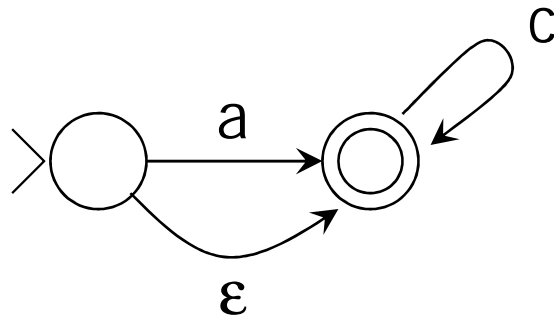


Finite-State Methods



Finite state acceptors (FSAs)



Defines the
language $a? c^*$

$= \{a, ac, acc, accc, \dots,$
 $\epsilon, c, cc, ccc, \dots\}$

- Things you may know about FSAs:
 - Equivalence to regexps
 - Union, Kleene $*$, concat, intersect, complement, reversal
 - Determinization, minimization
 - Pumping, Myhill-Nerode

n-gram models not good enough

- Want to model grammaticality
- A “training” sentence known to be grammatical:

BOS mouse traps catch mouse traps EOS

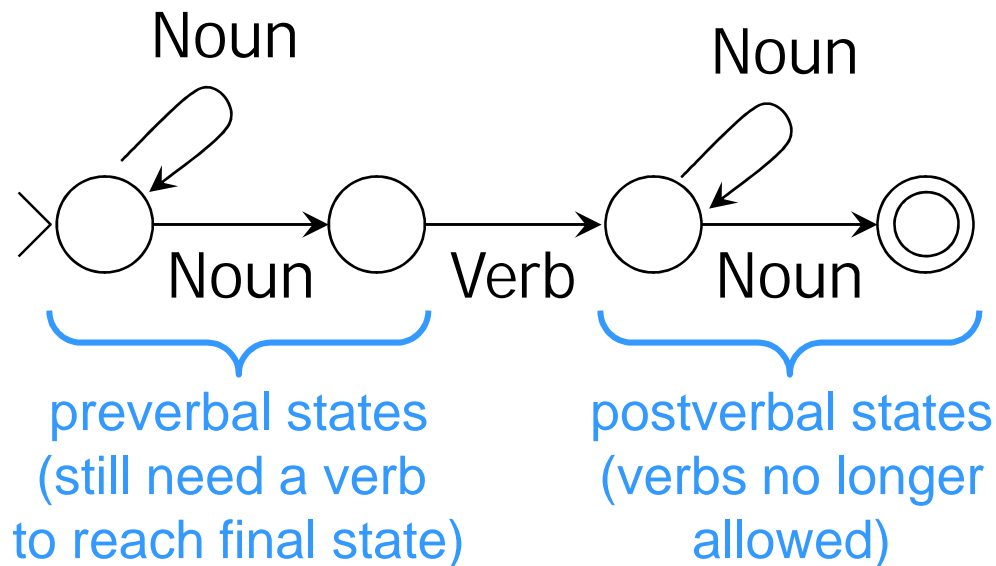
trigram model must allow these trigrams

- Resulting trigram model has to overgeneralize:
 - allows sentences with 0 verbs
BOS mouse traps EOS
 - allows sentences with 2 or more verbs
BOS mouse traps catch mouse traps
catch mouse traps catch mouse traps EOS
- Can't remember whether it's in subject or object (i.e., whether it's gotten to the verb yet)

Finite-state models can “get it”

- Want to model grammaticality
BOS **mouse traps catch mouse traps** EOS
- Finite-state can capture the generalization here:

Noun + Verb Noun +



Allows arbitrarily long NPs (just keep looping around for another Noun modifier).

Still, never forgets whether it's preverbal or postverbal!

(Unlike 50-gram model)

How powerful are regexps / FSAs?

- More powerful than n-gram models
 - The hidden state may “remember” arbitrary past context
 - With k states, can remember which of k “types” of context it’s in
- Equivalent to HMMs
 - In both cases, you observe a sequence and it is “explained” by a hidden path of states. The FSA states are like HMM tags.
- Appropriate for phonology and morphology
 - Word = Syllable+
 - = (Onset Nucleus Coda?)+
 - = (C+ V+ C*)+
 - = ((b|d|f|...) + (a|e|i|o|u) + (b|d|f|...)*)+

How powerful are regexps / FSAs?

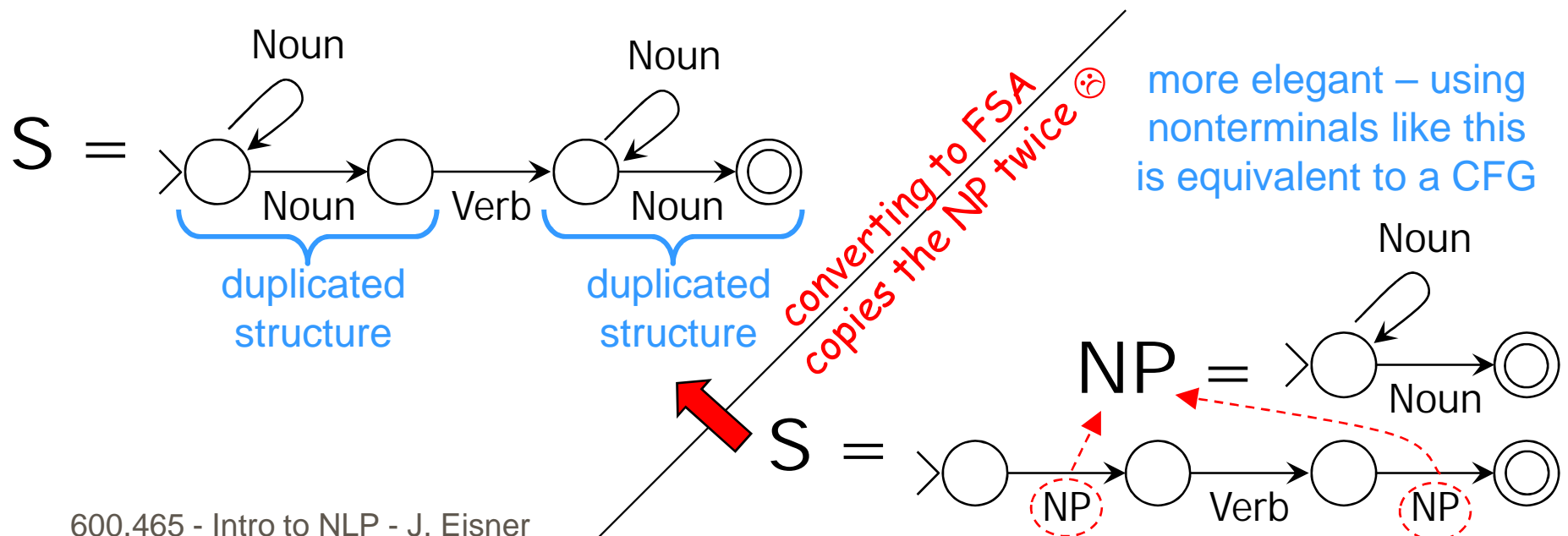
- But less powerful than CFGs / pushdown automata
 - Can't do recursive center-embedding
 - Hmm, humans have trouble processing those constructions too ...
- This is the rat that ate the malt.
- This is the malt that the rat ate.
- This is the cat that bit the rat that ate the malt.
- This is the malt that the rat that the cat bit ate.
- This is the dog that chased the cat that bit the rat that ate the malt.
- This is the malt that [the rat that [the cat that [the dog chased] bit] ate].

finite-state can
handle this pattern
(can you write the
regexp?)

but not this pattern,
which requires a CFG

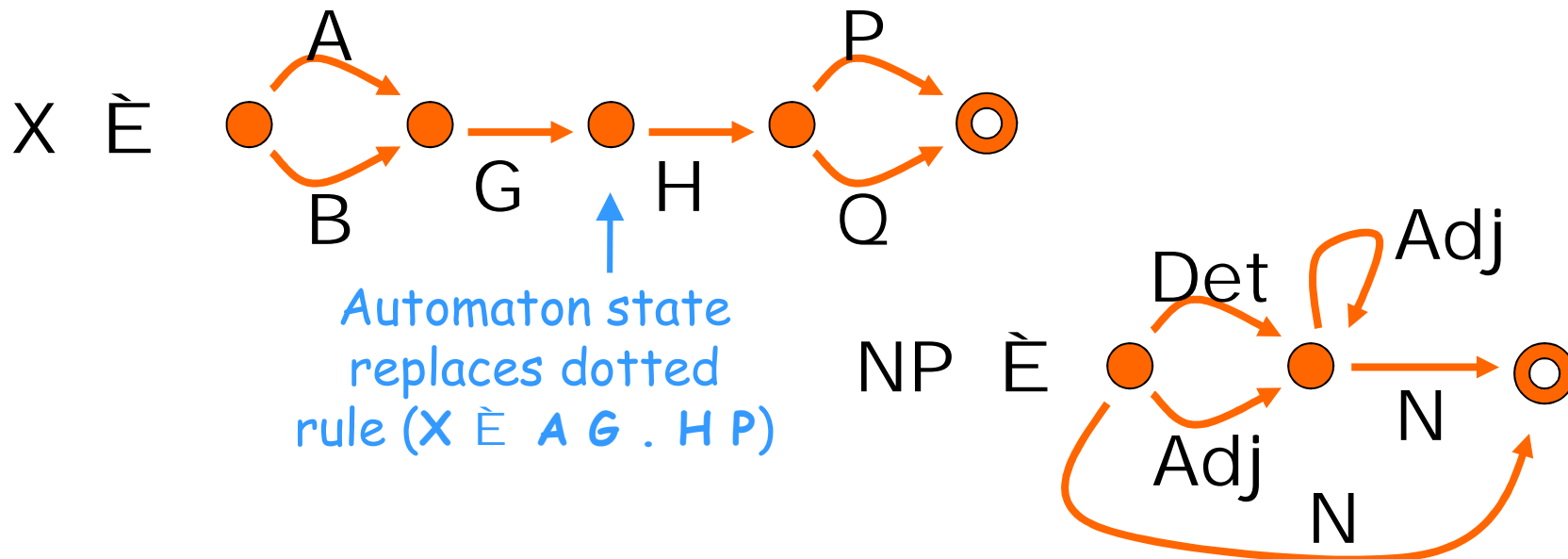
How powerful are regexps / FSAs?

