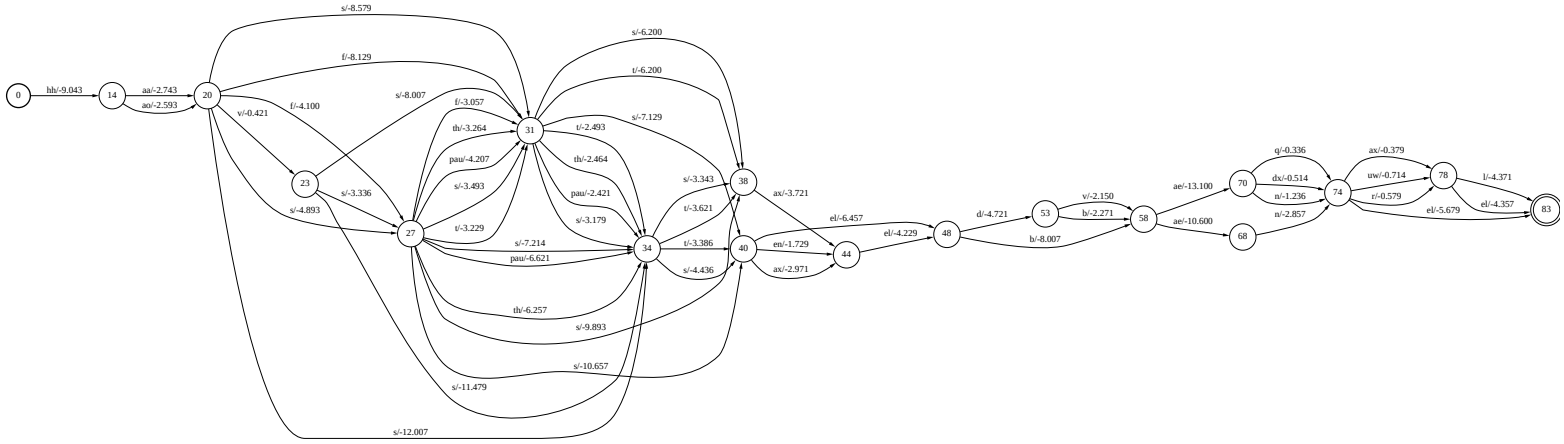
- Word pronunciations D_{data} : phones $\rightarrow$ words



Dictionary: $D = \left(\sum_w D_w\right)^*$

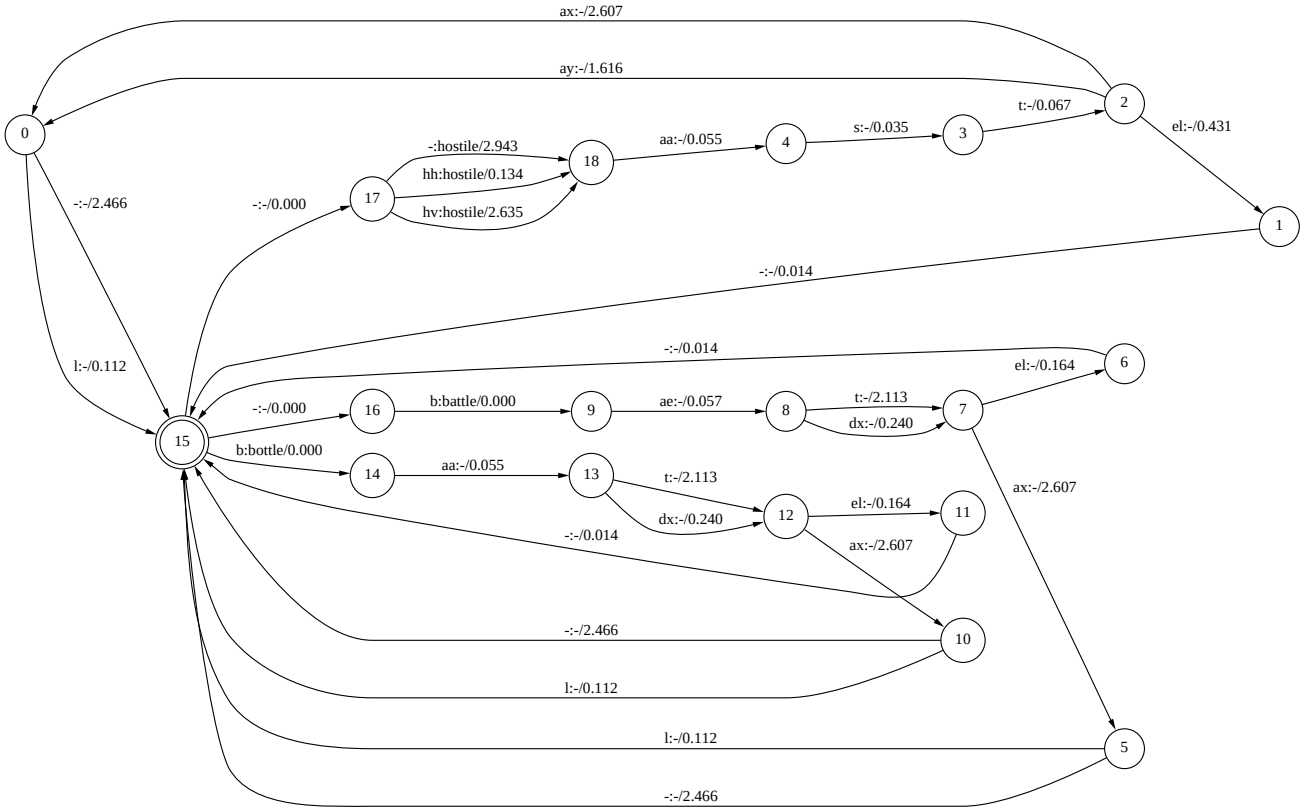
Example: Phone Lattice $O \circ A$

- *Lattices:* Weighted acyclic graphs representing possible interpretations of an utterance as sequences of units at a given level of representation (phones, syllables, words,. . .)
- Example: result of composing observation sequence for *hostile battle* with acoustic model:



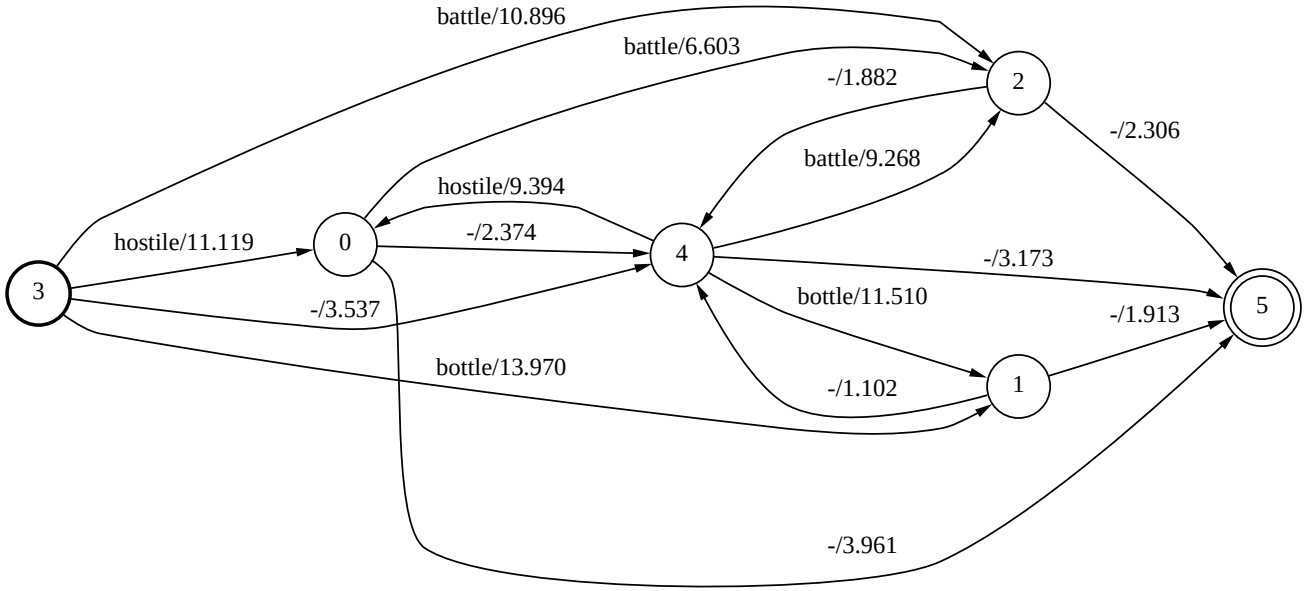
Sample Pronunciation Dictionary D

Dictionary with *hostile*, *battle* and *bottle* as a weighted transducer:



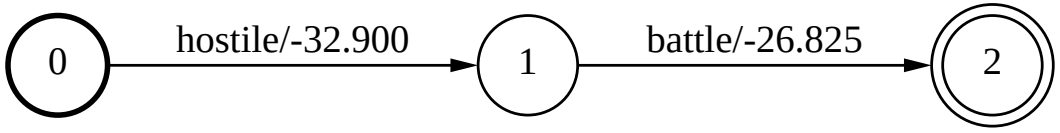
Sample Language Model M

Simplified language model as a weighted acceptor:

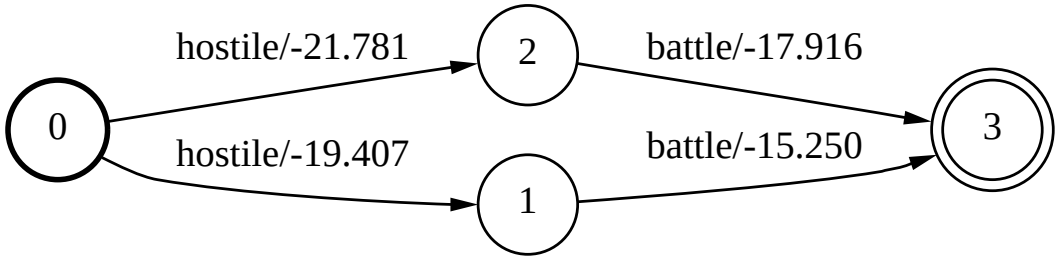


Recognition by Composition

- *From phones to words:* compose dictionary with phone lattice to yield word lattice with combined acoustic and pronunciation costs:



- *Applying language model:* Compose word lattice with language model to obtain word lattice with combined acoustic, pronunciation and language model costs:

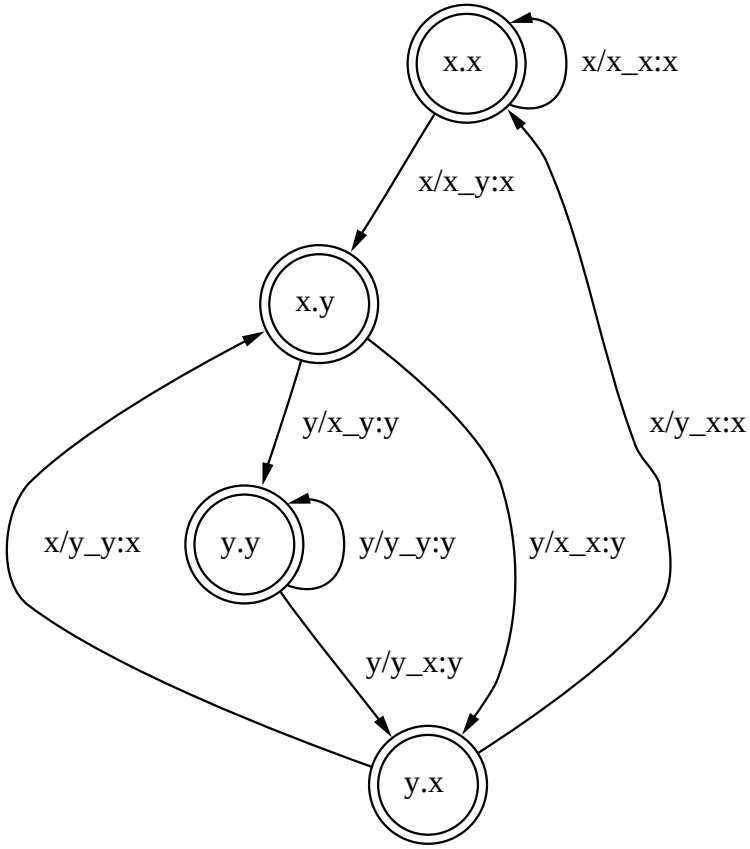


Context-Dependency Examples

- **Context-dependent phone models:** Maps from CI units to CD units. Example: $ae/b\_\_d \rightarrow ae_{b,d}$
- **Context-dependent allophonic rules:** Maps from baseforms to detailed phones. Example: $t/V'\_\_V \rightarrow dx$
- **Difficulty:** Cross-word contexts – where several words enter and leave a state in the grammar, substitution does not apply.

