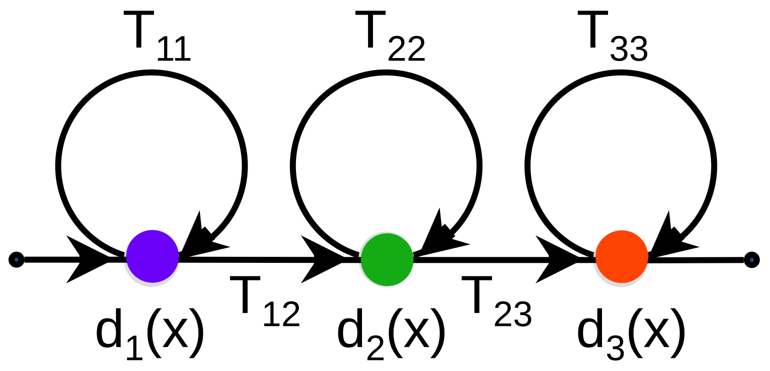
Design and Implementation of Speech Recognition Systems

Spring 2013

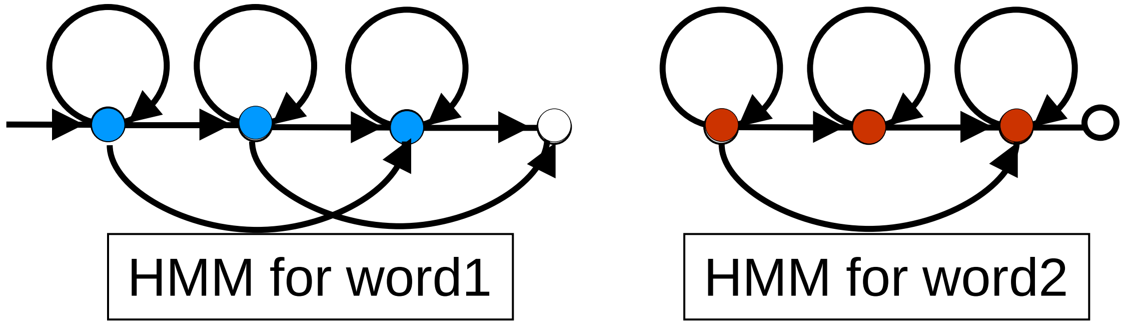
Class 13: Grammars
4 Mar 2013

Recap: HMMs are Generalized Templates



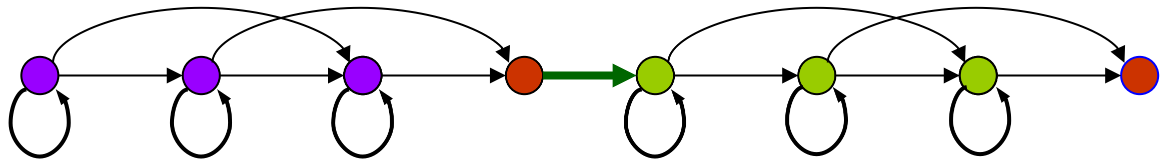
- A set of "states"
  - A distance function associated with each state
- A set of transitions
  - Transition-specific penalties

Recap: Isolated word recognition with HMMs



- An HMM for each word
- Score incoming speech against each HMM
- Pick word whose HMM scores best
  - Best == lowest cost
  - Best == highest score
  - Best == highest probability