- But less powerful than CFGs / pushdown automata
- More important: Less explanatory than CFGs
 - An CFG without recursive center-embedding can be converted into an equivalent FSA – but the FSA will usually be far larger
 - Because FSAs can't reuse the same phrase type in different places



We've already used FSAs this way ...

- CFG with regular expression on the right-hand side:
 $X \rightarrow (A \mid B) G H (P \mid Q)$
 $NP \rightarrow (Det \mid v) Adj^* N$
- So each nonterminal has a finite-state automaton, giving a "recursive transition network (RTN)"



We've already used FSAs once ..

NP È rules from the WSJ grammar become a single DFA

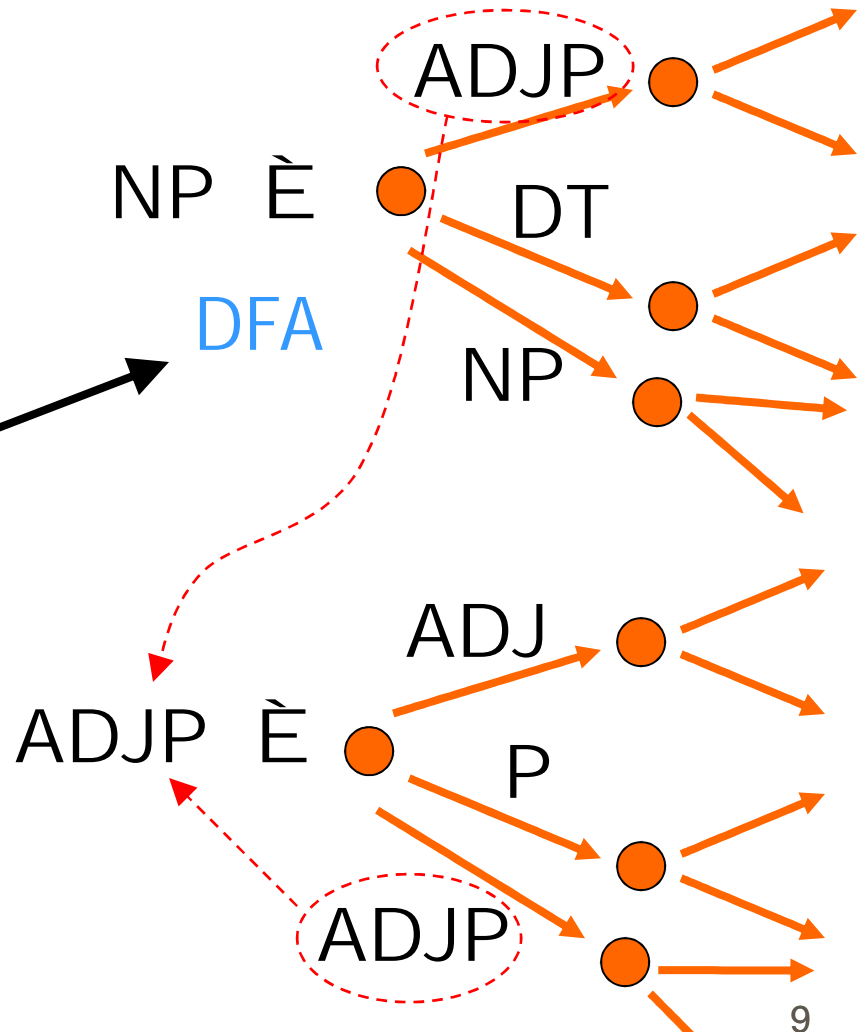
- NP È ADJP ADJP JJ JJ NN NNS
- | ADJP DT NN
- | ADJP JJ NN
- | ADJP JJ NN NNS
- | ADJP JJ NNS
- | ADJP NN
- | ADJP NN NN
- | ADJP NN NNS
- | ADJP NNS
- | ADJP NPR
- | ADJP NPRS
- | DT
- | DT ADJP
- | DT ADJP , JJ NN
- | DT ADJP ADJP NN
- | DT ADJP JJ JJ NN
- | DT ADJP JJ NN
- | DT ADJP JJ NN NN

etc.

regular expression

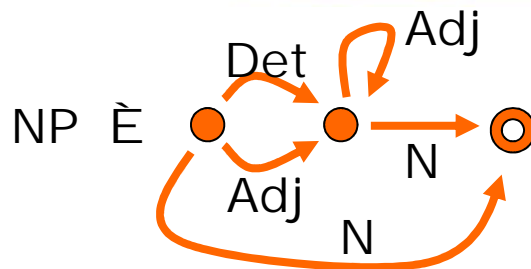


DFA

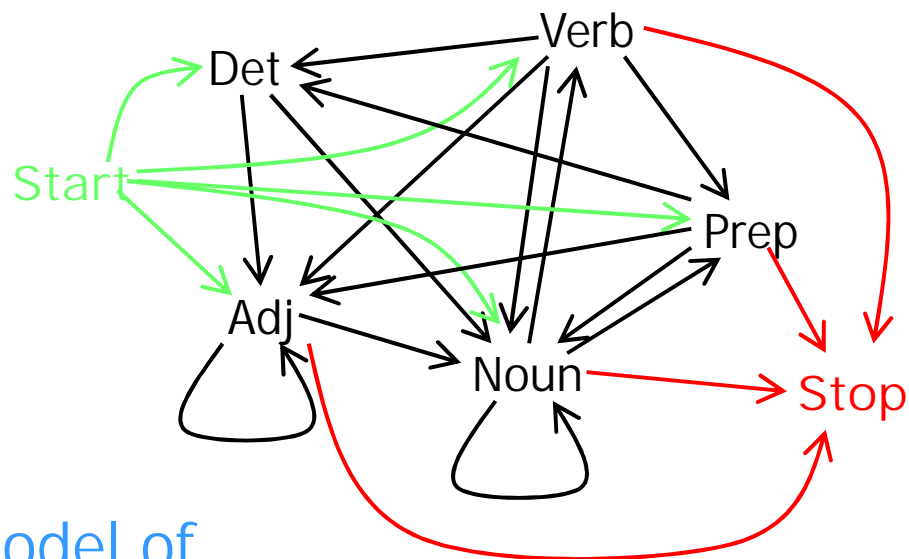


But where can we put our weights?

- CFG / RTN



- bigram model of words or tags (first-order Markov Model)

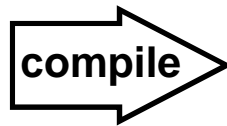


- Hidden Markov Model of words and tags together??

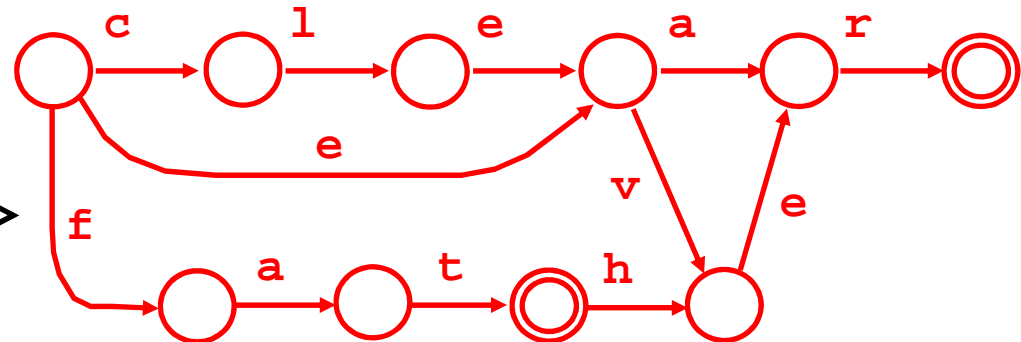
Another useful FSA ...

Wordlist

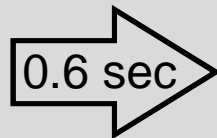
clear
clever
ear
ever
fat
father



Network



`/usr/dict/words`
25K words
206K chars

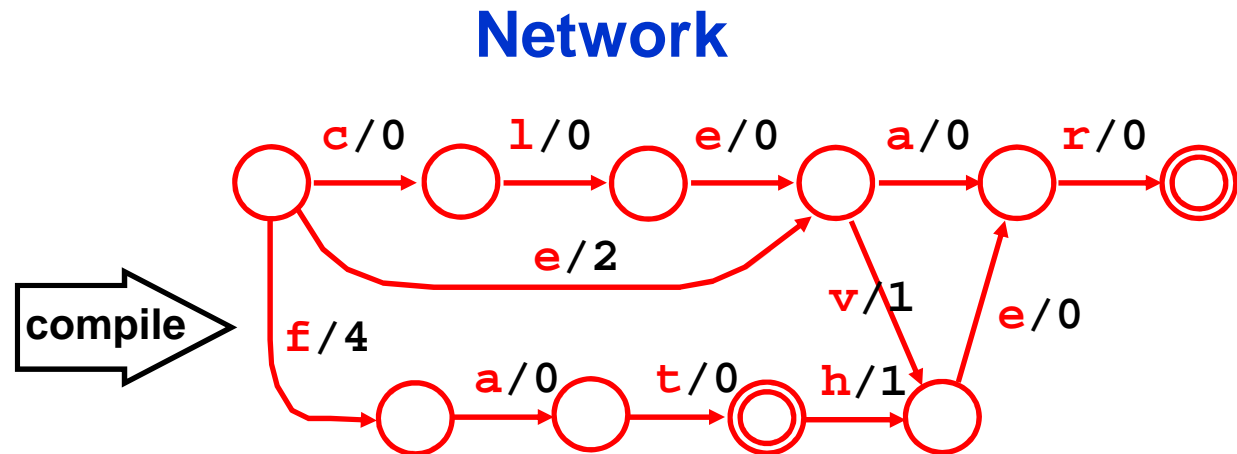


FSM
17728 states,
37100 arcs

Weights are useful here too!