Context-Dependency Transducers

Example — triphonic context transducer for two symbols x and y.



Generalized State Machines

All of the above networks have *bounded context* and thus can be represented as *generalized state machines*. A generalized state machine M:

- **Supports these operations:**
  - $M.start$ – returns start state
  - $M.final(state)$ – returns 1 if final, 0 if non-final state
  - $M.arcs(state)$ – returns transitions $(a_1, a_2, \ldots, a_N)$ leaving $state$, where $a_i = (ilabel, olabel, weight, nextstate)$
- **Does *not* necessarily support:**
  - providing the number of states
  - expanding states that have not been already *discovered*

On-Demand Composition [69, 53]

Create generalized state machine C for composition $A \circ B$.

- $C.start := (A.start, B.start)$
- $C.final((s1, s2)) := A.final(s1) \wedge B.final(s2)$
- $C.arcs((s1, s2)) := Merge(A.arcs(s1), B.arcs(s2))$

Merged arcs defined as:

$$(l1, l3, x + y, (ns1, ns2)) \in Merge(A.arcs(s1), B.arcs(s2))$$

iff

$$(l1, l2, x, ns1) \in A.arcs(s1) \text{ and } (l2, l3, y, ns2) \in B.arcs(s2)$$

State Caching

Create generalized state machine B for input machine A.

- $B.start := A.start$
- $B.final(state) := A.final(state)$
- $B.arcs(state) := A.arcs(state)$

Cache Disciplines:

- Expand each state of A exactly once, i.e. always save in cache (memoize).
- Cache, but forget 'old' states using a least-recently used criterion.
- Use instructions (ref counts) from user (decoder) to save and forget.

On Demand Composition – Results

ATIS Task - class-based trigram grammar, full cross-word triphonic context-dependency.

	states	arcs
context	762	40386
lexicon	3150	4816
grammar	48758	359532
full expansion	$\sim 1.6 \times 10^6$	$5.1\times \sim 10^6$

For the same recognition accuracy as with a static, fully expanded network, on-demand composition expands just 1.6% of the total number of arcs.

Determinization in Large Vocabulary Recognition

- For large vocabularies, 'string' lexicons are very non-deterministic
- Determinizing the lexicon solves this problem, but can introduce non-coassessible states during its composition with the grammar
- Alternate Solutions:
  - Off-line compose, determinize, and minimize:

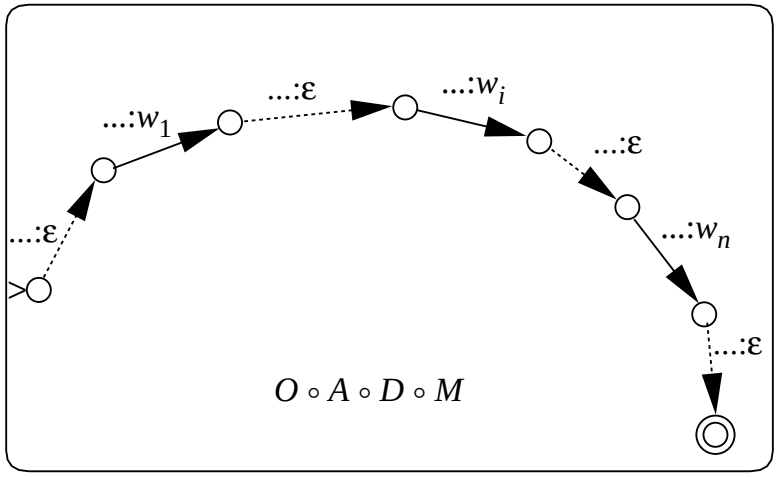
$$Lexicon \circ Grammar$$

  - Pre-tabulate non-coassessible states in the composition of:

$$Det(Lexicon) \circ Grammar$$

Search in Recognition Cascades

- Reminder: *Cost* $\equiv -\log$ *probability*
- Example recognition problem: $\hat{\mathbf{w}} = \underset{\mathbf{w}}{\text{argmax}}(O \circ A \circ D \circ M)(\mathbf{o}, \mathbf{w})$
- *Viterbi search*: approximate $\hat{\mathbf{w}}$ by the output word sequence for the lowest-cost path from the start state to a final state in $O \circ A \circ D \circ M$ — ignores summing over multiple paths with same output:



- Composition preserves acyclicity, O is acyclic $\Rightarrow$ acyclic search graph

Single-source Shortest Path Algorithms [83]

- Meta-algorithm:

  $Q \leftarrow \{s_0\}; \forall\, s, Cost(s) \leftarrow \infty$

  While Q not empty, $s \leftarrow$ DEQUEUE(Q)

  For each $s' \in Adj[s]$ such that $Cost(s') > Cost(s) + cost(s, s')$

  $Cost(s') \leftarrow Cost(s) + cost(s, s')$

  ENQUEUE(Q, s)

- Specific algorithms:

Name	Queue type	Cycles	Neg. Weights	Complexity
acyclic	topological	no	yes	$O(\|V\| + \|E\|)$
Dijkstra	best-first	yes	no	$O(\|E\| \log \|V\|)$
Bellman-Ford	FIFO	yes	yes	$O(\|V\| \cdot \|E\|)$

The Search Problem

- *Obvious first approach*: use an appropriate single-source shortest-path algorithm
- *Problem:* impractical to visit all states, can we do better?
  - *Admissible* methods: guarantee finding best path, but reorder search to avoid exploring provably bad regions
  - *Non-admissible* methods: may fail to find best path, but may need to explore much less of the graph
- Current practical approaches:
  - Heuristic cost functions
  - Beam search
  - Multipass search
  - Rescoring

Heuristic Cost Function — A* Search [4, 56, 17]

- States in search ordered by

$$\text{cost-so-far}(s) + \text{lower-bound-to-complete}(s)$$

- With a tight bound, states not on good paths are not explored
- With a loose lower bound no better than Dijkstra's algorithm
- Where to find a tight bound?
  - Full search of a composition of smaller automata (homomorphic automata with lower-bounding costs?)
  - Non-admissible A* variants: use averaged estimate of cost-to-complete, not a lower-bound

Beam Search [35]

- Only explore states with costs within a *beam* (threshold) of the cost of the best *comparable* state
- Non-admissible
- *Comparable states* $\equiv$ states corresponding to (approximately) the same observations
- Synchronous (Viterbi) search: explore composition states in chronological observation order
- Problem with synchronous beam search: too local, some observation subsequences are unreliable and may locally put the best overall path outside the beam

Beam-Search Tradeoffs [68]

Word lattice: result of composing observation sequence, level transducers and language model.

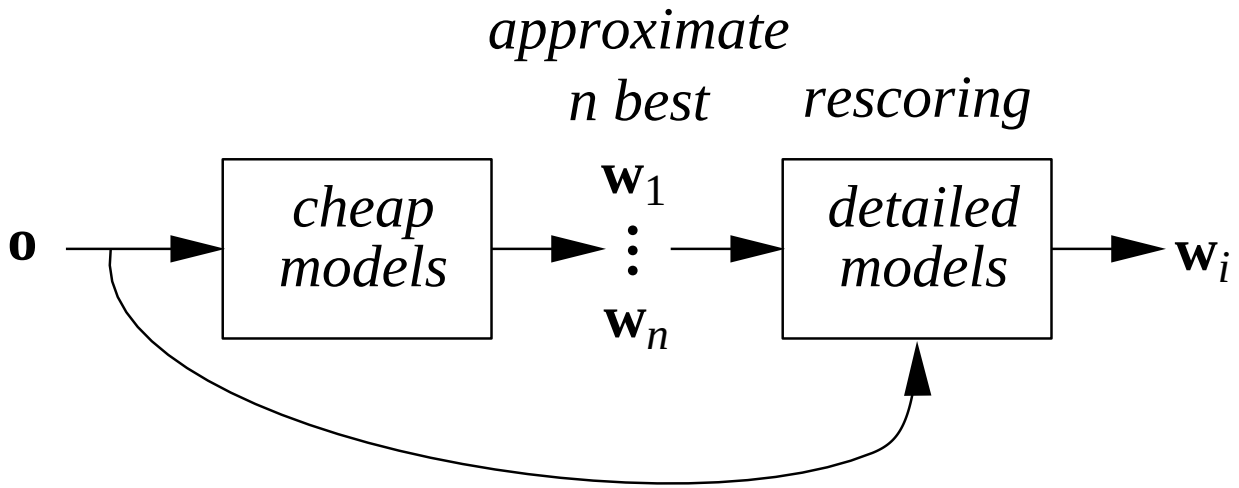
Beam	Word lattice error rate	Median number of edges
4	7.3%	86.5
6	5.4%	244.5
8	4.4%	827
10	4.1%	3520
12	4.0%	13813.5

Multipass Search [52, 3, 68]

- Use a succession of binary compositions instead of a single n-way composition — combinable with other methods
- *Prune*: Use two-pass variant of composition to remove states not in any path close enough to the best
- Pruned intermediate lattices are smaller, lower number of state pairings considered
- *Approximate*: use simpler models (context-independent phone models, low-order language models)
- *Rescore*. . .