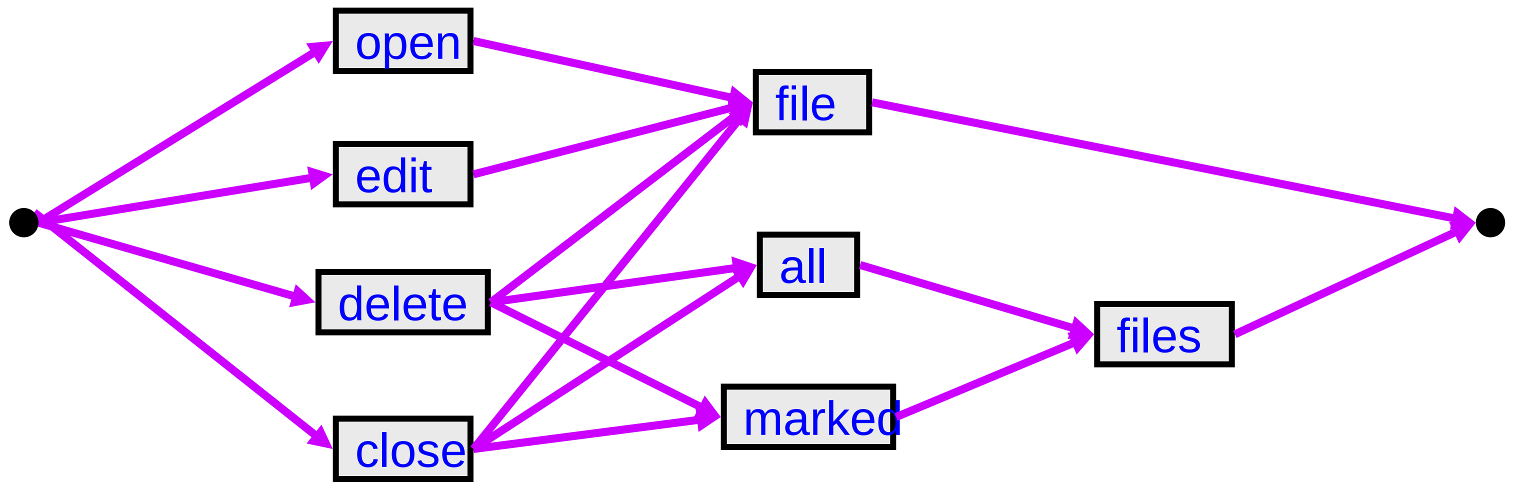
Recap: Recognizing word sequences



Combined HMM for the sequence word 1 word 2

- Train HMMs for words
- Create HMM for each word sequence
  - – Recognize as in isolated word case

Recap: Recognizing word sequences



- Create word graph HMM representing all word sequences
  - Word sequence obtained from best state sequence

Motivation

- So far, we have looked at speech recognition without worrying about *language structure*
  - i.e. we've treated all word sequences as being equally plausible
  - But this is rarely the case

- Using language knowledge is crucial for recognition accuracy
  - Humans use a tremendous amount of *context* to "fill in holes" in what they hear, and to disambiguate between confusable words
  - Speech recognizers should do so too!

- Such knowledge used in a decoder is called a *language model* (LM)

Impact of Language Models on ASR

- Example with a 20K word vocabulary system:
  - Without an LM ("any word is equally likely" model):

    AS COME ADD TAE ASIAN IN THE ME AGE OLE FUND IS MS. GROWS INCREASING ME IN TENTS MAR PLAYERS AND INDUSTRY A PAIR WILLING TO SACRIFICE IN TAE GRITTY IN THAN ANA IF PERFORMANCE

  - With an appropriate LM ("knows" what word sequences make sense):

    AS COMPETITION IN THE MUTUAL FUND BUSINESS GROWS INCREASINGLY INTENSE MORE PLAYERS IN THE INDUSTRY APPEAR WILLING TO SACRIFICE INTEGRITY IN THE NAME OF PERFORMANCE

Syntax and Semantics

- However, human knowledge about context is far too rich to capture in a formal model
  - In particular, humans rely on *meaning*

- Speech recognizers only use models relating to word sequences
  - *i.e.* focus on *syntax* rather than *semantics*