Wordlist

clear	0
clever	1
ear	2
ever	3
fat	4
father	5

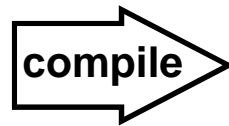


Computes a perfect hash!
Sum the weights along a word's accepting path.

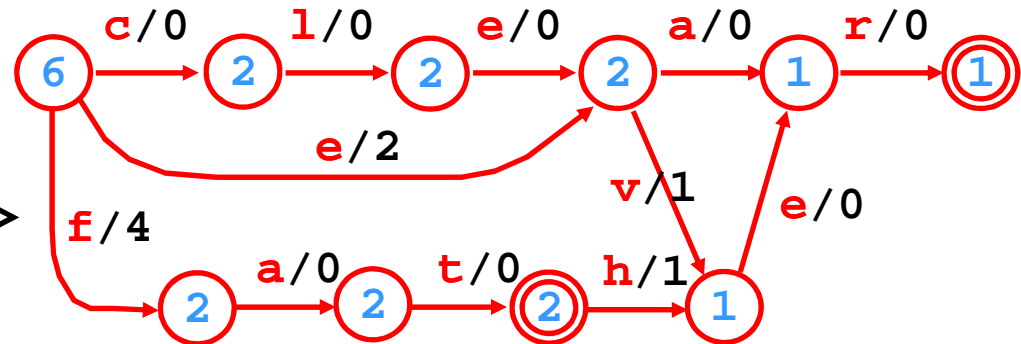
Example: Weighted acceptor

Wordlist

clear	0
clever	1
ear	2
ever	3
fat	4
father	5



Network



- Compute **number of paths** from each state (**Q: how?**)
A: recursively, like DFS
- Successor states partition the path set
- Use offsets of successor states as arc weights
- **Q: Would this work for an arbitrary numbering of the words?**

Example: Unweighted transducer

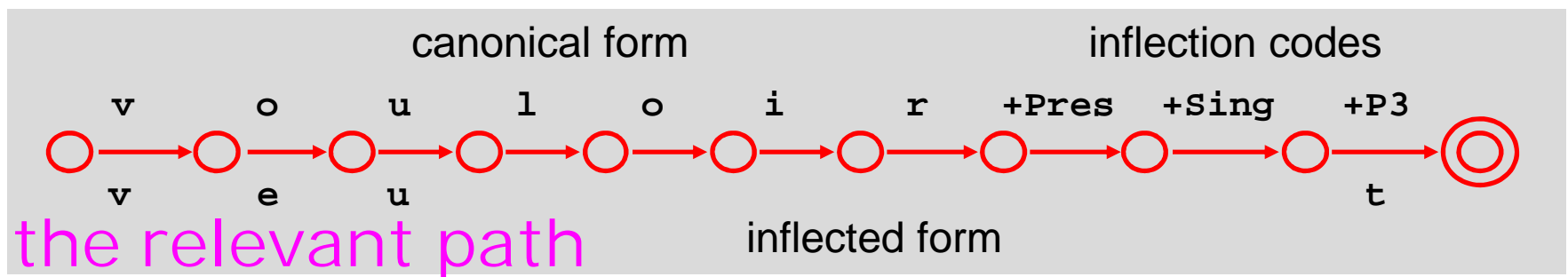
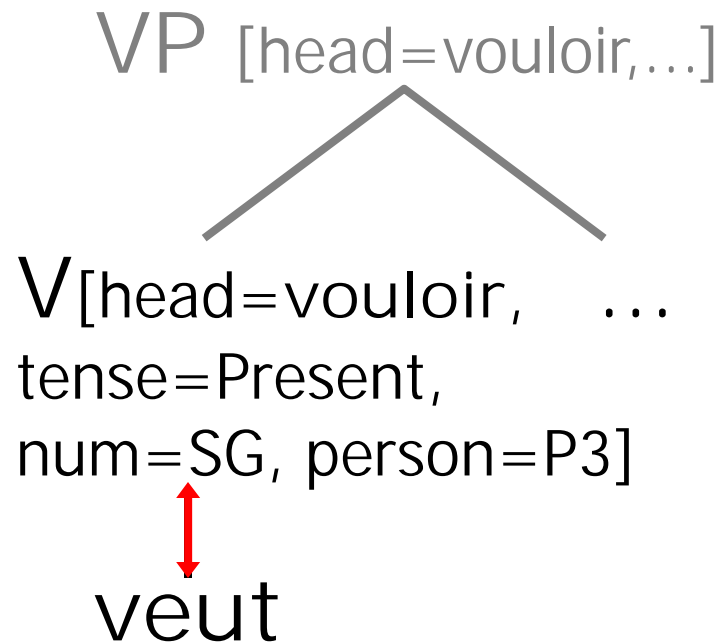
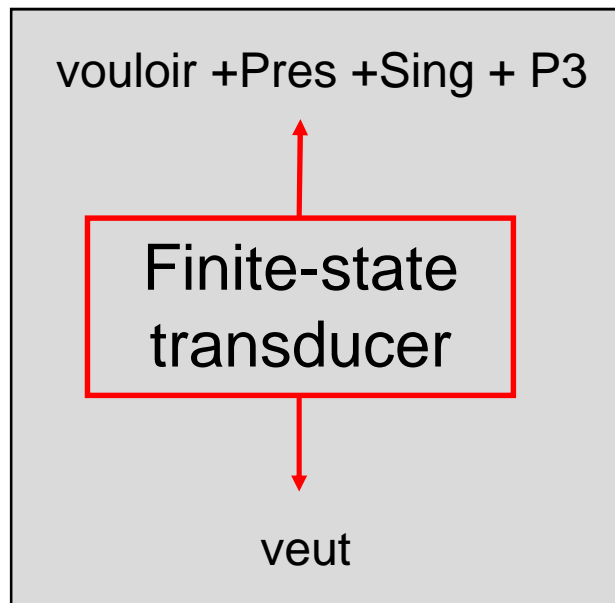
VP [head=vouloir,...]

V[head=vouloir, ...
tense=Present,
num=SG, person=P3]

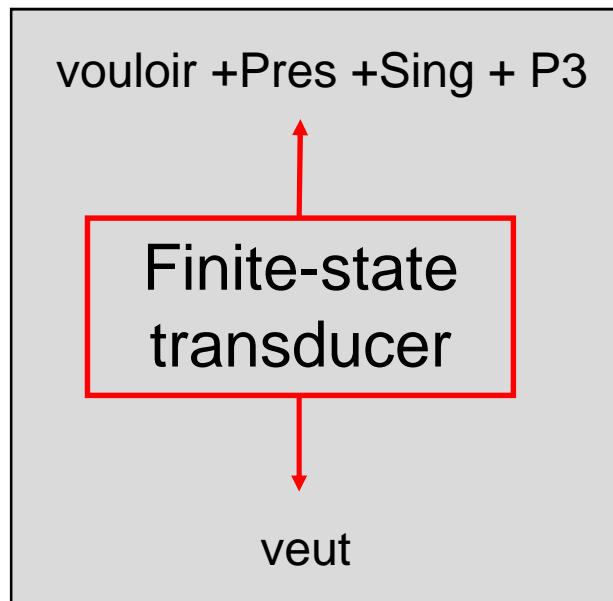
veut

the problem
of **morphology**
("word shape") -
an area of linguistics

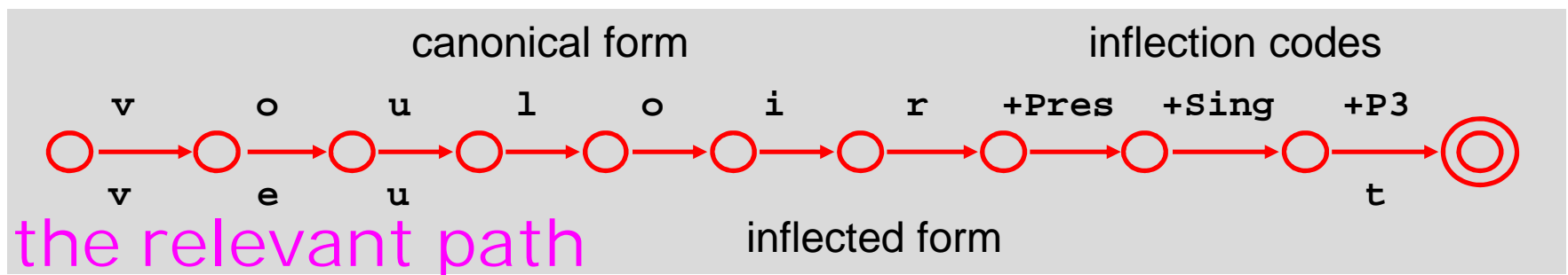
Example: Unweighted transducer



Example: Unweighted transducer



- Bidirectional: generation or analysis
- Compact and fast
- Xerox sells for about 20 languages including English, German, Dutch, French, Italian, Spanish, Portuguese, Finnish, Russian, Turkish, Japanese, ...
- Research systems for many other languages, including Arabic, Malay

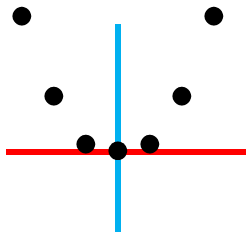


What is a function?