Rescoring

Most successful approach in practice:



- Small pruned result built by composing approximate models
- Composition with full models, observations
- Find lowest-cost path

PART III
Finite State Methods in Language Processing

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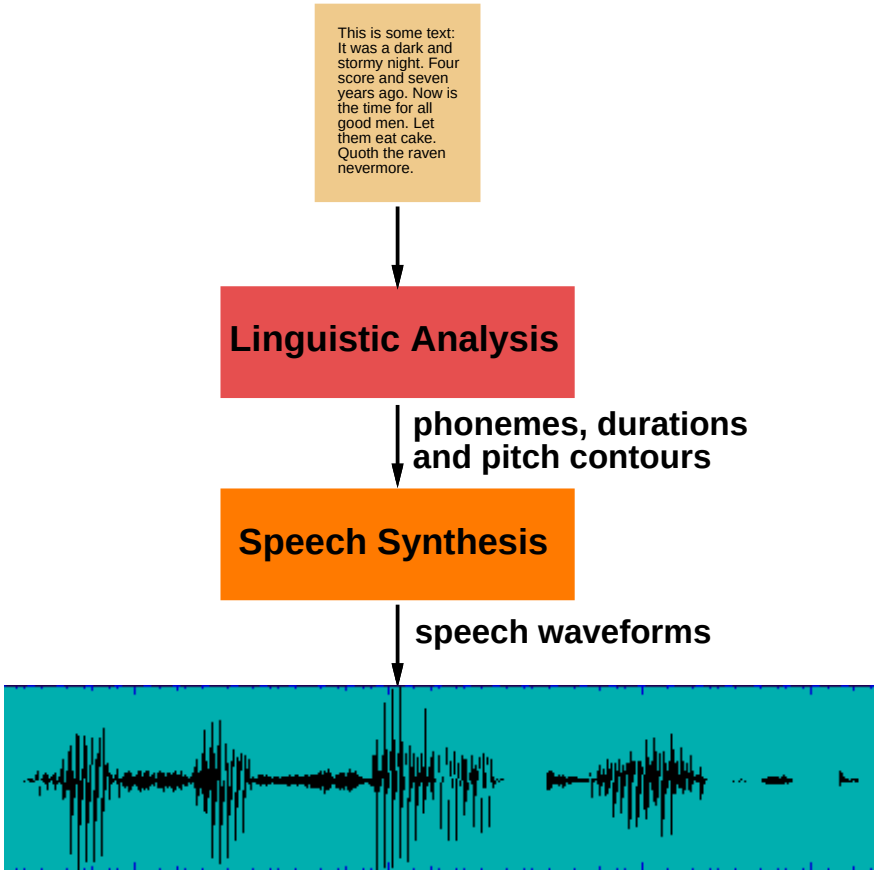
Overview

- Text-analysis for Text-to-Speech (TTS) Synthesis
  - A rich domain with lots of linguistic problems
  - Probably the least familiar application of NLP technologies
- Syntactic analysis
- Some thoughts on text indexation

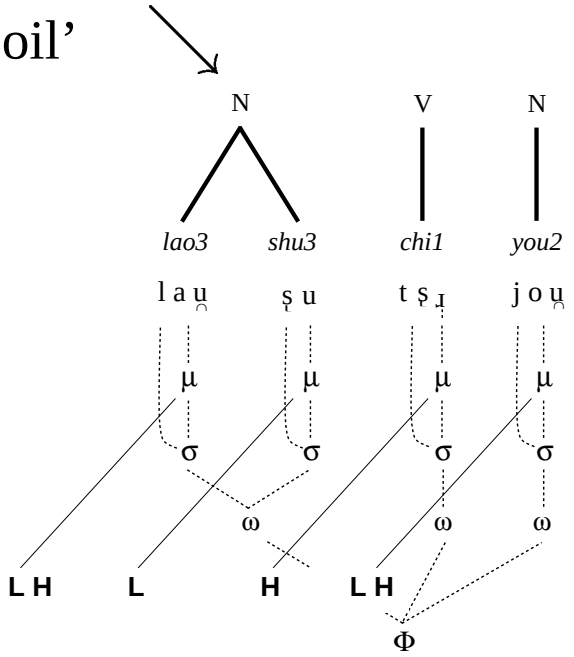
The Nature of the TTS Problem



From Text to Linguistic Representation

老鼠吃油。

‘The rat is eating the oil’



Russian Percentages: The Problem

How do you say '%' in Russian?

		Adjectival forms when modifying nouns
20% скидка	⇒	двадцат и -процентн ая скидка
'20% discount'		*dvadcat i -procent naja skidka*
с 20% раствором	⇒	с двадцат и -процент ным раствором
'with 20% solution'		*s dvadcat i -procent nym rastvorom*
		Nominal forms otherwise
21%	⇒	двадцать один процент
		dvadcat' odin procent
23%	⇒	двадцать три процент а
		dvadcat' tri procent a
20%	⇒	двадцать процент ов
		dvadcat' procent ov
с 20%	⇒	с двадцать ю процент ами
'with 20%'		*s dvadcat' ju procent ami*

Text Analysis Problems

- Segment text into words.
- Segment text into sentences, checking for and expanding abbreviations:

St. Louis is in Missouri.

- Expand numbers
- Lexical and morphological analysis
- Word pronunciation
  - Homograph disambiguation
- Phrasing
- Accentuation

Desiderata for a Model of Text Analysis for TTS

- Delay decisions until have enough information to make them

- Possibly *weight* various alternatives

Weighted Finite-State Transducers offer an attractive computational model

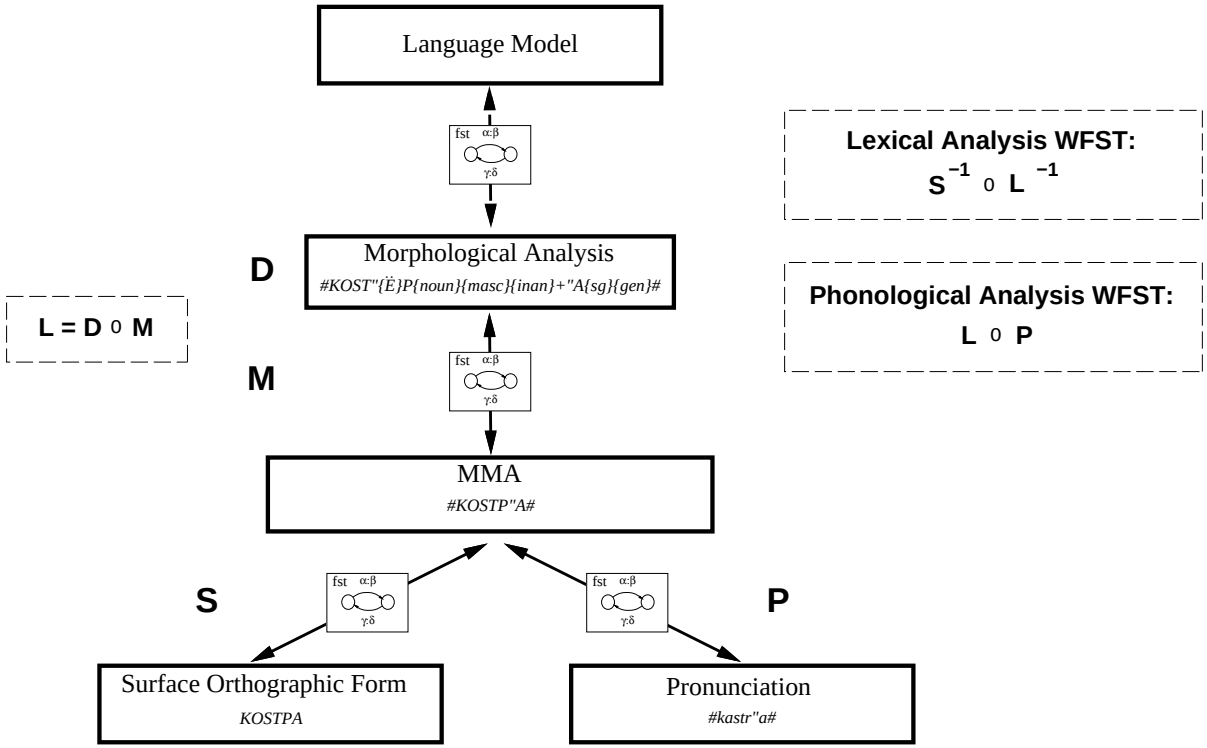
Overall Architectural Matters

Example: word pronunciation in Russian

- Text form: кострa<kostra> (bonfire+genitive.singular)
- Morphological analysis:
  кост′Ёр{noun}{masc}{inan}+′а{sg}{gen}
- Pronunciation: /kʌstr′a/
- Minimal Morphologically-Motivated Annotation (MMA): костр′а

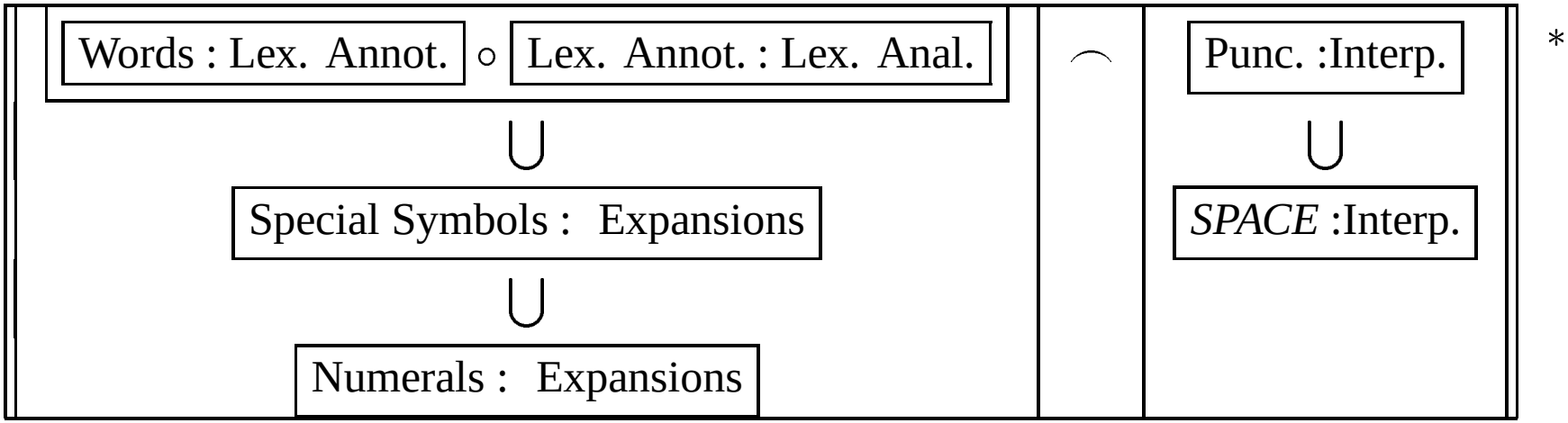
(Sproat, 1996)

Overall Architectural Matters



Orthography $\rightarrow$ Lexical Representation

A Closer Look



SPACE: white space in German, Spanish, Russian . . .

ϵ in Japanese, Chinese . . .