Importance of Semantics

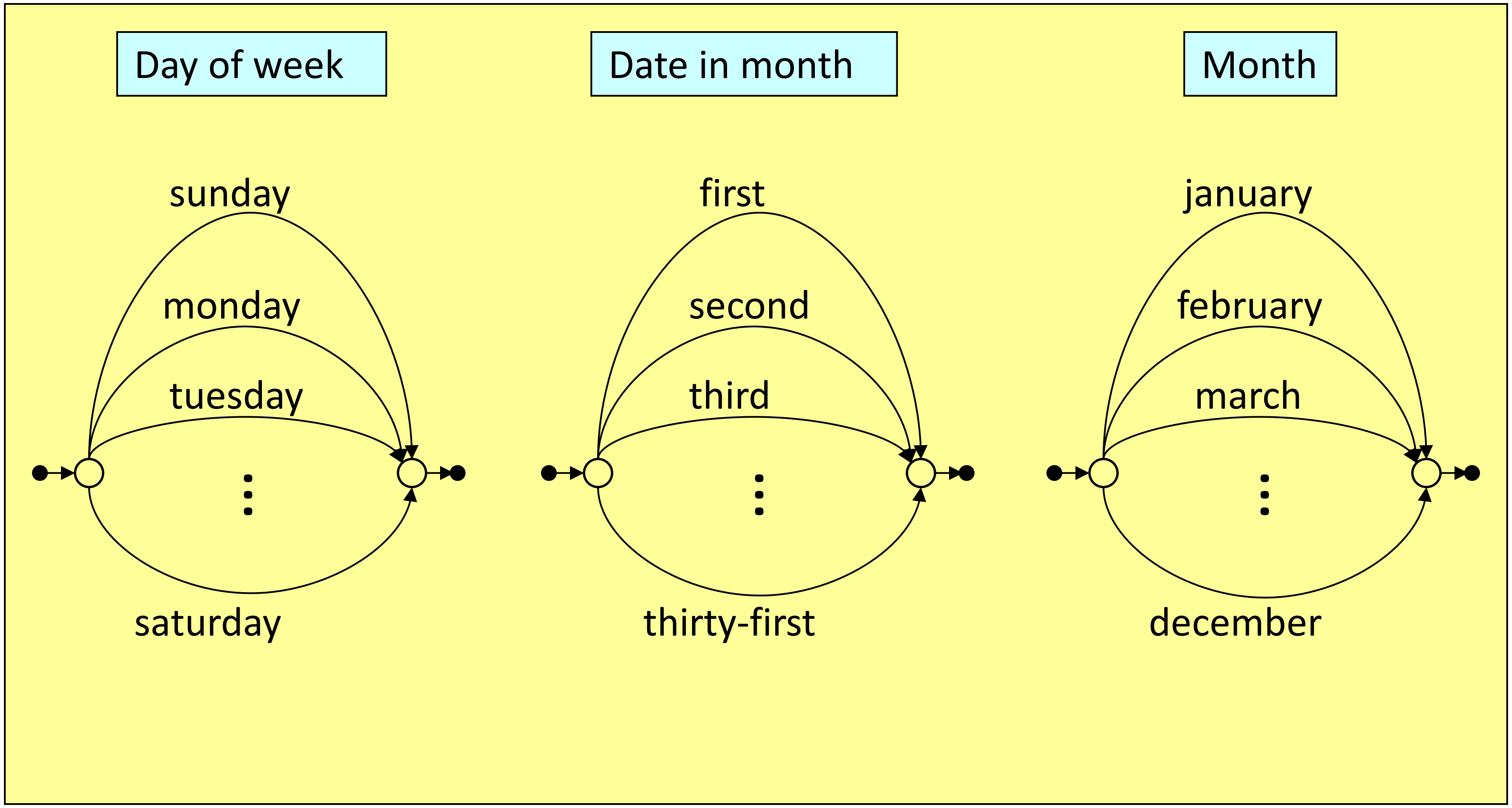
- From *Spoken Language Processing*, by Huang, Acero and Hon:
  - Normal language, 5K word vocabulary:
    - ASR: 4.5% word error rate (WER)
    - Humans: 0.9% WER
  - Synthetic language generated from a *trigram* LM, 20K word vocabulary:
    - Example: *BECAUSE OF COURSE AND IT IS IN LIFE AND …*
    - ASR: 4.4% WER
    - Humans: 7.6% WER
  - Deprived of context, humans flounder just as badly, or worse
- Still, we will focus only on the syntactic level

Types of LMs

- We will use *grammars* or LMs to constrain the search algorithm
- This gives the decoder a *bias*, so that not all word sequences are equally likely
- Our topics include:
  - *Finite state* grammars (FSGs)
  - *Context free* grammars (CFGs)
  - Decoding algorithms using them
- These are suitable for small/medium vocabulary systems, and highly structured systems
- For large vocabulary applications, we use *N-gram* LMs, which will be covered later

Finite State Grammar Examples

- Three simple finite state grammars (FSGs):



A More Complex Example

- A robot control application:
  - TURN 10 DEGREES CLOCKWISE
  - TURN 30 DEGREES ANTI CLOCKWISE
  - GO 10 METERS
  - GO 50 CENTI METERS
  - Allowed angles: 10 20 30 40 50 60 70 80 90 (clk/anticlk)
  - Allowed distances: 10 20 30 40 50 60 70 80 90 100 (m/cm)

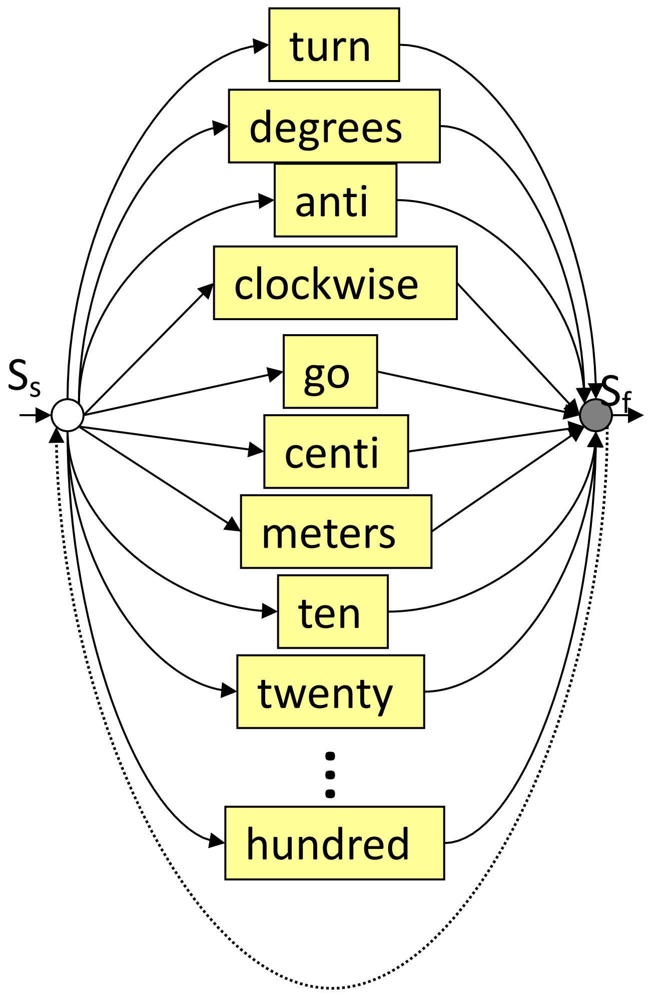
- Vocabulary of this application = 17 words:
  - TURN DEGREES CLOCKWISE ANTI
    GO METERS CENTI and TEN TWENTY … HUNDRED
  - Assume we have word HMMs for all 17 words