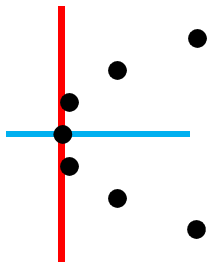
- Formally, a set of $\langle \text{input}, \text{output} \rangle$ pairs where each $\text{input} \in \text{domain}$, $\text{output} \in \text{co-domain}$.
- Moreover, $\forall x \in \text{domain}, \exists$ exactly one y such that $\langle x, y \rangle \in \text{the function}$.

- domain co-domain
↓ ↓
- square: $\text{int} \rightarrow \text{int}$
 $= \{ \langle 0, 0 \rangle, \langle 1, 1 \rangle, \langle -1, 1 \rangle, \langle 2, 4 \rangle, \langle -2, 4 \rangle, \langle 3, 9 \rangle, \langle -3, 9 \rangle, \dots \}$
 - $\text{domain}(\text{square}) = \{0, 1, -1, 2, -2, 3, -3, \dots\}$
 - $\text{range}(\text{square}) = \{0, 1, 4, 9, \dots\}$

What is a relation?



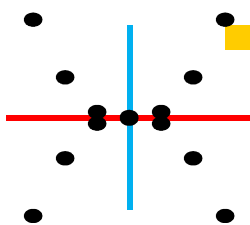
- square: $\text{int} \rightarrow \text{int}$
 $= \{ \langle 0,0 \rangle, \langle 1,1 \rangle, \langle -1,1 \rangle, \langle 2,4 \rangle, \langle -2,4 \rangle, \langle 3,9 \rangle, \langle -3,9 \rangle, \dots \}$



- inverse(square): $\text{int} \rightarrow \text{int}$
 $= \{ \langle 0,0 \rangle, \langle 1,1 \rangle, \langle 1,-1 \rangle, \langle 4,2 \rangle, \langle 4,-2 \rangle, \langle 9,3 \rangle, \langle 9,-3 \rangle, \dots \}$

- Is inverse(square) a function?

- $0 \mapsto \{0\}$ $9 \mapsto \{3,-3\}$ $7 \mapsto \{\}$ $-1 \mapsto \{\}$



- No - we need a more general notion!

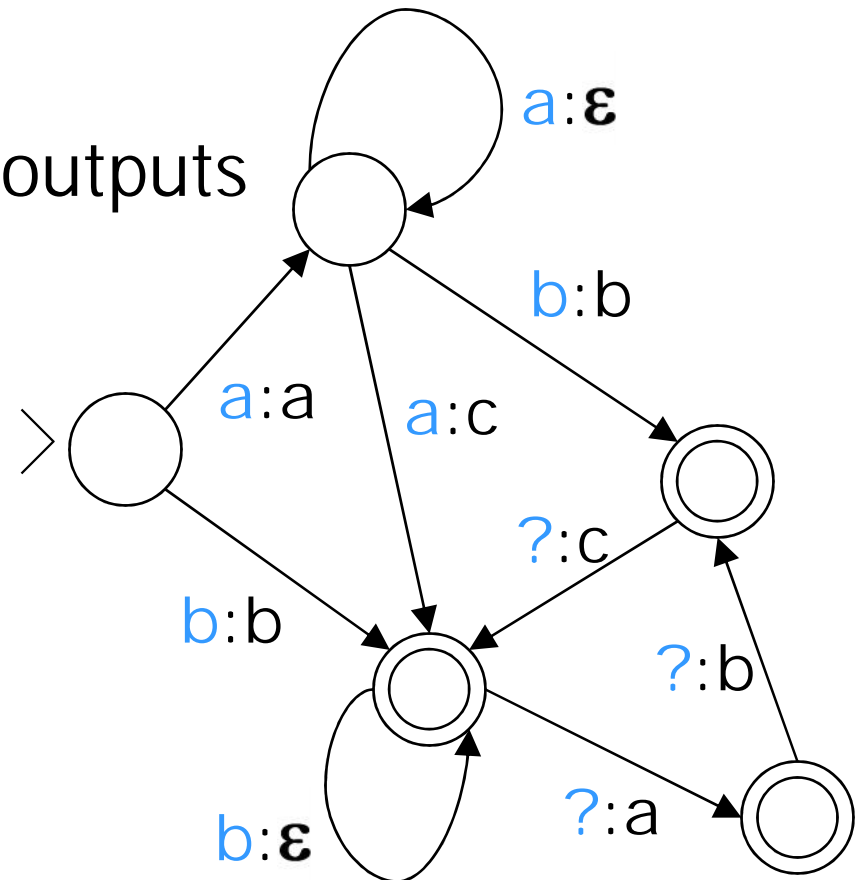
- A relation is any set of $\langle \text{input}, \text{output} \rangle$ pairs

Regular Relation (of strings)

- Relation: like a function, but multiple outputs ok
- Regular: finite-state
- Transducer: automaton w/ outputs

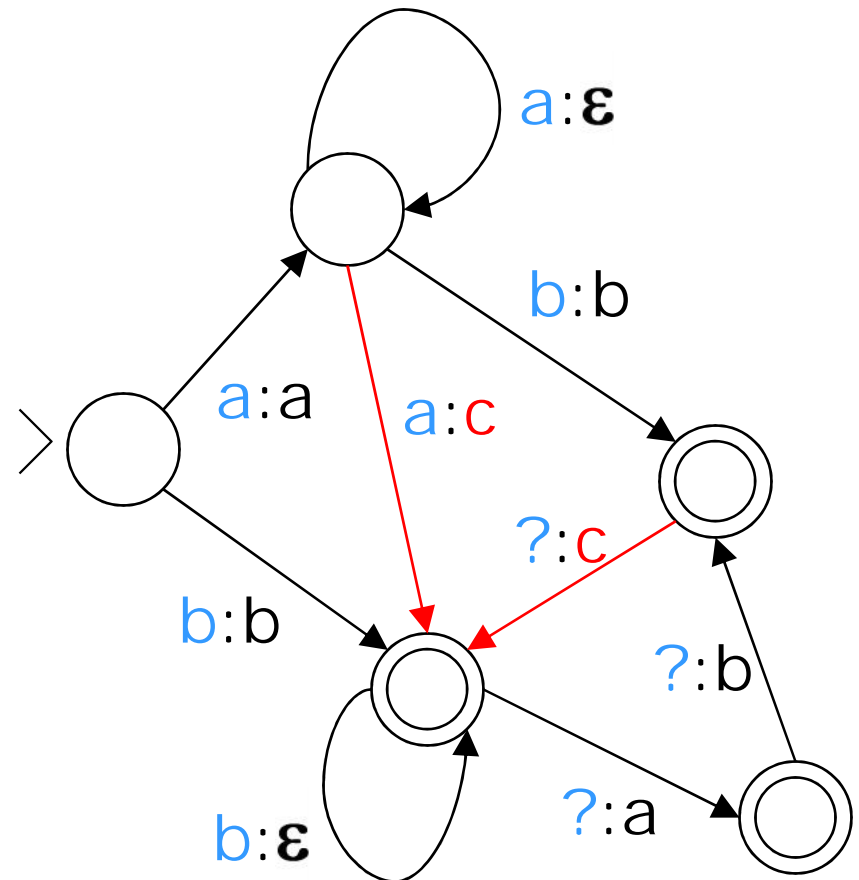
- $b \rightarrow \{b\}$ $a \rightarrow \{\}$
- $aaaaa \rightarrow \{ac, aca, acab, acabc\}$

- Invertible?
- Closed under composition?



Regular Relation (of strings)