Chinese Word Segmentation

了	→	了$_1$asp$_{4.68}$	*le0*	PERF
了解	→	了$_2$解$_1$vb$_{8.11}$	*liao3jie3*	understand
大	→	大$_1$vb$_{5.56}$	*da4*	big
大街	→	大$_1$街nc$_{11.45}$	*da4jie1*	avenue
不	→	不$_2$adv$_{4.58}$	*bu4*	not
在	→	在vb$_{4.45}$	*zai4*	at
忘	→	忘vb$_{11.77}$	*wang4*	forget
忘不了	→	忘vb++不$_2$了$_2$npot$_{12.23}$	*wang4+bu4liao3*	unable to forget
我	→	我np$_{4.88}$	*wo3*	I
放	→	放vb$_{8.05}$	*fang4*	place
放大	→	放大$_1$vb$_{10.70}$	*fang4da4*	enlarge
哪裡	→	哪$_1$裡nc$_{11.02}$	*na3li3*	where
街	→	街nc$_{10.35}$	*jie1*	avenue
解放	→	解$_1$放nc$_{10.92}$	*jie3fang4*	liberation
解放大	→	解$_3$放大$_1$urnp$_{42.23}$	*xie4 fang4da4*	NAME

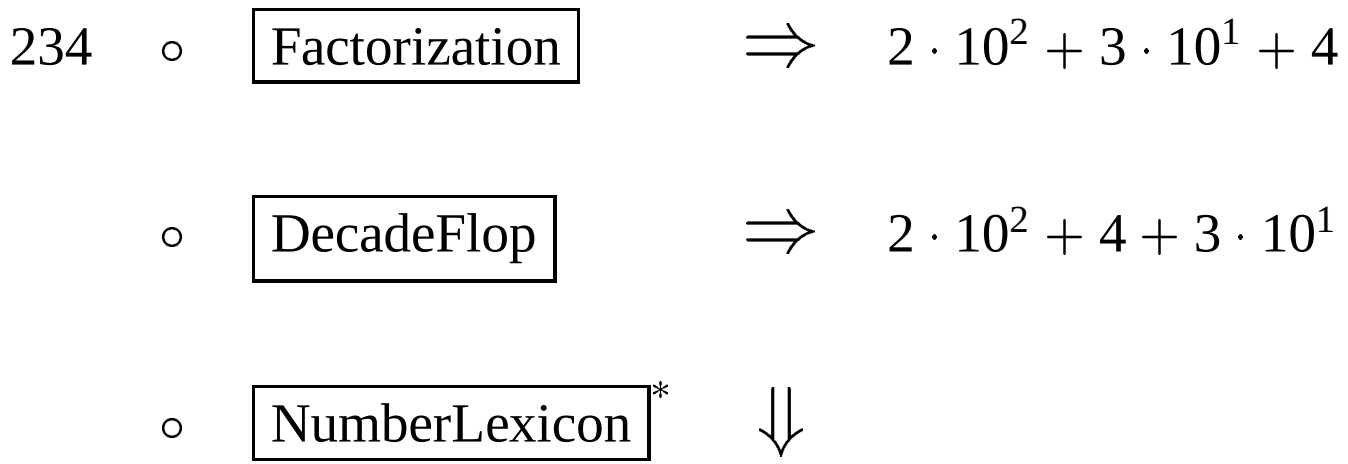
Chinese Word Segmentation

Space $= \epsilon : \#$

$\mathrm{L} = Space \frown (Dictionary \frown (Space \cup Punc))^{+}$

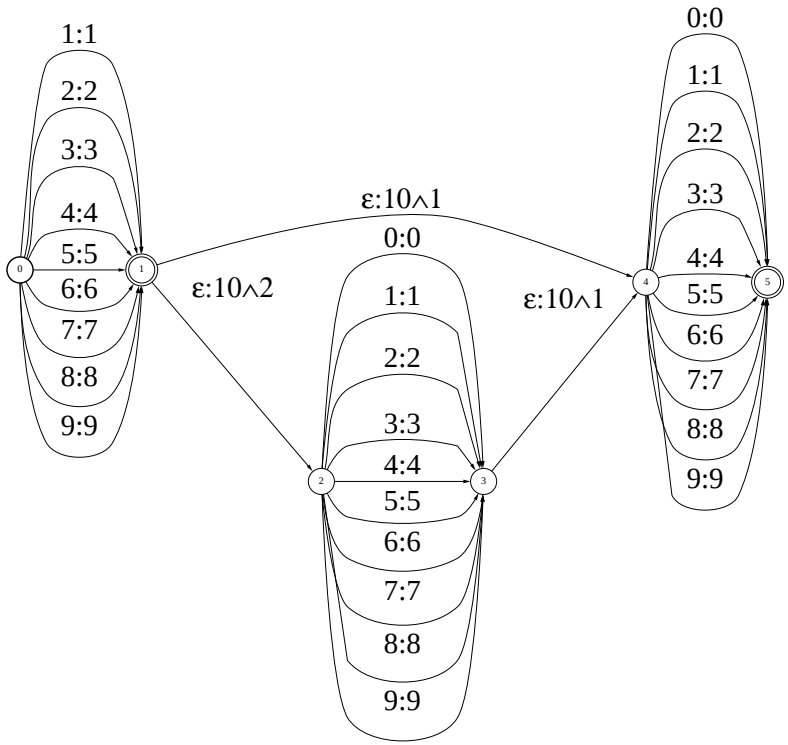
BestPath(我忘不了解放大街在哪裡 $\circ$ L) =
我$\mathrm{pro}_{4.88}$#忘vb+不了$_2\mathrm{npot}_{12.23}$# 解$_1$放$\mathrm{nc}_{10.92}$大$_1$街$\mathrm{nc}_{11.45}$ . . .
‘I couldn’t forget where Liberation Avenue is.’

Numeral Expansion



zwei+hundert+vier+und+dreißig

Numeral Expansion



German Numeral Lexicon

/{1}	:	(’eins{num}({masc}|{neut}){sg}{##})/
/{2}	:	(zw’ei{num}{##})/
/{3}	:	(dr’ei{num}{##})/
	⋮	
/({0}{+++}{1}{10∧1})	:	(z’ehn{num}{##})/
/({1}{+++}{1}{10∧1})	:	(’elf{num}{##})/
/({2}{+++}{1}{10∧1})	:	(zw’ölf{num}{##})/
/({3}{+++}{1}{10∧1})	:	(dr’ei{++}zehn{num}{##})/
	⋮	
/({2}{10∧1})	:	(zw’an{++}zig{num}{##})/
/({3}{10∧1})	:	(dr’ei{++}ßig{num}{##})/
	⋮	
/({10∧2})	:	(h’undert{num}{##})/
/({10∧3})	:	(t’ausend{num}{neut}{##})/

Morphology: Paradigmatic Specifications

Paradigm	{A1}	
		# starke Flektion (z.B. nach unbestimmtem Artikel)
Suffix	{++}er	{sg}{masc}{nom}
Suffix	{++}en	{sg}{masc}({gen}|{dat}|{acc})
Suffix	{++}e	{sg}{femi}({nom}|{acc})
Suffix	{++}en	{sg}({femi}|{neut})({gen}|{dat})
Suffix	{++}es	{sg}{neut}({nom}|{acc})
Suffix	{++}e	{pl}({nom}|{acc})
Suffix	{++}er	{pl}{gen}
Suffix	{++}en	{pl}{dat}

Morphology: Paradigmatic Specifications

```
                                  ##### Possessiva ("mein, euer")
Paradigm    {A6}
Suffix      {++}{Eps}     {sg}({masc}|{neut}){nom}
Suffix      {++}e         {sg}{femi}{nom}
Suffix      {++}es        {sg}({masc}|{neut}){gen}
Suffix      {++}er        {sg}{femi}({gen}|{dat})
Suffix      {++}em        {sg}({masc}|{neut}){dat}
Suffix      {++}en        {sg}{masc}{acc}
Suffix      {++}{Eps}     {sg}{neut}{acc}
Suffix      {++}e         {pl}({nom}|{acc})
Suffix      {++}er        {pl}{gen}
Suffix      {++}en        {pl}{dat}
```

Morphology: Paradigmatic Specifications

/{A1} : ('aal{++}glatt{adj})/

/{A1} : ('ab{++}änder{++}lich{adj}{umlt})/

/{A1} : ('ab{++}artig{adj})/

/{A1} : ('ab{++}bau{++}würdig{adj}{umlt})/

⋮

/{A6} : (d'ein{adj})/

/{A6} : ('euer{adj})/

/{A6} : ('ihr{adj})/

/{A6} : ('Ihr{adj})/

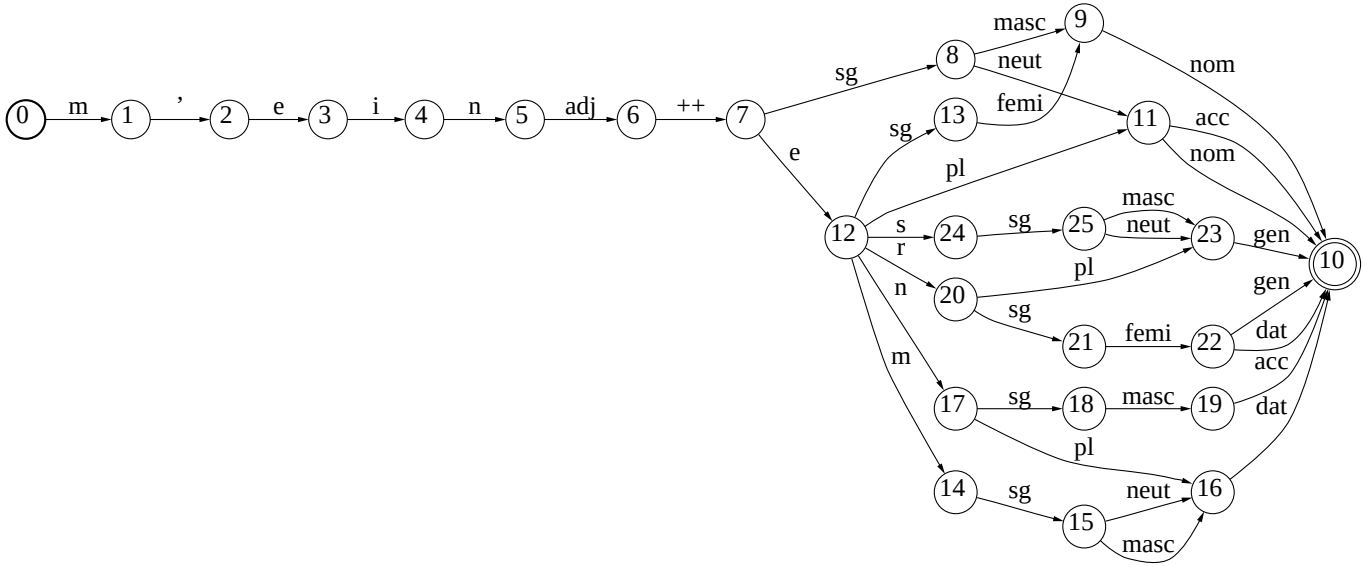
/{A6} : (m'ein{adj})/

/{A6} : (s'ein{adj})/

/{A6} : ('unser{adj})/

Morphology: Paradigmatic Specifications

$$\text{Project}((\{\text{A6}\} \frown \text{Endings}) \circ ((\{\text{A6}\}\text{:Stems}) \frown \text{Id}(\Sigma^*))) \Rightarrow$$



Morphology: Finite-State Grammar

START	PREFIX	{Eps}
PREFIX	STEM	{Eps}
PREFIX	STEM	t"ele{++}<1.0>
	⋮	
STEM	SUFFIX	’abend
STEM	SUFFIX	’abenteuer
	⋮	
SUFFIX	PREFIX	{++}<1.0>
SUFFIX	FUGE	{Eps}<1.0>
SUFFIX	WORD	{Eps}<2.0>
	⋮	

Morphology: Finite-State Grammar

FUGE	SECOND	{++}<1.5>
FUGE	SECOND	{++}s{++}<1.5>
	⋮	
SECOND	PREFIX	{Eps}<1.0>
SECOND	STEM	{Eps}<2.0>
SECOND	WORD	{Eps}<2.0>
	⋮	
WORD		

Morphology: Finite-State Grammar

Unanständigkeitsunterstellung
‘allegation of indecency’

"un{++}"an{++}st’änd{++}ig{++}keit{++}s{++}unter{++}st’ell{++}ung

Rewrite Rule Compilation

Context-dependent rewrite rules

General form:

$$\phi \rightarrow \psi / \lambda \_\_ \rho$$

$\phi, \psi, \lambda, \rho$ regular expressions.