- How can we build a continuous speech recognizer for this application?

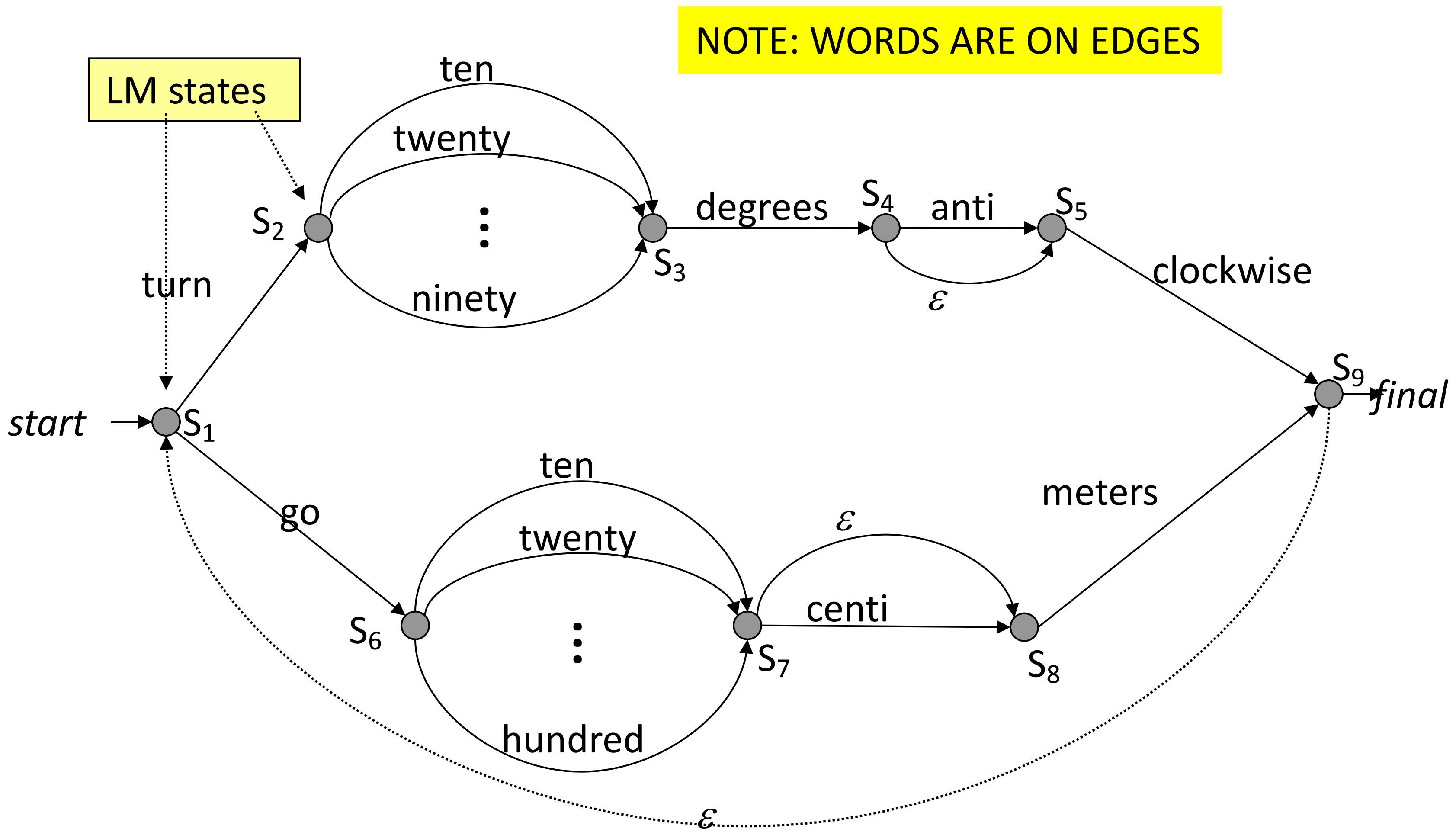
A More Complex Example

- One possibility: Build an "any word can follow any word" sentence HMM using the word HMMs
- Allows many word sequences that simply do not make any sense!
  - The recognizer would search through many meaningless paths
  - Greater chance of misrecognitions
- Must *tell* the system about the *legal* set of sentences
- We do this using an FSG