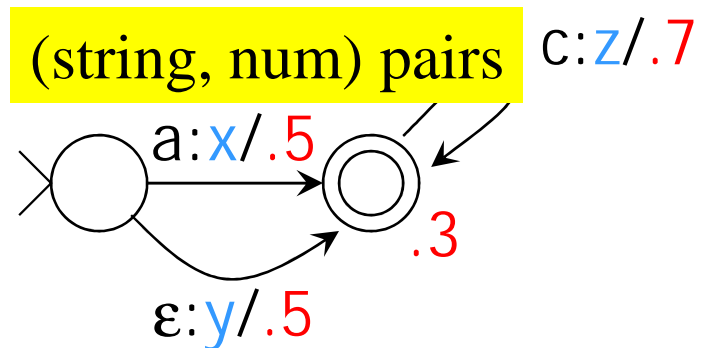
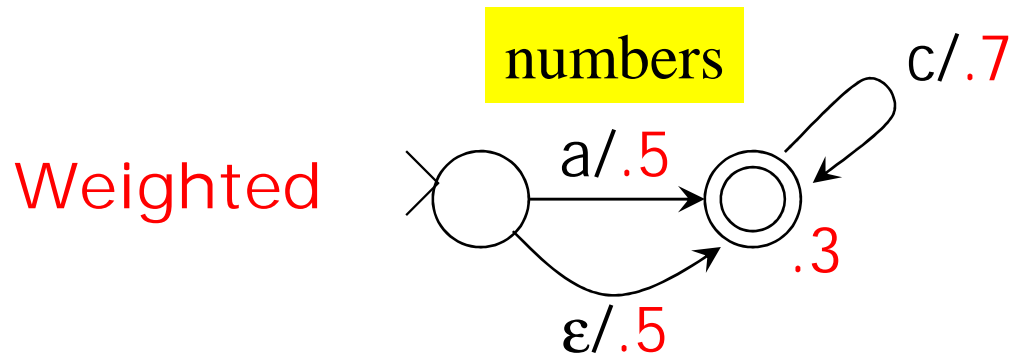
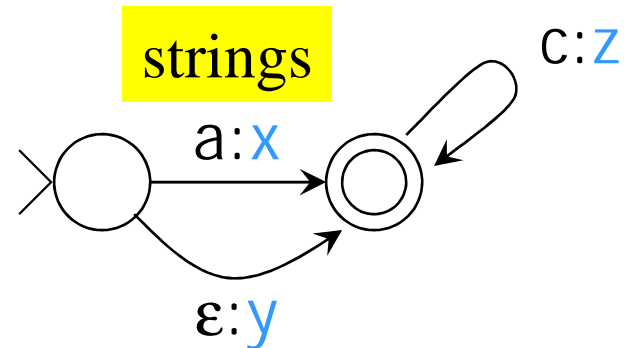
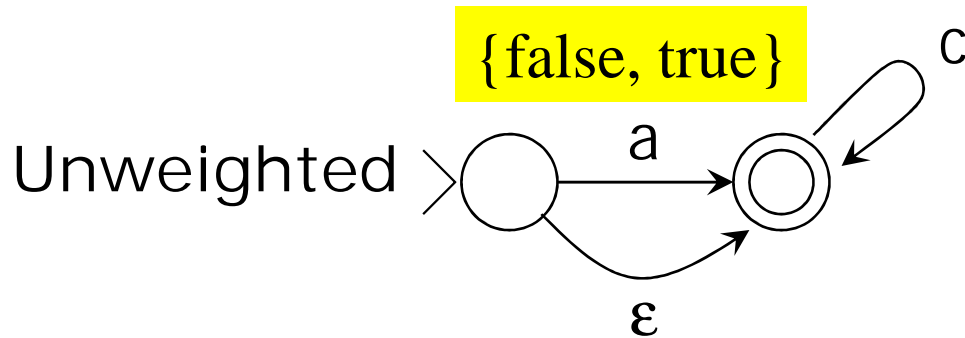
- Can weight the arcs: \rightarrow vs. \rightarrow
- $b \rightarrow \{b\}$ $a \rightarrow \{\}$
- $aaaaa \rightarrow \{ac, aca, acab, acabc\}$
- How to find best outputs?
 - For $aaaaa$?
 - For all inputs at once?



Function from strings to ...

Acceptors (FSAs)

Transducers (FSTs)



Sample functions

Acceptors (FSAs)

Transducers (FSTs)

Unweighted

{false, true}

Grammatical?

strings

Markup

Correction

Translation

Weighted

numbers

How grammatical?

Better, how probable?

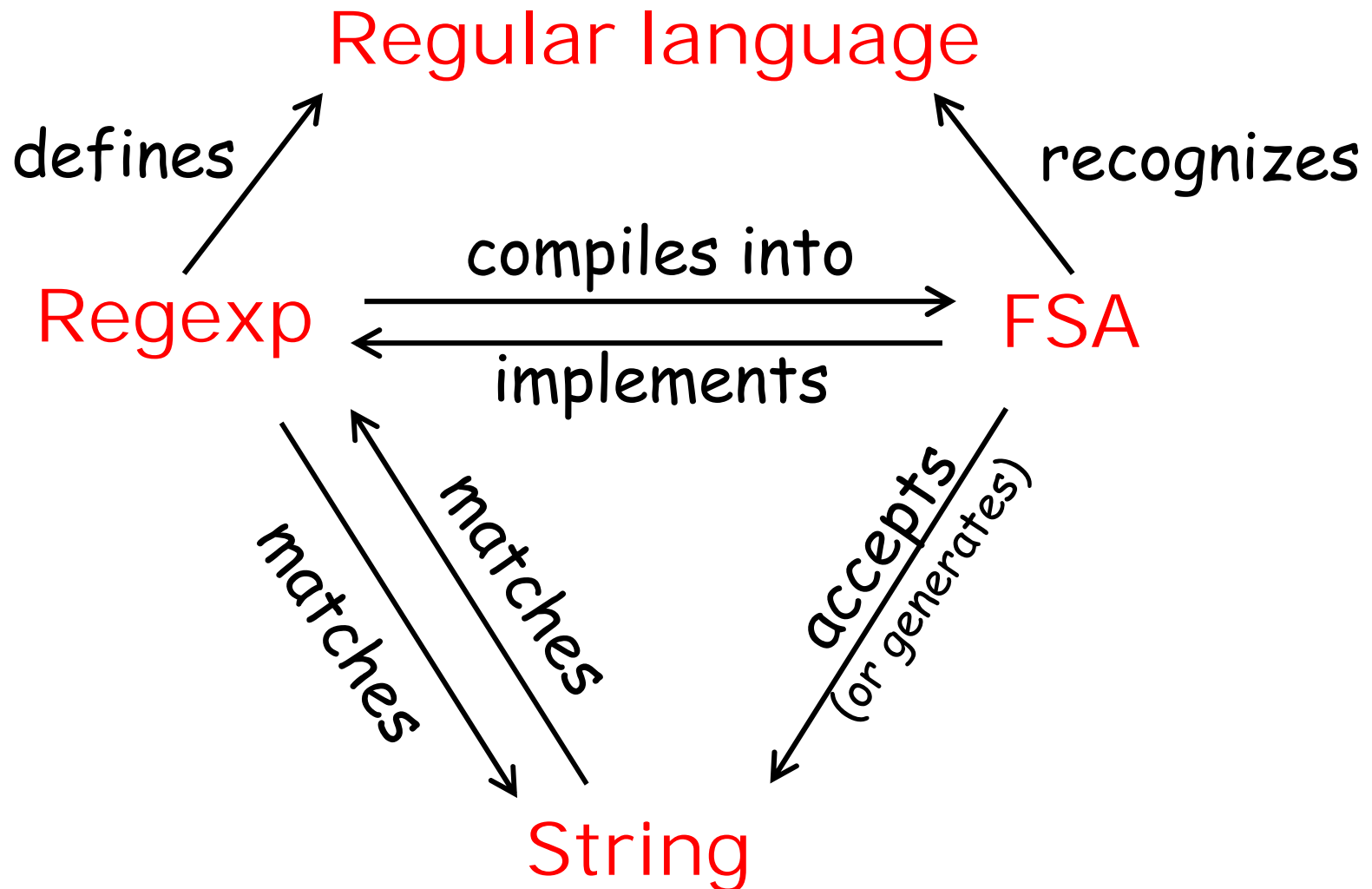
(string, num) pairs

Good markups

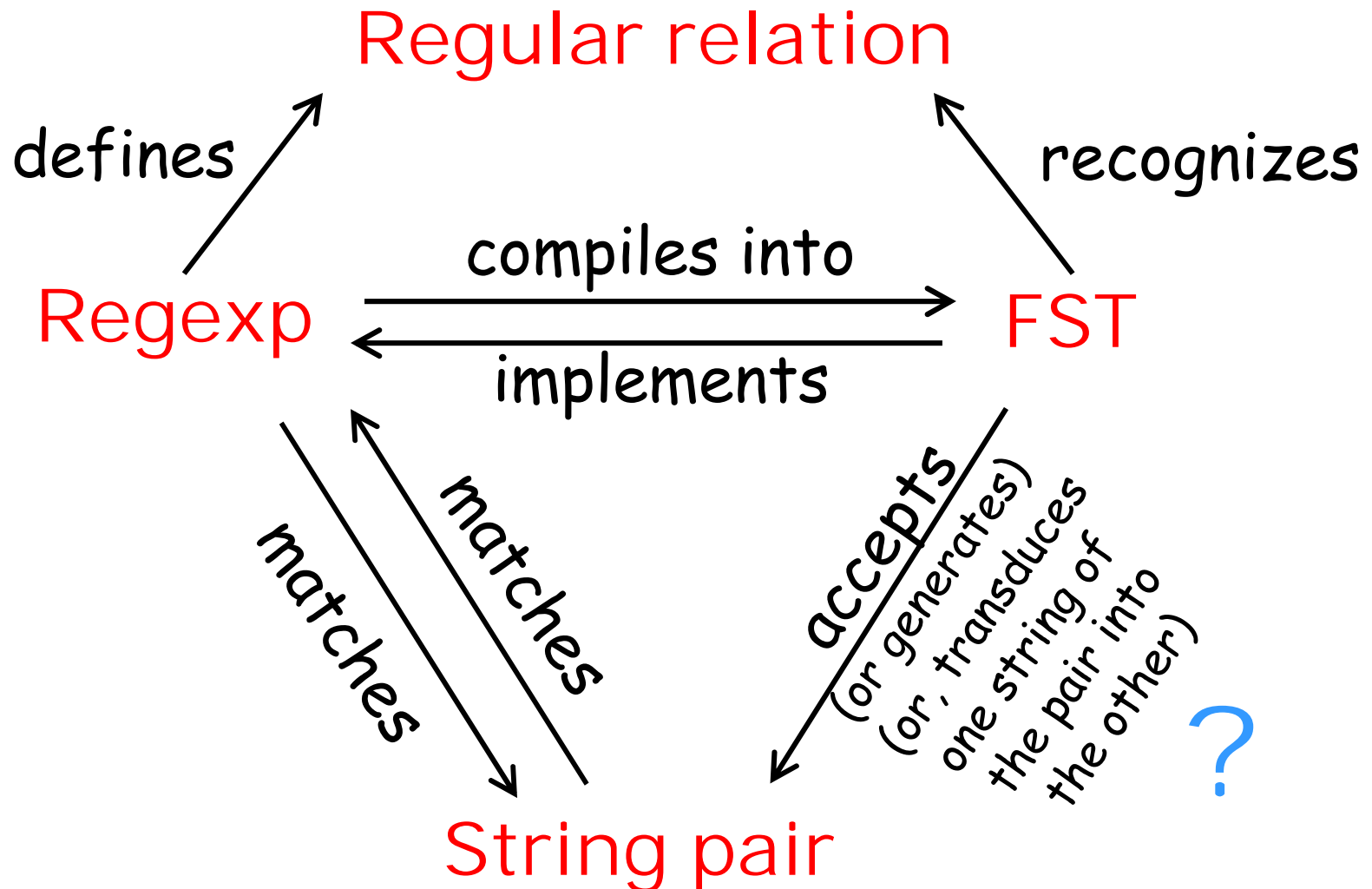
Good corrections

Good translations

Terminology (acceptors)