Constraint: ψ cannot be rewritten but can be used as a context

Example:

$$a \rightarrow b / c \_\_ b$$

(Johnson, 1972; Kaplan & Kay, 1994; Karttunen, 1995; Mohri & Sproat, 1996)

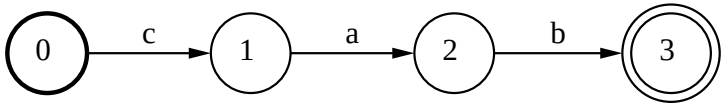
Example

$$a \rightarrow b / c \_\_ b$$

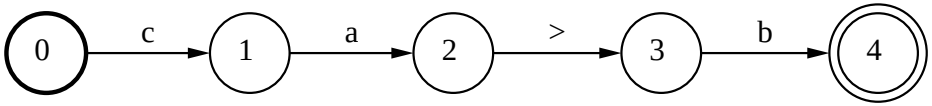
$$w = cab$$

Example

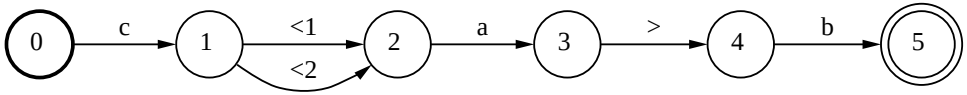
Input:



After *r*:

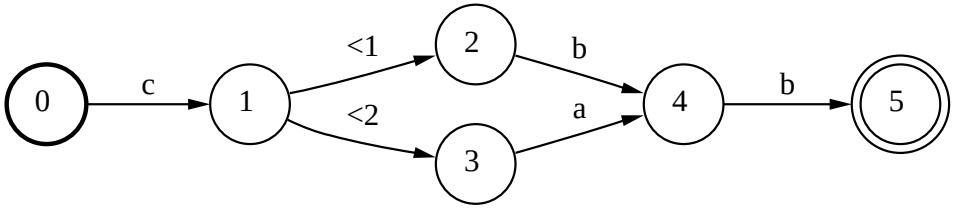


After *f*:

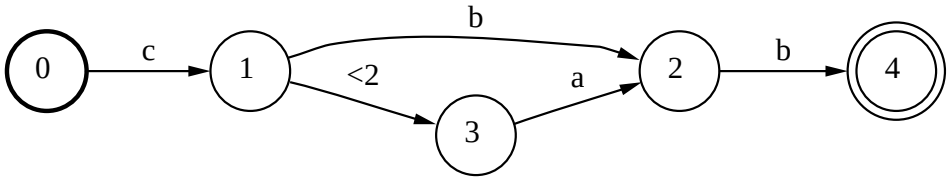


Example

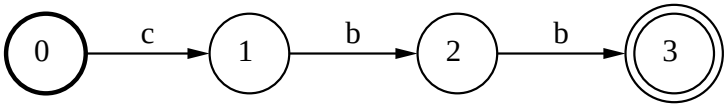
After *replace*:



After l_1:



After l_2:



Rewrite Rule Compilation

- Principle
  - Based on the use of marking transducers
  - Brackets inserted only where needed
- Efficiency
  - 3 determinizations + additional linear time work
  - Smaller number of compositions

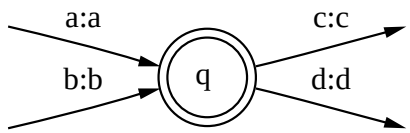
Rule Compilation Method

$$r \circ f \circ replace \circ l_1 \circ l_2$$

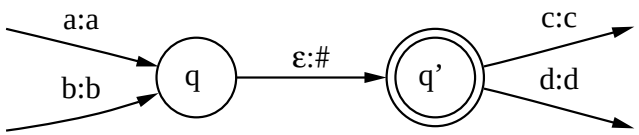
$$
\begin{array}{ll}
r: & \Sigma^* \rho \rightarrow \Sigma^* > \rho \\
f: & (\Sigma \cup \{>\})^* \phi > \rightarrow (\Sigma \cup \{>\})^* \{<_1, <_2\} \phi > \\
replace: & <_1 \phi > \rightarrow <_1 \psi \\
l_1: & \Sigma^* \lambda <_1 \rightarrow \Sigma^* \lambda \\
l_2: & \Sigma^* \overline{\lambda} <_2 \rightarrow \Sigma^* \overline{\lambda}
\end{array}
$$

Marking Transducers

Proposition Let α be a deterministic automaton representing $\Sigma^* \beta$, then the transducer τ post-marks occurrences of β by #.

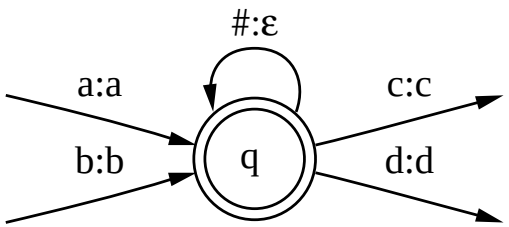


Final state q with entering and leaving transitions of $Id(\alpha)$.



States and transitions after modifications, transducer τ.

Marker of Type 2

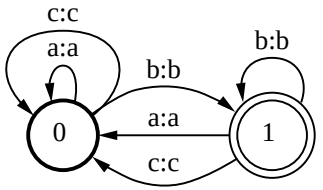


The Transducers as Expressions using *Marker*

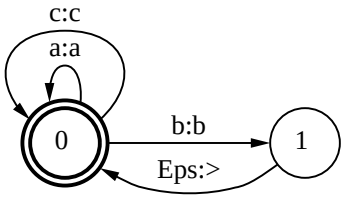
$$
\begin{aligned}
r &= [reverse(Marker(\Sigma^* reverse(\rho), 1, \{>\}, \emptyset))] \\
f &= [reverse(Marker((\Sigma \cup \{>\})^* reverse(\phi_> >), 1, \{<_1, <_2\}, \emptyset))] \\
l_1 &= [Marker(\Sigma^* \lambda, 2, \emptyset, \{<_1\})]_{<_2:<_2} \\
l_2 &= [Marker(\Sigma^* \lambda, 3, \emptyset, \{<_2\})]
\end{aligned}
$$

Example: r for rule $a \rightarrow b / c\_\_b$

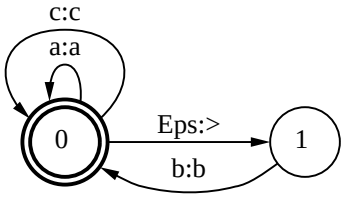
$$\Sigma^* reverse(\rho) =$$



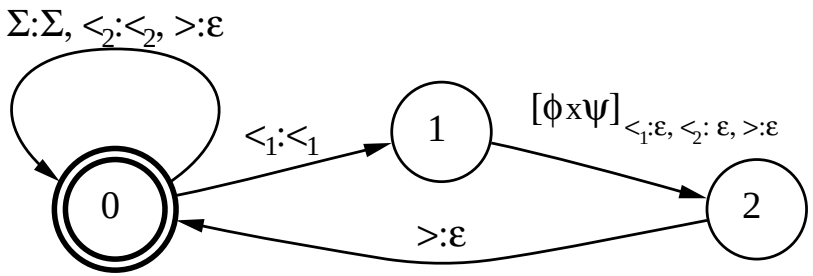
$$Marker(\Sigma^* reverse(\rho), 1, \{>\}, \emptyset) =$$



$$\boxed{reverse(Marker(\Sigma^* reverse(\rho), 1, \{>\}, \emptyset))} =$$



The *Replace* Transducer



Extension to Weighted Rules

Weighted context-dependent rules:

$$\phi \to \psi / \lambda \_\_ \rho$$

- ϕ, λ, ρ regular expressions,
- ψ formal power series on the tropical semiring

Example:

$$c \to (.9c) + (.1t) / a \_\_ t$$

Rational power series

Functions $S : \Sigma^* \to \mathcal{R}_+ \cup \{\infty\}$, *Rational* power series

- *Tropical semiring*: $(\mathcal{R}_+ \cup \{\infty\}, \min, +)$
- Notation: $S = \sum_{w \in \Sigma^*} (S, w)$
- Example: $S = (2a)(3b)(4b)(5b) + (5a)(3b)^*$
  $(S, abbb) = \min\{2 + 3 + 4 + 5 = 14, 5 + 3 + 3 + 3 = 11\} = 11$

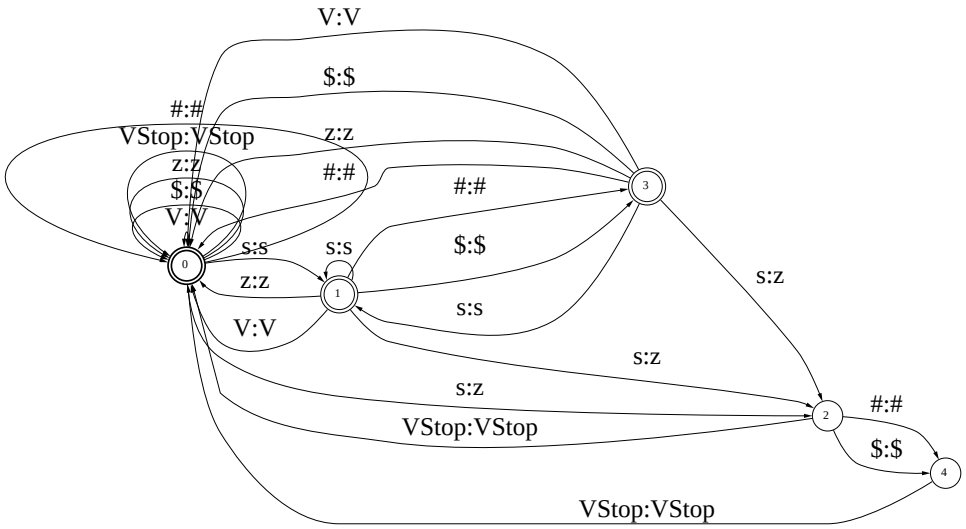
Theorem 6 *(Schützenberger, 1961): S is rational iff it is recognizable (representable by a weighted transducer).*

Compilation of weighted rules

- Extension of the composition algorithm to the weighted case
  - Efficient filter for ϵ-transitions
  - Addition of weights of matching labels
- Same compilation algorithm
- Single-source shortest paths algorithms to find the best path

Rewrite Rules: An Example

$$s \rightarrow z \;/\; \_\_\_ \; (\$|\#) \; VStop \; ;$$



/mismo/ ∘ Voicing = /mizmo/

Syllable structure

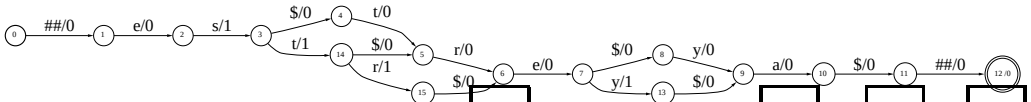
1 $(C^* \; V \; C^*_{1.0} \; \boxed{\$} \;)^+ \bigcap$

2 $\neg \; (\Sigma^* \; \boxed{\$} \; (CC \cap \neg \; (CG \cup OL)) \; \Sigma^*) \bigcap$

3 $\neg \; (\Sigma^* \; \boxed{\$} \; ([+cor] \cup /x/ \cup /\beta/) \; /l/ \; \Sigma^*) \bigcap$