ROBOT 0 GRAPH



Robot Control FSG (*ROBOT1*)



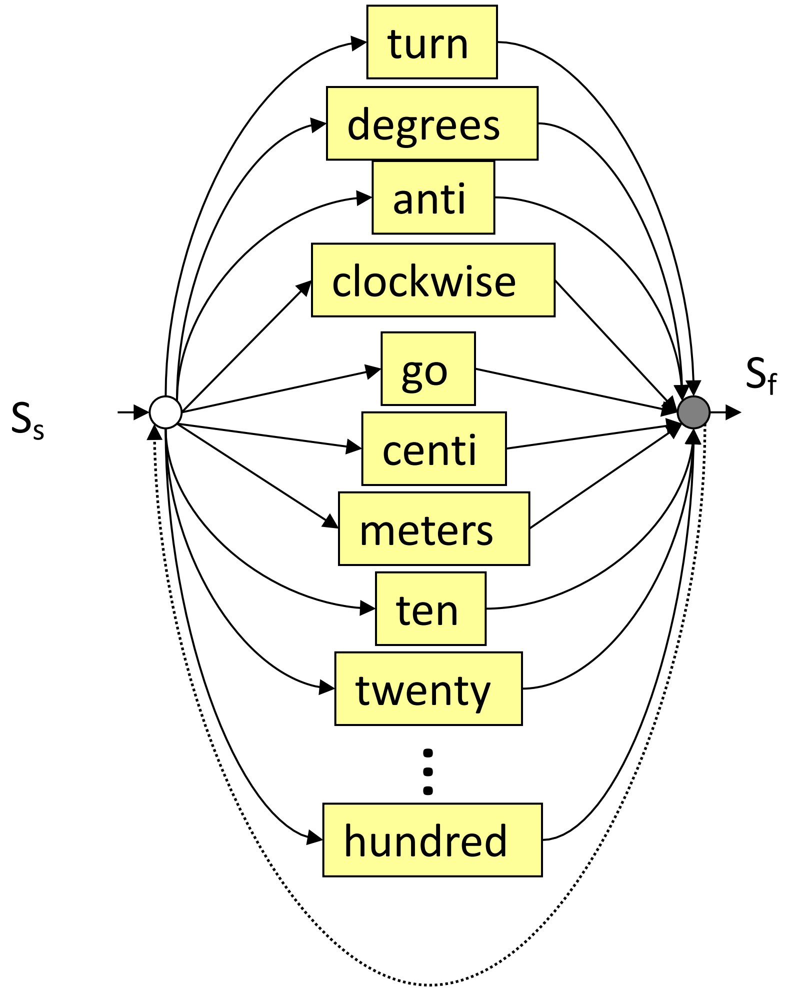
Elements of Finite State Grammars

- FSGs are defined by the following (very much like HMMs):
  - A *finite* set of states
    - These are generically called *LM states*
  - One or more of the states are *initial* or *start* states
  - One or more of the states are *terminal* or *final* states
  - *Transitions* between states, *optionally* labeled with words
    - The words are said to be *emitted* by those transitions
    - Unlabelled transitions are called *null* or *e* transitions
  - PFSG: Transitions have probabilities associated with them, as usual
    - All transitions out of a state without an explicit transition probability are assumed to be equally likely
- Any *path* from a start state to a final state emits a legal word sequence (called a *sentence*)
- The set of all possible sentences produced by the FSG is called its *language*