Terminology (transducers)



Perspectives on a Transducer

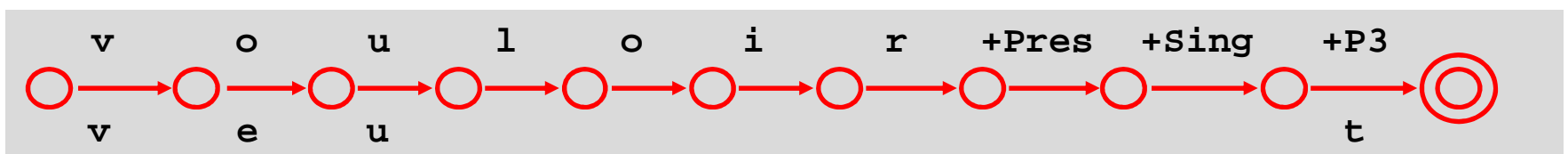
- Remember these CFG perspectives:

3 views of a context-free rule

- generation (production): $S \rightarrow NP VP$ (randsent)
- parsing (comprehension): $S \leftarrow NP VP$ (parse)
- verification (checking): $S = NP VP$

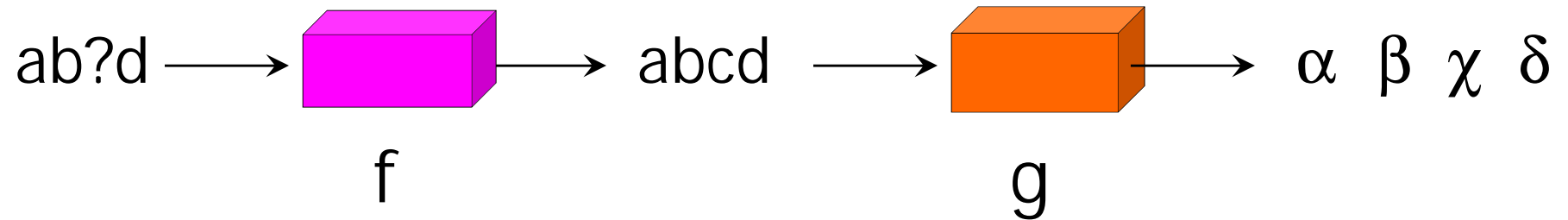
- Similarly, 3 views of a transducer:

- Given **0** strings, **generate** a new string pair (by picking a path)
- Given **one** string (upper or lower), **transduce** it to the other kind
- Given **two** strings (upper & lower), **decide** whether to accept the pair



FST just defines the regular relation (mathematical object: set of pairs). What's "input" and "output" depends on what one asks about the relation. The 0, 1, or 2 given string(s) constrain which paths you can use.

Functions



Functions



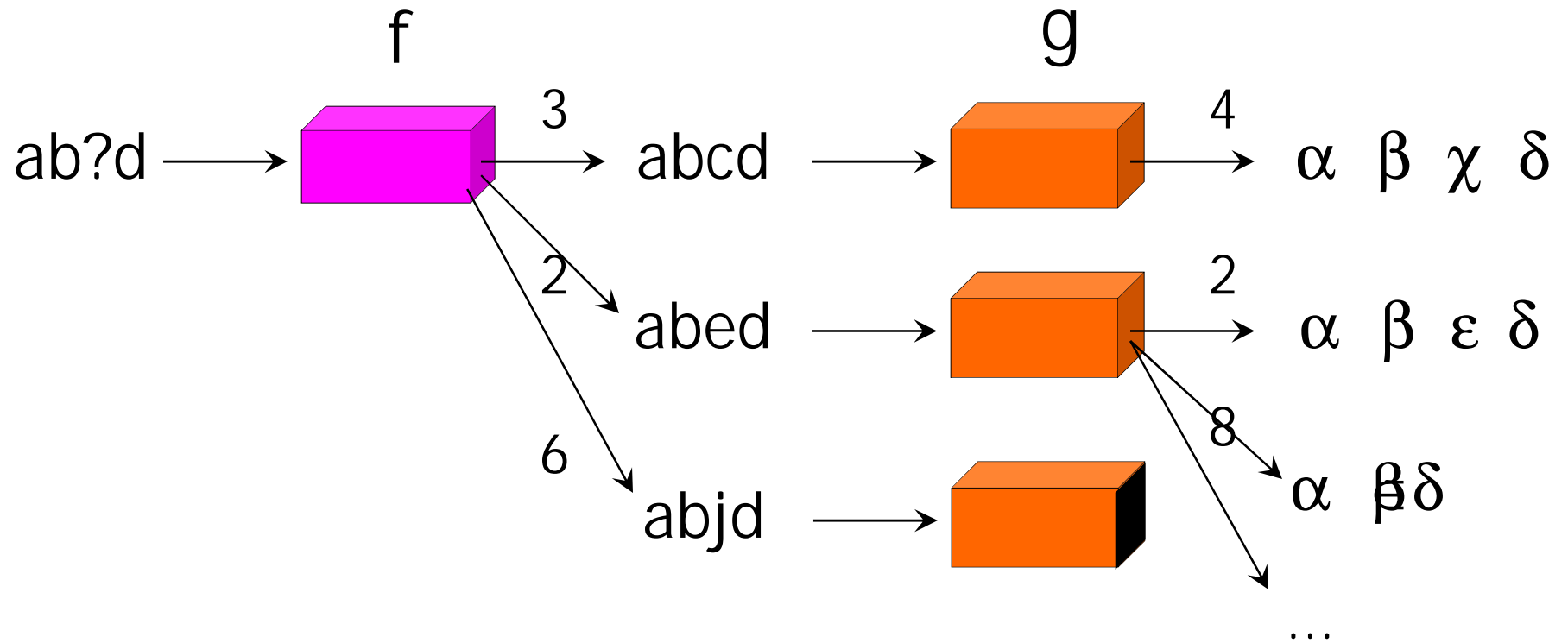
Function composition: $f \circ g$

[first f , then g – intuitive notation, but opposite of the traditional math notation]