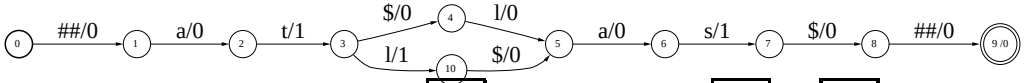
4 $\neg \; (\Sigma^* \; \boxed{\$} \; ([+cor,+strid] \cup /x/ \cup /\beta/) \; /r/ \; \Sigma^*)$

estrella: /estreya/ ∘ Intro($\boxed{\$}$) ∘ Syl ⇒



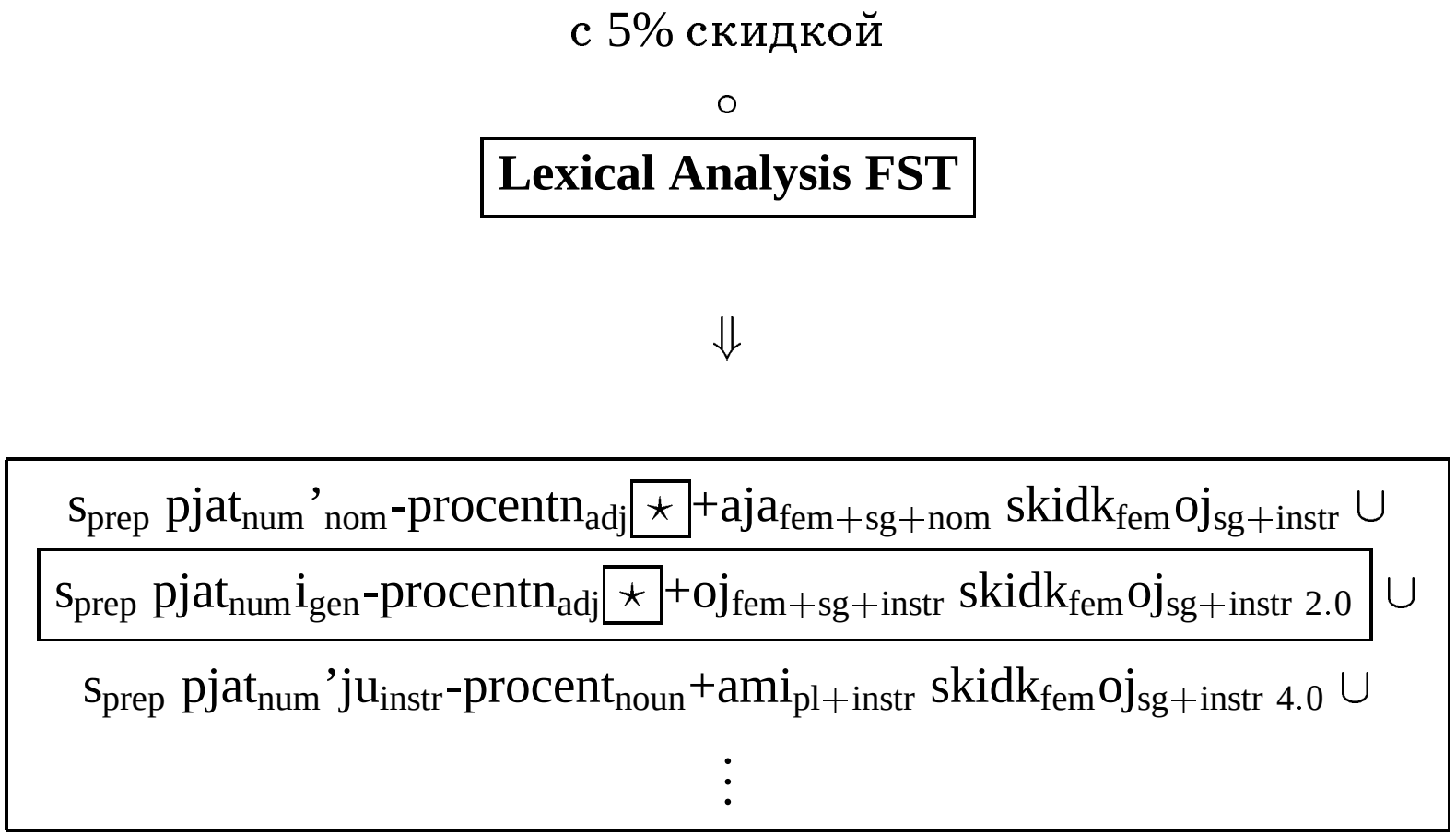
BestPath(/estreya/ ∘ Intro($\boxed{\$}$) ∘ Syl) = /es $\boxed{\$}$ tre $\boxed{\$}$ ya $\boxed{\$}$ /

atlas: /atlas/ ∘ Intro($\boxed{\$}$) ∘ Syl ⇒



BestPath(/atlas/ ∘ Intro($\boxed{\$}$) ∘ Syl) = /at $\boxed{\$}$ las $\boxed{\$}$ /

Russian Percentage Expansion: An example



Language Model FSTs:

$$\epsilon \rightarrow \boxed{\star} \;/\; \text{procent}_{\text{noun}}\ (\Sigma \cap \neg\#)^*\ \#\_\ (\Sigma \cap \neg\#)^*_{\text{noun}}$$

$$\boxed{\star} \rightarrow \epsilon \;/\; \text{procentn}_{\text{adj}}\ (\Sigma \cap \neg\#)^*\ \#\_\ (\Sigma \cap \neg\#)^*_{\text{noun}}$$

$\circ$

$$\epsilon \rightarrow \boxed{\star} \;/\; \text{procentn}\ (\Sigma \cap \neg\#)^*{}_{\text{Case} \cap \neg \text{instr}} \#\ \_\ (\Sigma \cap \neg\#)^*_{\text{instr}}$$

$$\epsilon \rightarrow \boxed{\star} \;/\; \text{procentn}\ (\Sigma \cap \neg\#)^*{}_{\text{sg}+\text{Case}} \#\ \_\ (\Sigma \cap \neg\#)^*_{\text{pl}}$$

$\circ$

$$\neg(\Sigma^* \boxed{\star} \Sigma^*)$$

$\Downarrow$

s pjati$_{\text{gen}}$-procentn$_{\text{adj}}$oj$_{\text{sg}+\text{instr}}$ skidkoj

Percentage Expansion: Continued

с 5% скидкой

$\Downarrow$

s pjati$_{\text{gen}}$-procentn$_{\text{adj}}$oj$_{\text{sg+instr}}$ skidkoj

$\circ$

$\boxed{\mathbf{L} \circ \mathbf{P}}$

$\Downarrow$

```
s # PiT"!p~r@c"Entn&y # sK"!tk&y
```

Phrasing Prediction

- **Problem**: predict intonational phrase boundaries in long unpunctuated utterences:

  For his part, Clinton told reporters in Little Rock, Ark., on Wednesday || that the pact can be a good thing for America || if we change our economic policy || to rebuild American industry here at home || and if we get the kind of guarantees we need on environmental and labor standards in Mexico || and a real plan || to help the people who will be dislocated by it.

- Bell Labs synthesizer uses a CART-based predictor trained on labeled corpora (Wang & Hirschberg 1992).

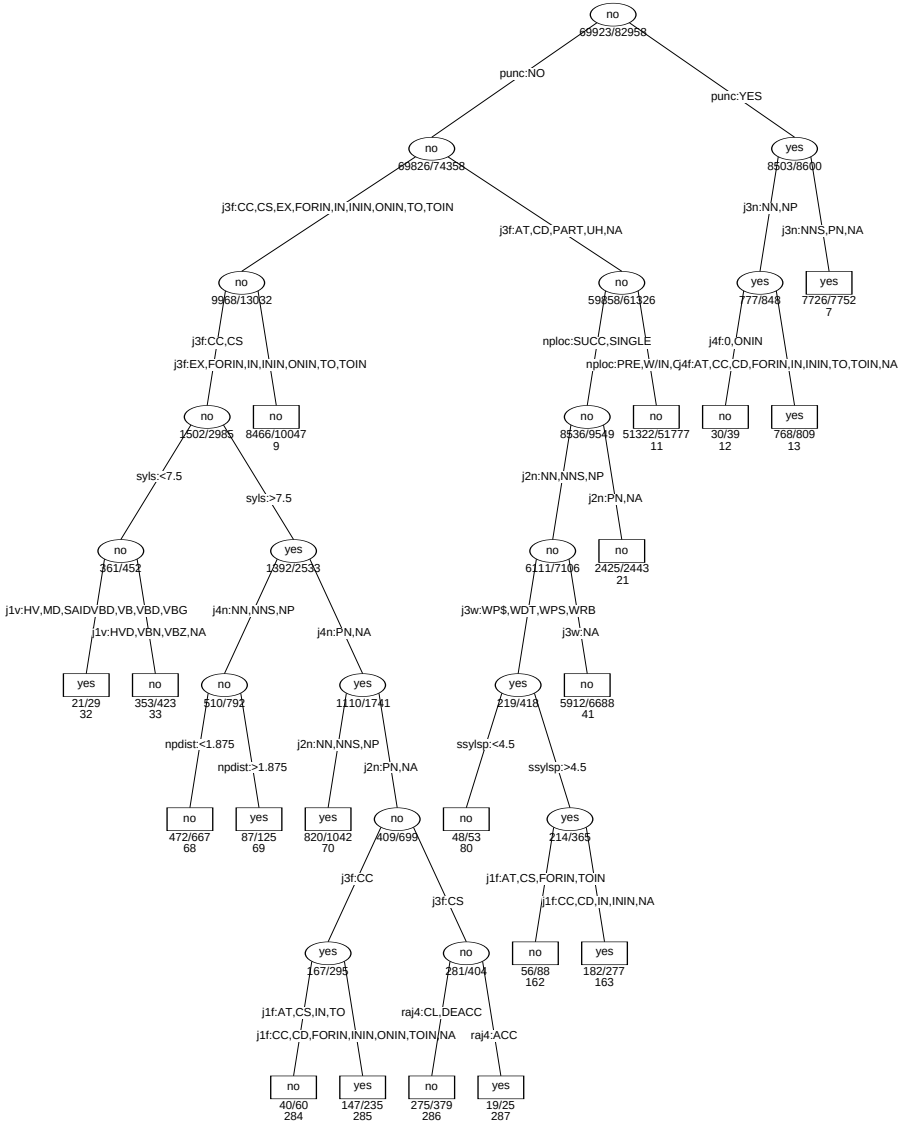
Phrasing Prediction: Variables

For each $< w_i, w_j >$:

- length of utterance; distance of w_i in syllables/ stressed syllables/words . . . from the beginning/end of the sentence
- automatically predicted pitch accent for w_i and w_j
- part-of-speech (POS) for a 4-word window around $< w_i, w_j >$;
- (largest syntactic constituent dominating w_i but not w_j and vice versa, and smallest constituent dominating them both)
- whether $< w_i, w_j >$ is dominated by an NP and, if so, distance of w_i from the beginning of that NP, the NP, and distance/length
- (mutual information scores for a four-word window around $< w_i, w_j >$)

The most successful of these predictors so far appear to be POS, some constituency information, and mutual information