The All-Word Model

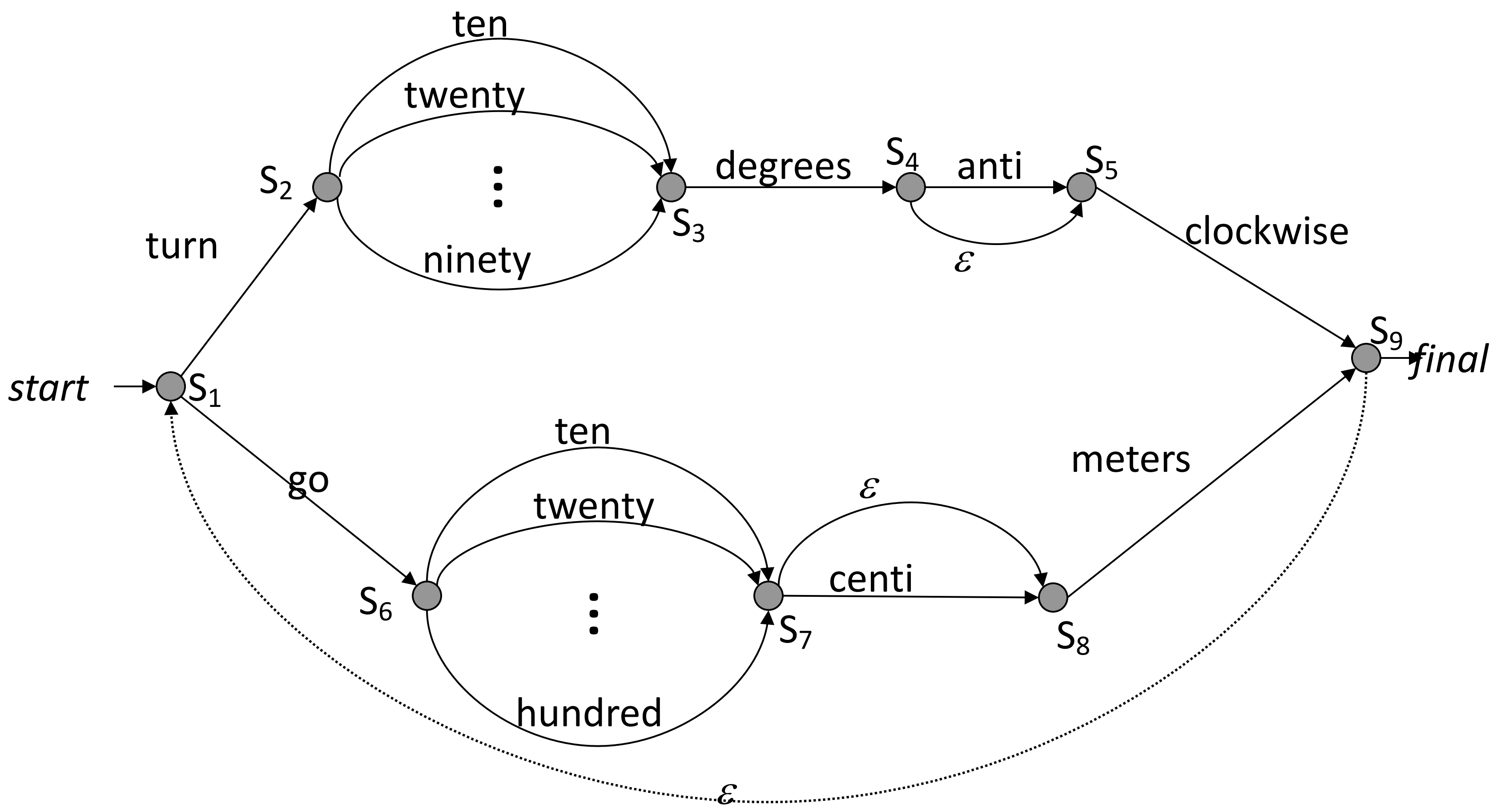
- Is the "any word can follow any word" model also an FSG?

  (*ROBOT0*)



Decoding with Finite State Grammars

- How can we incorporate our *ROBOT1* FSG into the Viterbi decoding scheme?



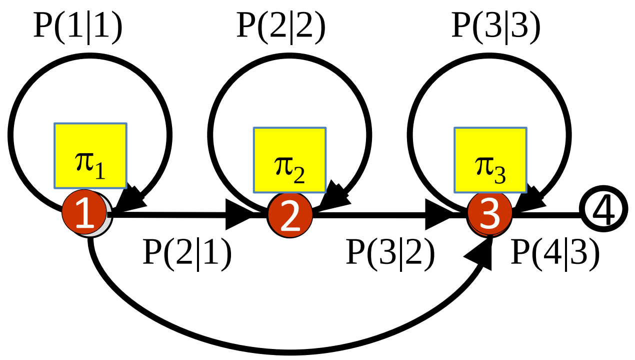
Decoding with Finite State Grammars

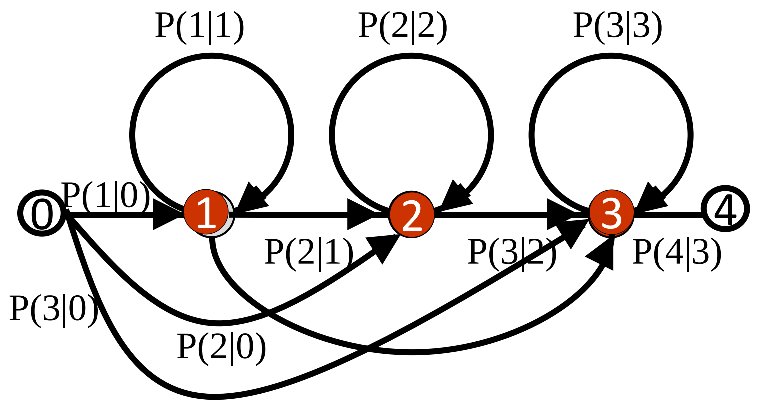
- Construct a *language HMM* from the given FSG
  - Replace edges in the FSG with the HMMs for words
  - We are now in familiar territory
    - Apply the standard time synchronous Viterbi search
  - Only modification needed: need to distinguish between LM states (see later)

- First, how do we construct the language HMM for an FSG?