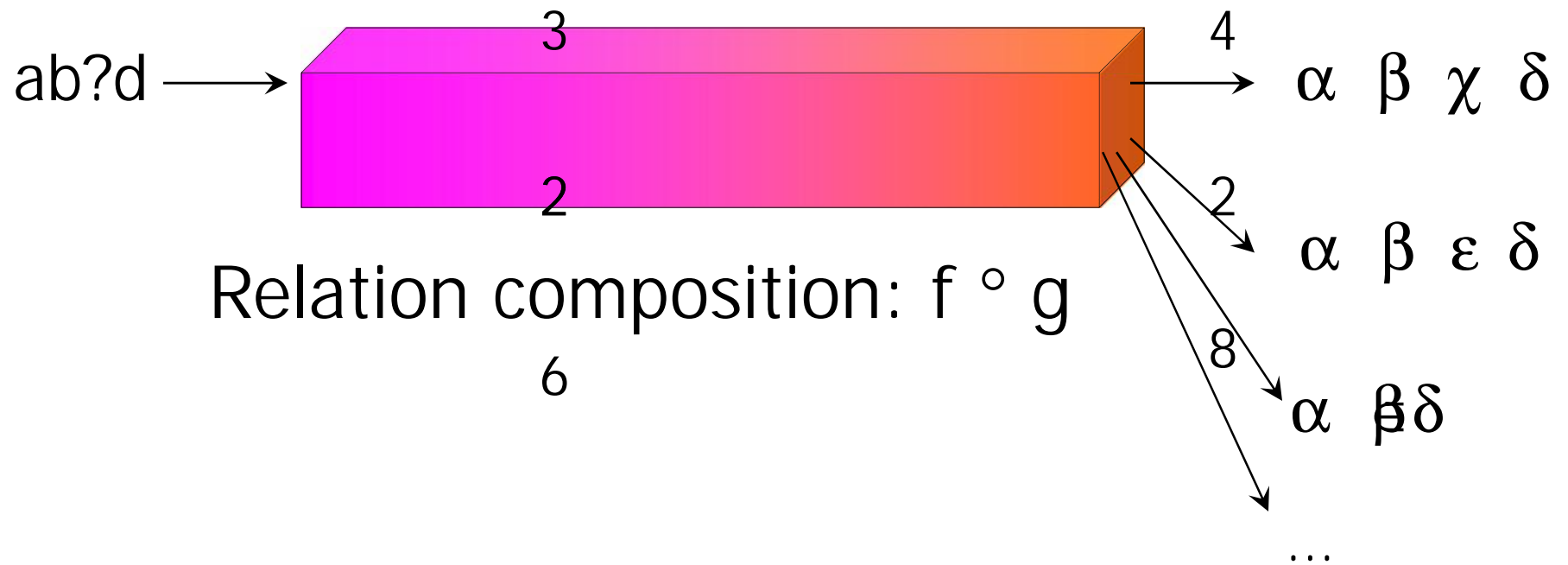
Like the Unix pipe: `cat x | f | g > y`

Example: Pass the input through a sequence of ciphers

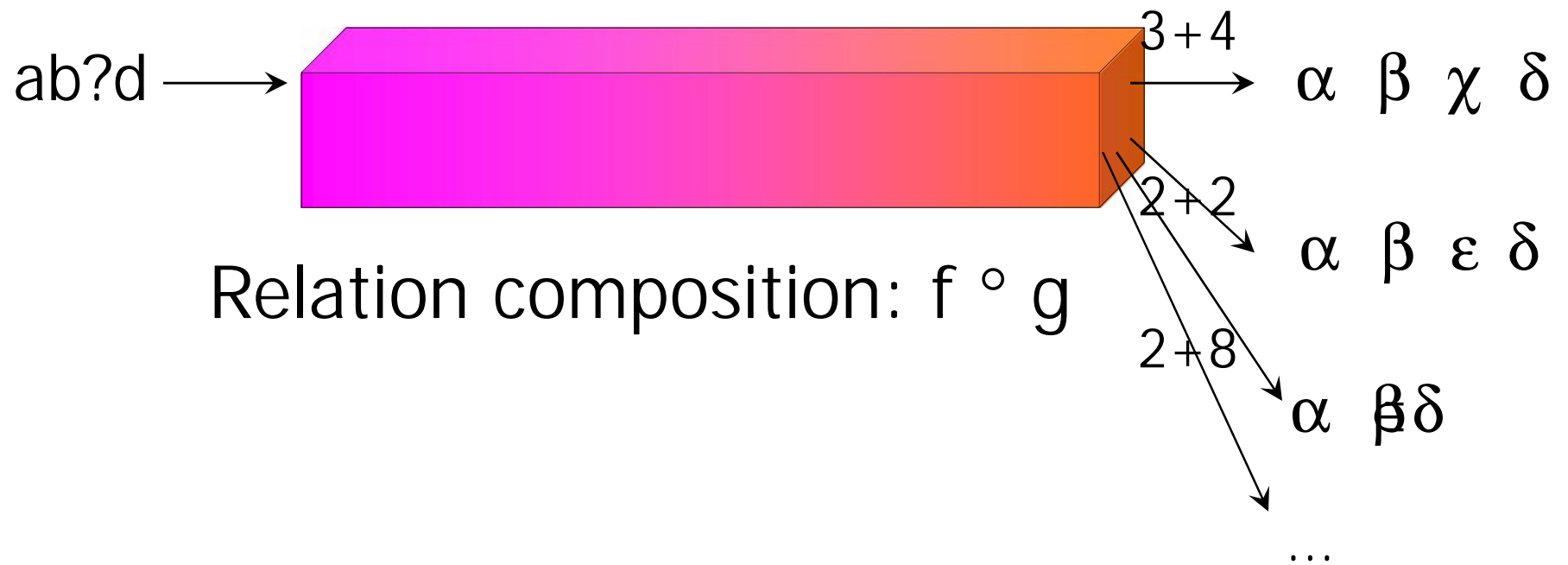
From Functions to Relations



From Functions to Relations



From Functions to Relations

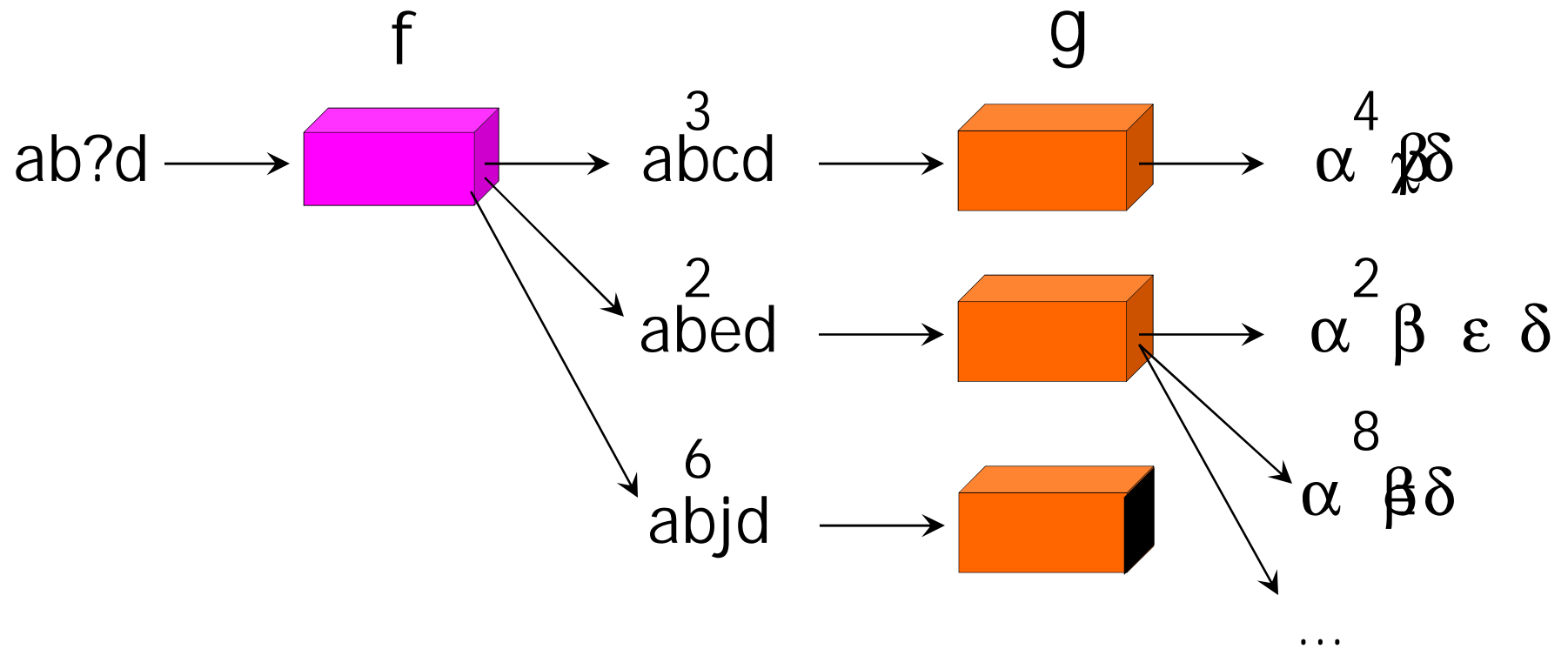


From Functions to Relations

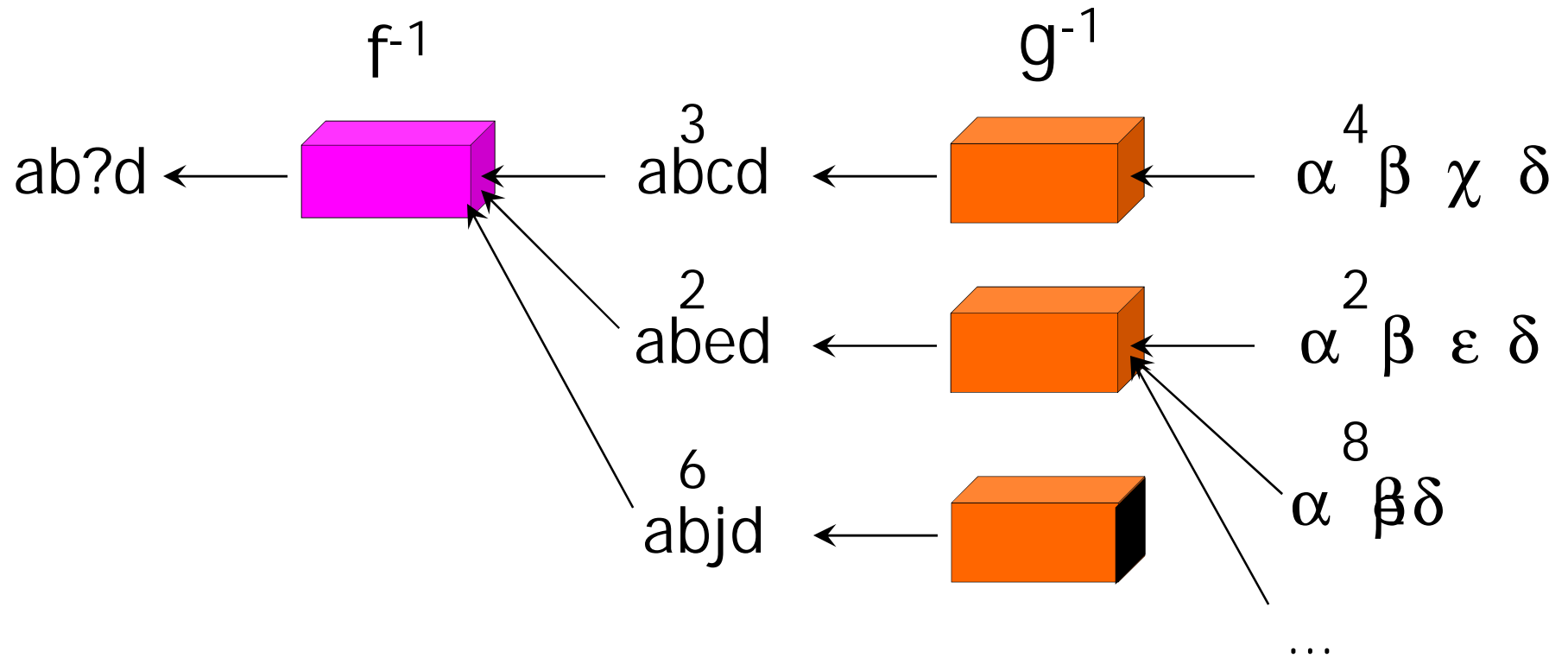


Often in NLP, all of the functions or relations involved can be described as finite-state machines, and manipulated using standard algorithms.