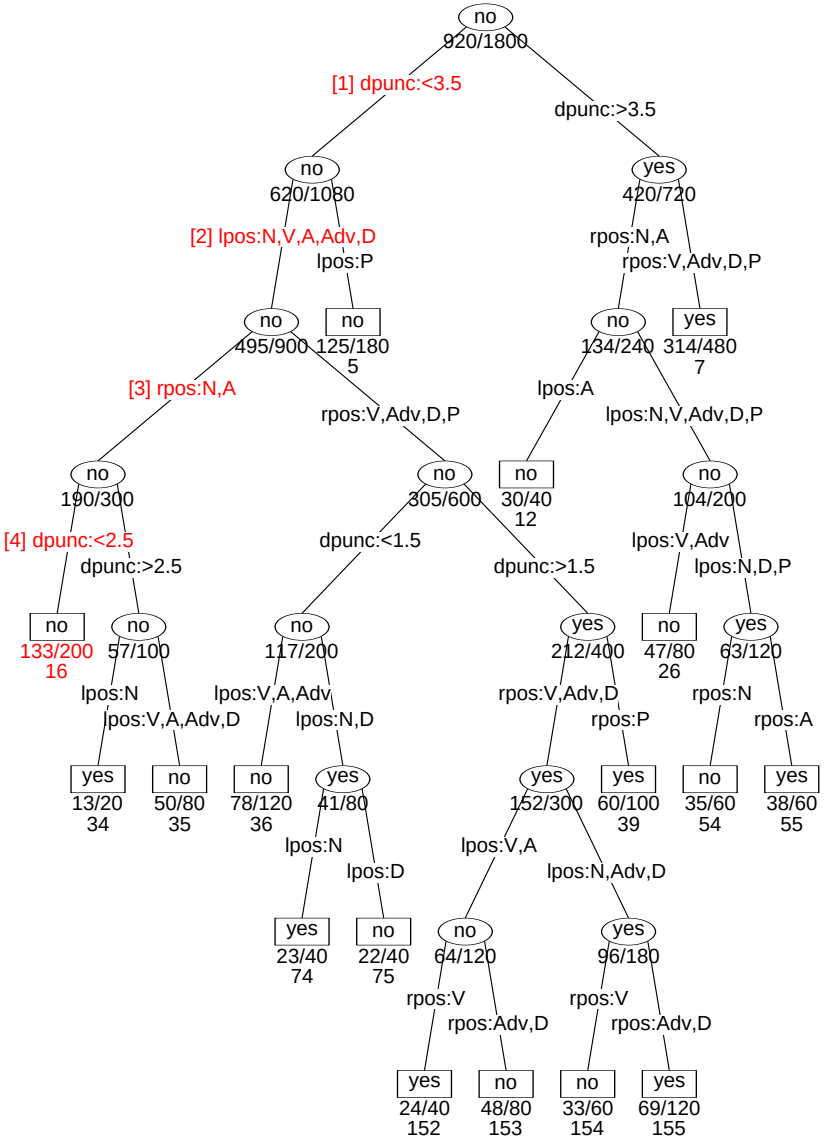
Phrasing Prediction: Sample Tree



Phrasing Prediction: Results

- Results for multi-speaker read speech:
  - major boundaries only: **91.2%**
  - collapsed major/minor phrases: **88.4%**
  - 3-way distinction between major, minor and null boundary: **81.9%**
- Results for spontaneous speech:
  - major boundaries only: **88.2%**
  - collapsed major/minor phrases: **84.4%**
  - 3-way distinction between major, minor and null boundary: **78.9%**
- Results for 85K words of hand-annotated text, cross-validated on training data: **95.4%**.

Tree-Based Modeling: Prosodic Phrase Prediction



The Tree Compilation Algorithm

(Sproat & Riley, 1996)

- Each *leaf* node corresponds to *single* rule defining a *constrained weighted mapping* for the input symbol associated with the tree
- Decisions at each node are stateable as regular expressions restricting the left or right context of the rule(s) dominated by the branch
- The full left/right context of the rule at a leaf node are derived by *intersecting* the expressions traversed between the root and leaf node
- The transducer for the entire tree represents the conjunction of all the constraints expressed at the leaf nodes; it is derived by *intersecting* together the set of WFSTs corresponding to each of the leaves
  - Note that intersection is defined for transducers that express same-length relations
- The *alphabet* is defined to be an alphabet of all correspondence pairs that were determined empirically to be possible

Interpretation of Tree as a Ruleset

Node 16	λ	ρ
	$\boxed{1}\ (\Sigma^*(I\omega \cup I\omega\#\omega \cup I\omega\#\omega\#\omega)) \cap$ $\boxed{2}\ (\Sigma^*(N \cup V \cup A \cup Adv \cup D)) \cap$ $\boxed{4}\ (\Sigma^*(I\omega \cup I\omega\#\omega))$	$\boxed{3}\ N \cup A$
$\# \Rightarrow (I_{1.09} \cup \#_{0.41})\ /\ I(\omega\#)?(N \cup V \cup A \cup Adv \cup D)$ ___ $N \cup A$		

Summary of Compilation Algorithm

Each rule represents a *weighted two-level surface coercion rule*

$$Rule_L = Compile(\phi_T \rightarrow \psi_L / \bigcap_{p \in P_L} \lambda_p \_\_ \bigcap_{p \in P_L} \rho_p)$$

Each tree/forest represents a set of simultaneous weighted two-level surface coercion rules

$$Rule_T = \bigcap_{L \in T} Rule_L$$

$$Rule_F = \bigcap_{T \in F} Rule_T$$

BestPath(,D#N#V#Adv#D#A#N $\circ$ Tree) $\Rightarrow$,D#N#V#Adv[,]D#A#N$_{2.76}$

Lexical Ambiguity Resolution

- *Word sense disambiguation*:

  She handed down a harsh **sentence**. *peine*

  This **sentence** is ungrammatical. *phrase*

- *Homograph disambiguation*:

  He plays **bass**. /beɨs/

  This lake contains a lot of **bass**. /bæs/

- *Diacritic restoration*:

  appeler l'autre **cote** de l'atlantique côté 'side'

  Cote d'Azur côte 'coast'

(Yarowsky, 1992; Yarowsky 1996; Sproat, Hirschberg & Yarowsky, 1992; Hearst 1991)

Homograph Disambiguation 1

- **N-Grams**

Evidence	lɛd	lid	Logprob
lead *level/N*	219	0	11.10
of lead *in*	162	0	10.66
the lead *in*	0	301	10.59
lead *poisoning*	110	0	10.16
lead *role*	0	285	10.51
narrow lead	0	70	8.49

- **Predicate-Argument Relationships**

follow/V + lead	0	527	11.40
take/V + lead	1	665	7.76

- **Wide Context**

zinc $\leftrightarrow$ lead	235	0	11.20
copper $\leftrightarrow$ lead	130	0	10.35

- **Other Features (e.g. Capitalization)**

Homograph Disambiguation 2

Sort by $Abs(Log(\frac{Pr(Pron_1|Collocation_i)}{Pr(Pron_2|Collocation_i)}))$

Decision List for *lead*		
Logprob	Evidence	Pronunciation
11.40	*follow/V* + lead	⇒ lid
11.20	*zinc* ↔ lead	⇒ lɛd
11.10	lead *level/N*	⇒ lɛd
10.66	*of* lead *in*	⇒ lɛd
10.59	*the* lead *in*	⇒ lid
10.51	lead *role*	⇒ lid
10.35	*copper* ↔ lead	⇒ lɛd
10.28	lead *time*	⇒ lid
10.16	lead *poisoning*	⇒ lɛd

Homograph Disambiguation 3: Pruning

- **Redundancy by subsumption**

Evidence	lid	lɛd	Logprob
lead *level/N*	219	0	11.10
lead *levels*	167	0	10.66
lead *level*	52	0	8.93

- **Redundancy by association**

Evidence	tɛɚ	tɪɚ
tear *gas*	0	1671
tear $\leftrightarrow$ *police*	0	286
tear $\leftrightarrow$ *riot*	0	78
tear $\leftrightarrow$ *protesters*	0	71

Homograph Disambiguation 4: Use

Choose single best piece of matching evidence.

Decision List for *lead*		
Logprob	Evidence	Pronunciation
11.40	*follow/V* + lead	⇒ lid
11.20	*zinc* ↔ lead	⇒ lɛd
11.10	lead *level/N*	⇒ lɛd
10.66	*of* lead *in*	⇒ lɛd
10.59	*the* lead *in*	⇒ lid
10.51	lead *role*	⇒ lid
10.35	*copper* ↔ lead	⇒ lɛd
10.28	lead *time*	⇒ lid
10.16	lead *poisoning*	⇒ lɛd

Homograph Disambiguation: Evaluation

Word	Pron1	Pron2	Sample Size	Prior	Performance
lives	laɪvz	lɪvz	33186	.69	.98
wound	waʊnd	wund	4483	.55	.98
Nice	naɪs	nis	573	.56	.94
Begin	bɪˈgɪn	beɪgɪn	1143	.75	.97
Chi	tʃi	kaɪ	1288	.53	.98
Colon	koʊˈloʊn	ˈkoʊlən	1984	.69	.98
lead (N)	lid	lɛd	12165	.66	.98
tear (N)	tɛɚ	tɪɚ	2271	.88	.97
axes (N)	ˈæksiz	ˈæksɪz	1344	.72	.96
IV	aɪ vi	fɔɹθ	1442	.76	.98
Jan	dʒæn	jɑn	1327	.90	.98
routed	ɹutɪd	ɹaʊtɪd	589	.60	.94
bass	beɪs	bæs	1865	.57	.99
TOTAL			63660	.67	.97

Decision Lists: Summary

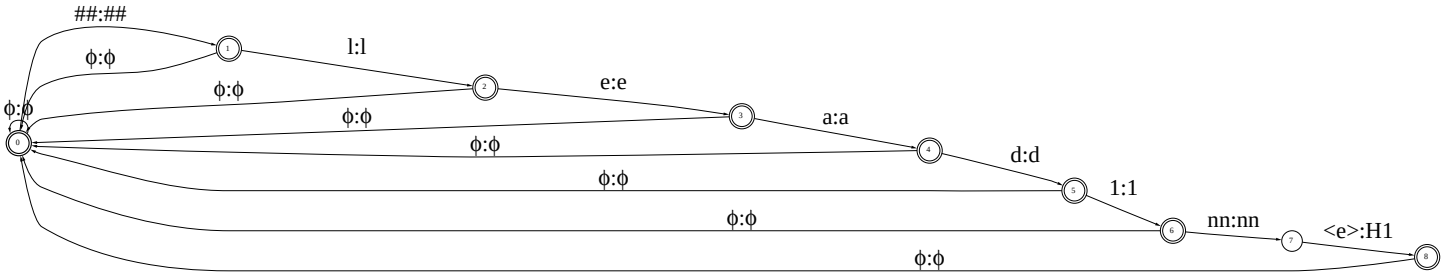
- Efficient and flexible use of data.

- Easy to interpret and modify.

Decision Lists as WFSTs

The *lead* example

- Construct 'homograph taggers' H_0, H_1 . . . that find and tag instances of a homograph set in a lexical analysis. For example, H_1 is:



Decision Lists as WFSTs

- Construct an *environmental classifier* consisting of a pair of transducers C_1 and C_2, where
  - C_1 optionally rewrites any symbol except the word boundary or the homograph tags H0, H1 . . . , as a single dummy symbol Δ
  - C_2 classifies contextual evidence from the decision list according to its type, and assigns a cost equal to the position of the evidence in the list; and otherwise passes Δ, word boundary and H0, H1 . . . through:

## follow vb ##	$\rightarrow$	## Δ V0 ## <1>
## zinc nn ##	$\rightarrow$	## Δ C1 ## <2>
## level(s?) nn ##	$\rightarrow$	## Δ R1 ## <3>
## of pp ##	$\rightarrow$	## Δ [1 ## <2>
## in pp ##	$\rightarrow$	## Δ 1] ## <2>
	$\vdots$	

Decision Lists as WFSTs

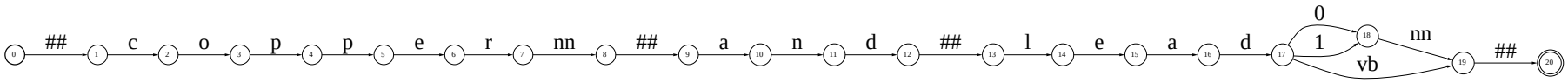
- Construct a *disambiguator* D from a set of *optional* rules of the form:

$$
\begin{array}{llll}
\text{H0} & \rightarrow & \diamond & / \quad \text{V0}\ \Sigma^*\ \underline{\quad} \\
\text{H1} & \rightarrow & \diamond & / \quad \text{C1}\ \Sigma^*\ \underline{\quad} \\
\text{H1} & \rightarrow & \diamond & / \quad \underline{\quad}\ \Sigma^*\ \text{C1} \\
\text{H0} & \rightarrow & \diamond & / \quad \underline{\quad}\ \#\#\ \Delta^*\ \text{R0} \\
\text{H1} & \rightarrow & \diamond & / \quad \underline{\quad}\ \#\#\ \Delta^*\ \text{R1} \\
\text{H0} & \rightarrow & \diamond & / \quad [0\ \#\#\ \Delta^*\ \underline{\quad}\ \#\#\ \Delta^*\ 0] \\
\text{H1} & \rightarrow & \diamond & / \quad [1\#\#\ \Delta^*\ \underline{\quad}\ \#\#\ \Delta^*\ 1] \\
 & \vdots & & \\
\text{H0} & \rightarrow & \diamond < 20 > & \\
\text{H1} & \rightarrow & \diamond < 40 > &
\end{array}
$$

- Construct a *filter* F that removes all paths containing H0, H1 . . . .