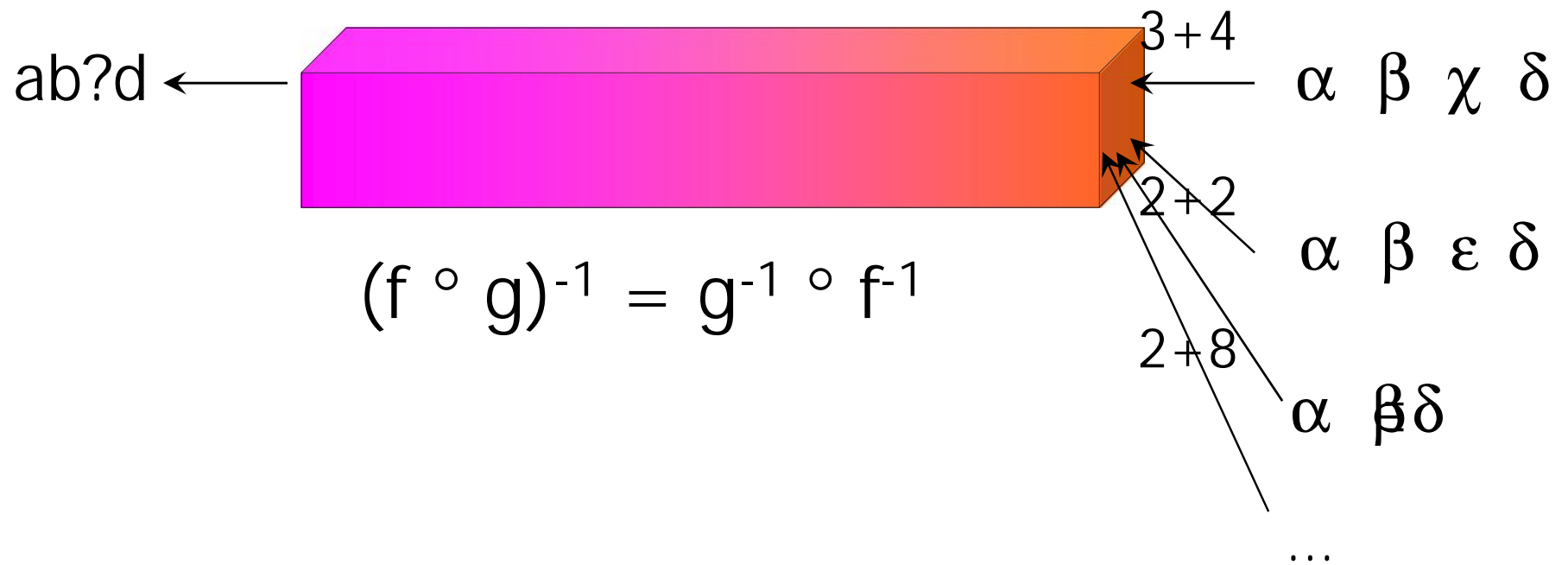
Inverting Relations



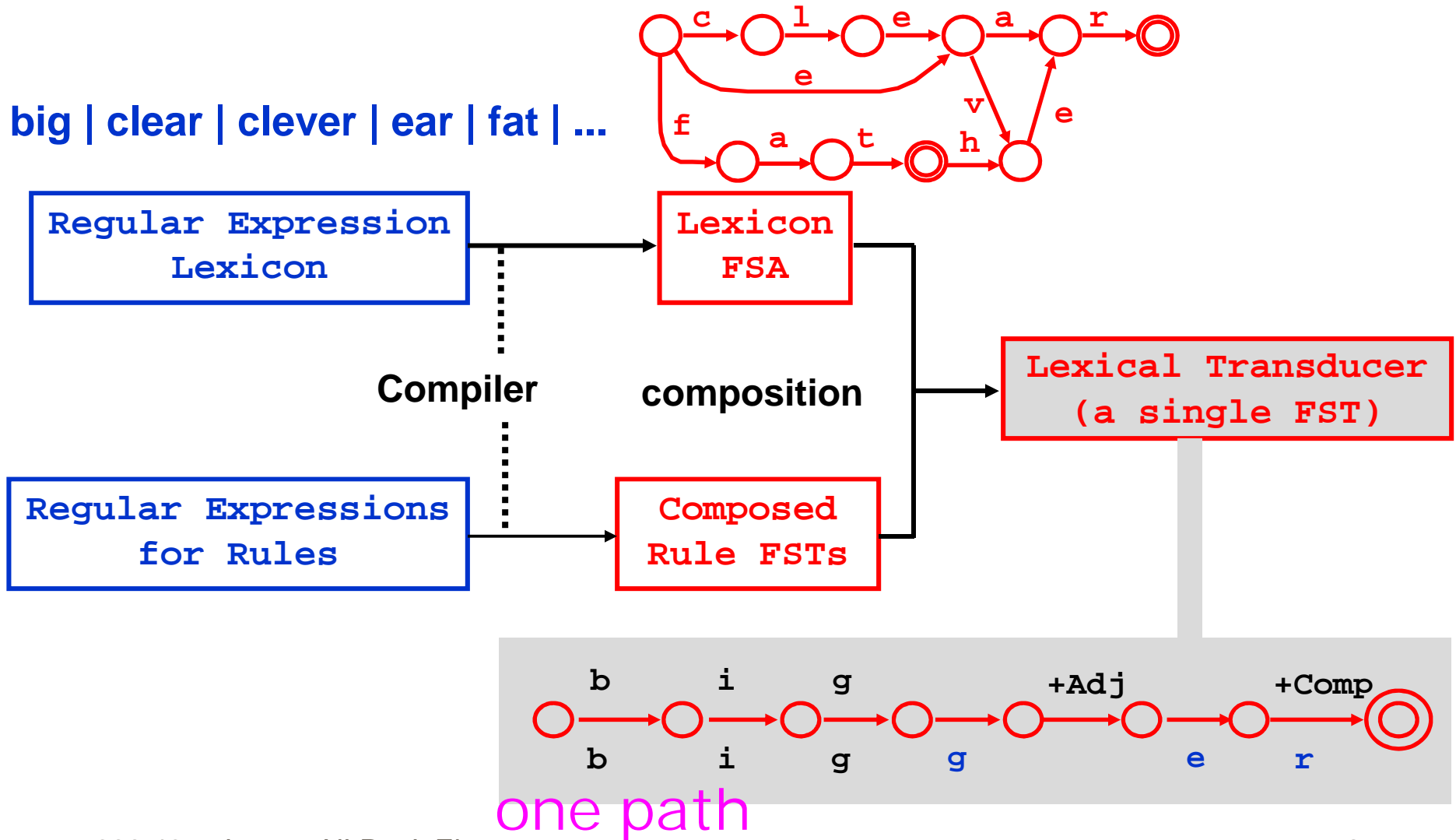
Inverting Relations



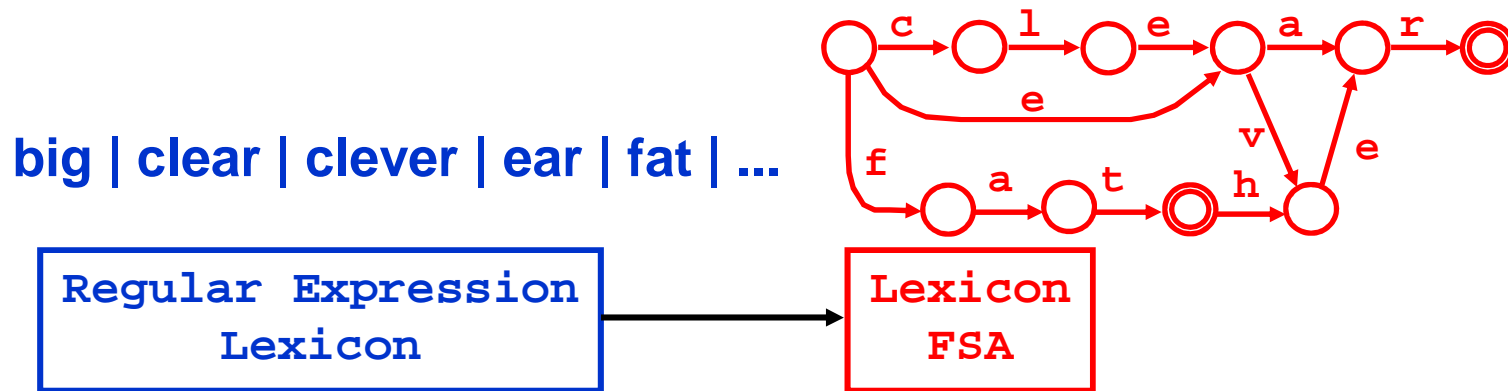
Inverting Relations



Building a lexical transducer



Building a lexical transducer



- Actually, the lexicon must contain elements like **big +Adj +Comp**
- So write it as a more complicated expression:
(big | clear | clever | fat | ...) +Adj (v | +Comp | +Sup) ← adjectives
| (ear | father | ...) +Noun (+Sing | +Pl) ← nouns
| ... ← ...
- Q: Why do we need a lexicon at all?

Weighted version of transducer: Assigns a weight to each string pair