Decision Lists as WFSTs

- Let an example input T be:



- Then the disambiguated input T' is given by:

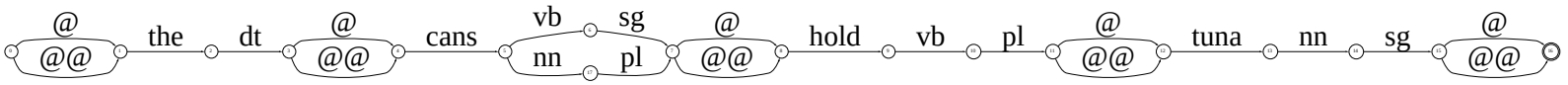
$$T \cap Project^{-1}[\, BestPath\, [\, T \circ H_0 \circ H_1 \circ C_1 \circ C_2 \circ D \circ F\,]\,]$$

Syntactic Parsing and Analysis

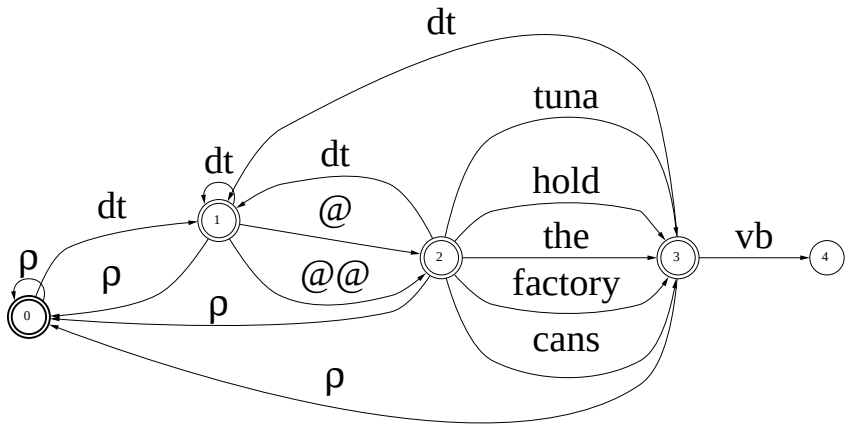
- Intersection grammars (Voutilainen, 1994, inter alia)
- FST simulation of top-down parsing (Roche, 1996)
- Local grammars implemented as failure function automata (Mohri, 1994)

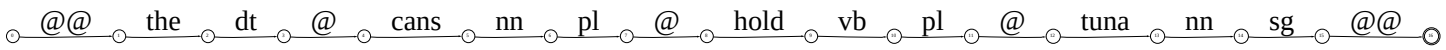
Intersection Grammars

- **Text automaton** consisting of all possible lexical analyses of the input, including analysis of boundaries.



- Series of syntactic FSAs to be intersected with the text automaton, constraining it.



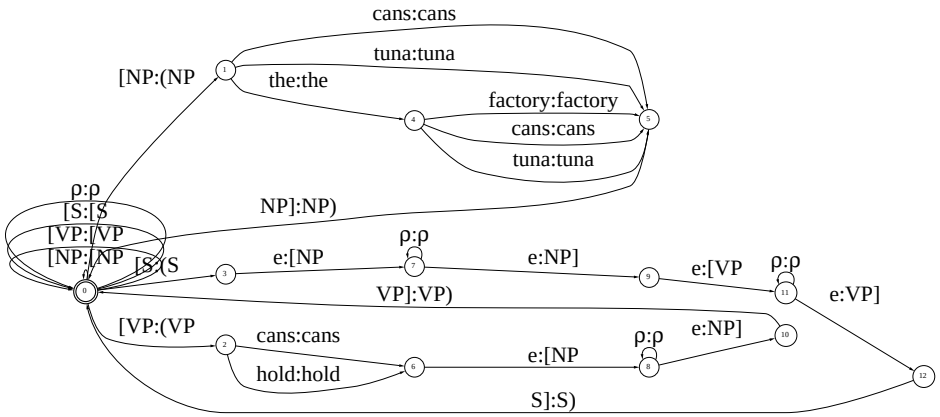


- Experimental grammars with a couple of hundred rules have been constructed.

Top Down Parsing

S = [S the cans hold tuna S]

T_{dic} =



$S \circ T_{dic}$ = (S [NP NP] [VP the cans hold tuna VP] S)

(S [NP the NP] [VP cans hold tuna VP] S)

(S [NP the cans NP] [VP hold tuna VP] S)

(S [NP the cans hold NP] [VP tuna VP] S)

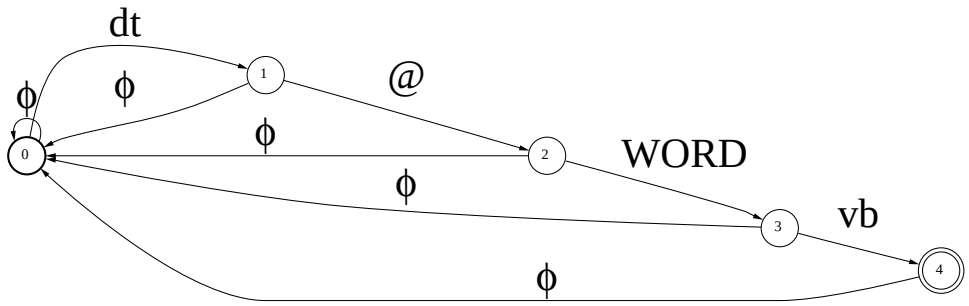
(S [NP the cans hold tuna NP] [VP VP] S)

$S \circ T_{dic} \circ T_{dic}$ = (S (NP the cans NP) (VP hold [NP tuna NP] VP) S)

Local Grammars

- Descriptions of *local* syntactic phenomena, compiled into efficient, compact deterministic automata, using failure functions. (Cf. the use of failure functions with (sets of) *strings* familiar from string matching — e.g. Crochemore & Rytter, 1994)

- Descriptions may be *negative* or *positive*.
  Example of a negative constraint:
  - Let $L(G)$ = DT @ WORD VB
  - Construct deterministic automaton for $\Sigma^* L(G)$



  - Given a sentence $L(S)$, compute $L(S) - \Sigma^* L(G) \Sigma^*$

Indexation of natural language texts

- Motivation
  - Use of linguistic knowledge in indexation
  - Optimal complexities
    - Preprocessing of a text t, $O(|t|)$
    - Search for positions of a string x, $O(|x| + NumOccurrences(x))$
- Existing efficient indexation algorithms (*PAT*), but not convenient (use with large linguistic information)

Example (1)

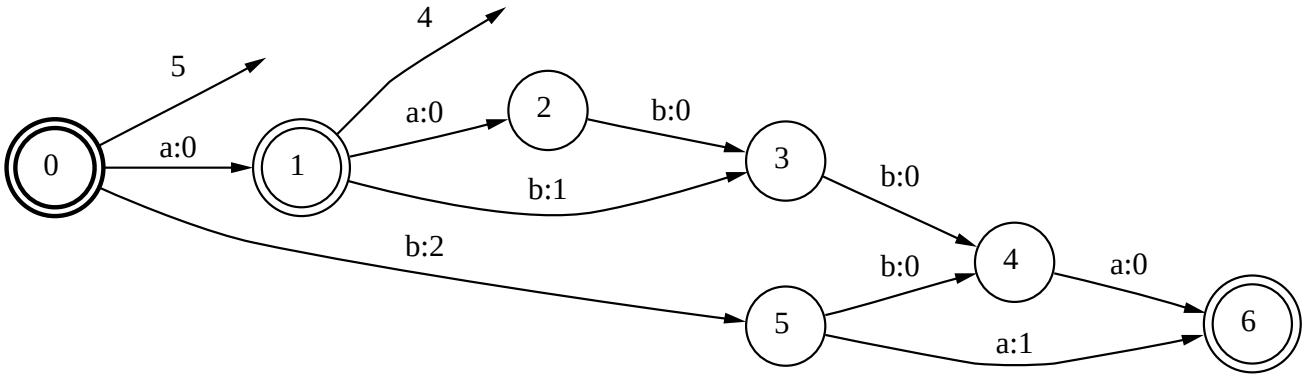


Figure 27: Indexation with subsequential transducers $t = aabba$.

Example (2)

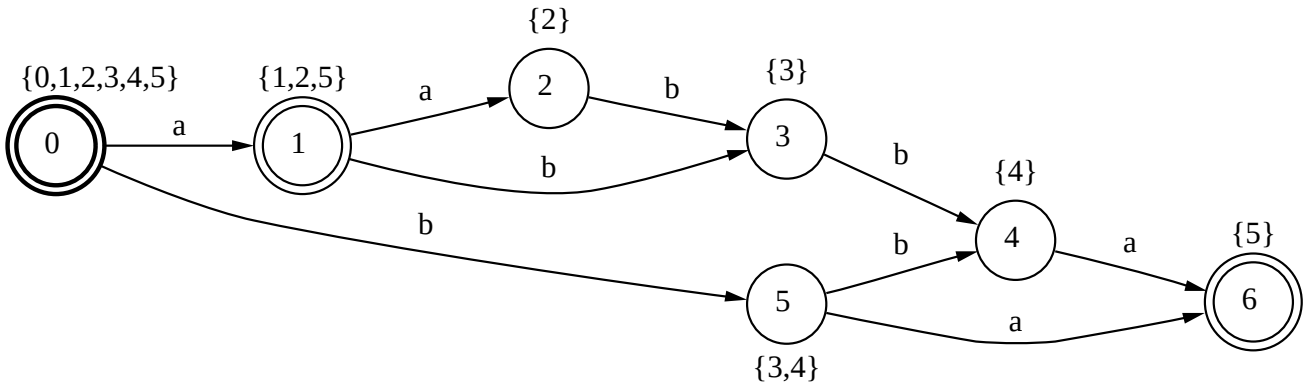


Figure 28: Indexation with automata $t = aabba$.

Algorithms

- Based on the definition of an equivalence relation R on Σ^*:
  $(w_1\ R\ w_2)$ iff w_1 and w_2 have the same set of ending positions in t
- Construction
  - Minimal machines (subsequential transducer or automaton)
  - Use of a failure function to distinguish equivalence classes
- Can be adapted to natural language text
  (not storing list of positions of short words)

Indexation with finite-state machines

- Complexity
  - Transducers (Crochemore, 1986): Preprocessing $O(|t|)$, Search $O(|x| + NumOccurrences(x))$ if using complex labels
  - Automata (Mohri, 1996b): Preprocessing quadratic, Search $O(|x| + NumOccurrences(x))$
- Advantage: use of linguistic information
  - Extended search: composition with morphological transducer
  - Refinement: composition with finite-state grammar
- Applications to WWW (Internet)

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