A Note on the Start State

- We have assumed that HMMs have an initial state probability for states
  - Represented π_s in figure to right
- This is identical to assuming an initial non-emitting state
  - Also more convenient in terms of segmentation and training
- Specification in terms of initial non-emitting state also enables control over permitted initial states
  - By fixing the topology





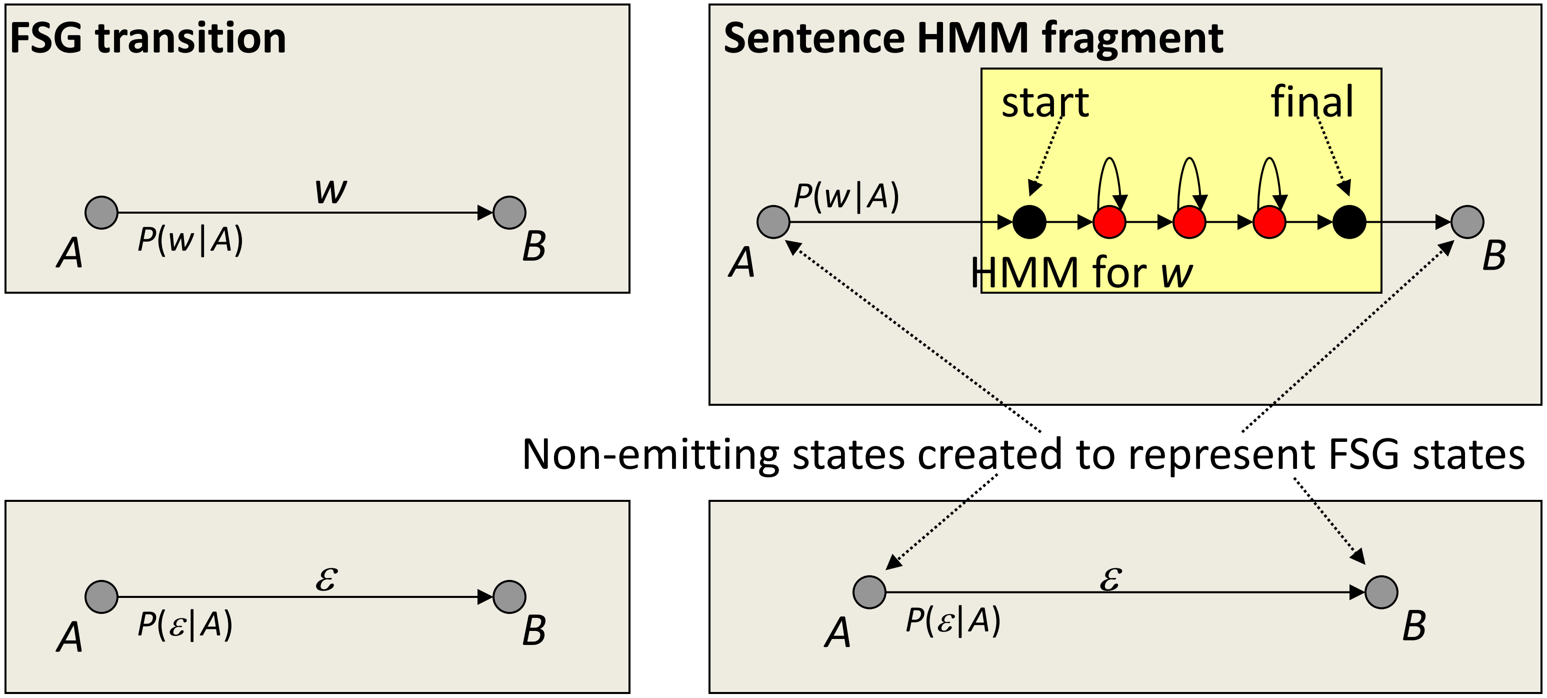
$P(1|0) = \pi_1$

$P(2|0) = \pi_2$

$P(3|0) = \pi_3$

Language HMMs from FSGs

- To construct a language HMM, using word HMMs, we will assume each word HMM has:
  - Exactly one non-emitting start and one non-emitting final state
- Replace each non-null FSG transition by a word HMM:

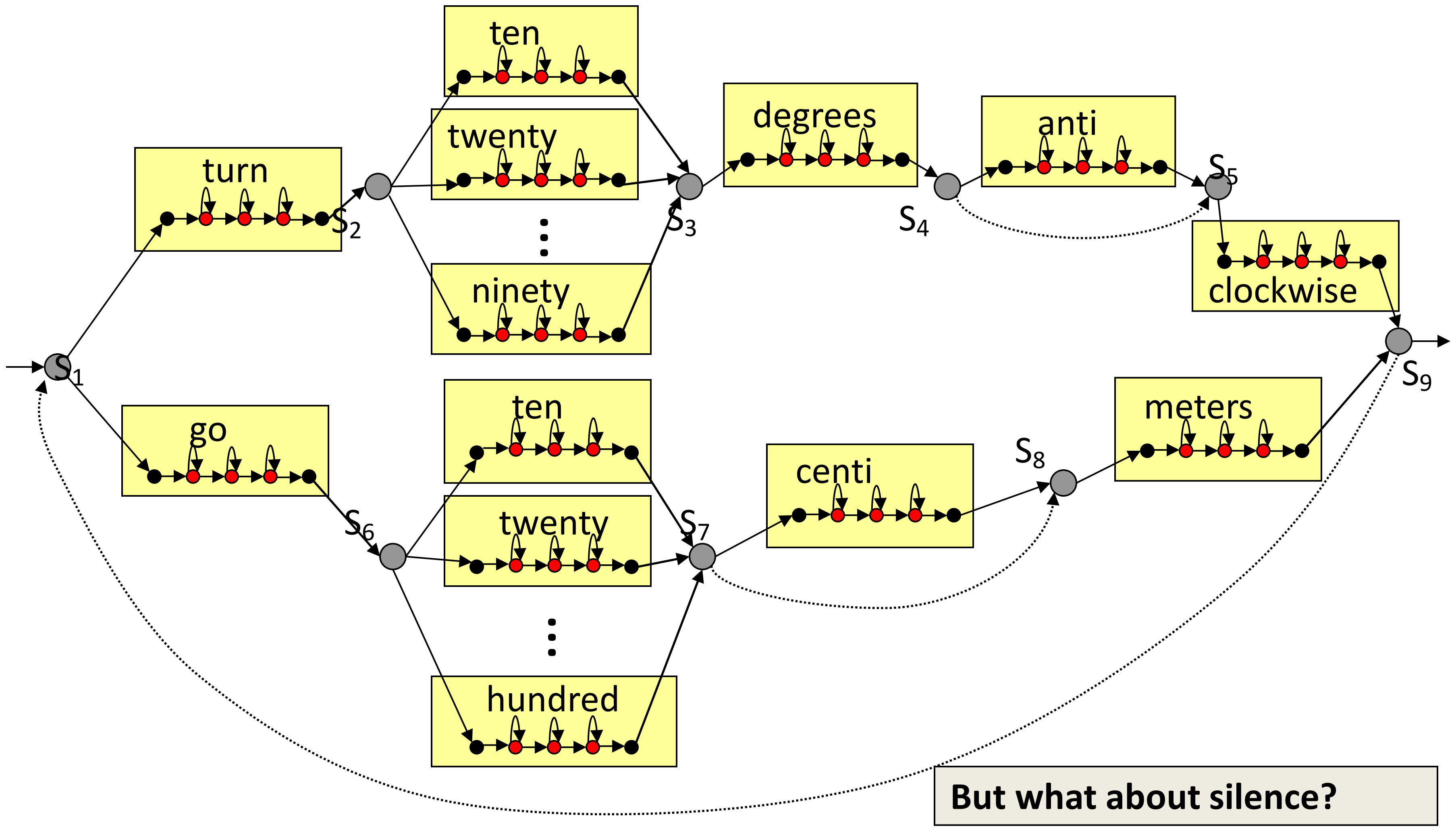


Language HMMs from FSGs (contd.)

- Every FSG state becomes a non-emitting state in the language HMM
- Every *non-null* FSG transition is replaced by a word HMM as shown previously
- Start and final states of sentence HMM = start and final states of FSG

Robot Control (*ROBOT1*) Language HMM

- The robot control FSG *ROBOT1* becomes this language HMM:

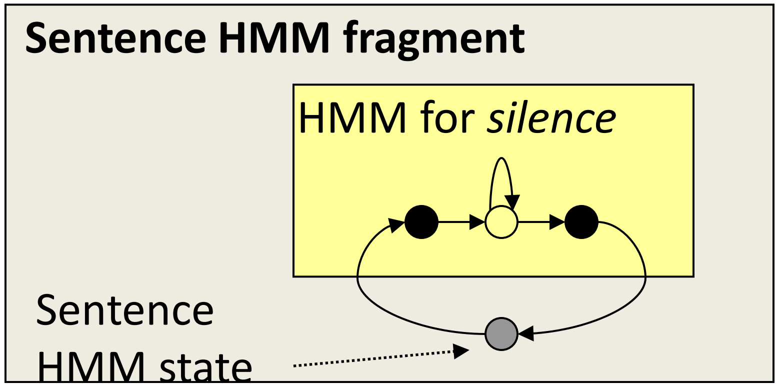


But what about silence?

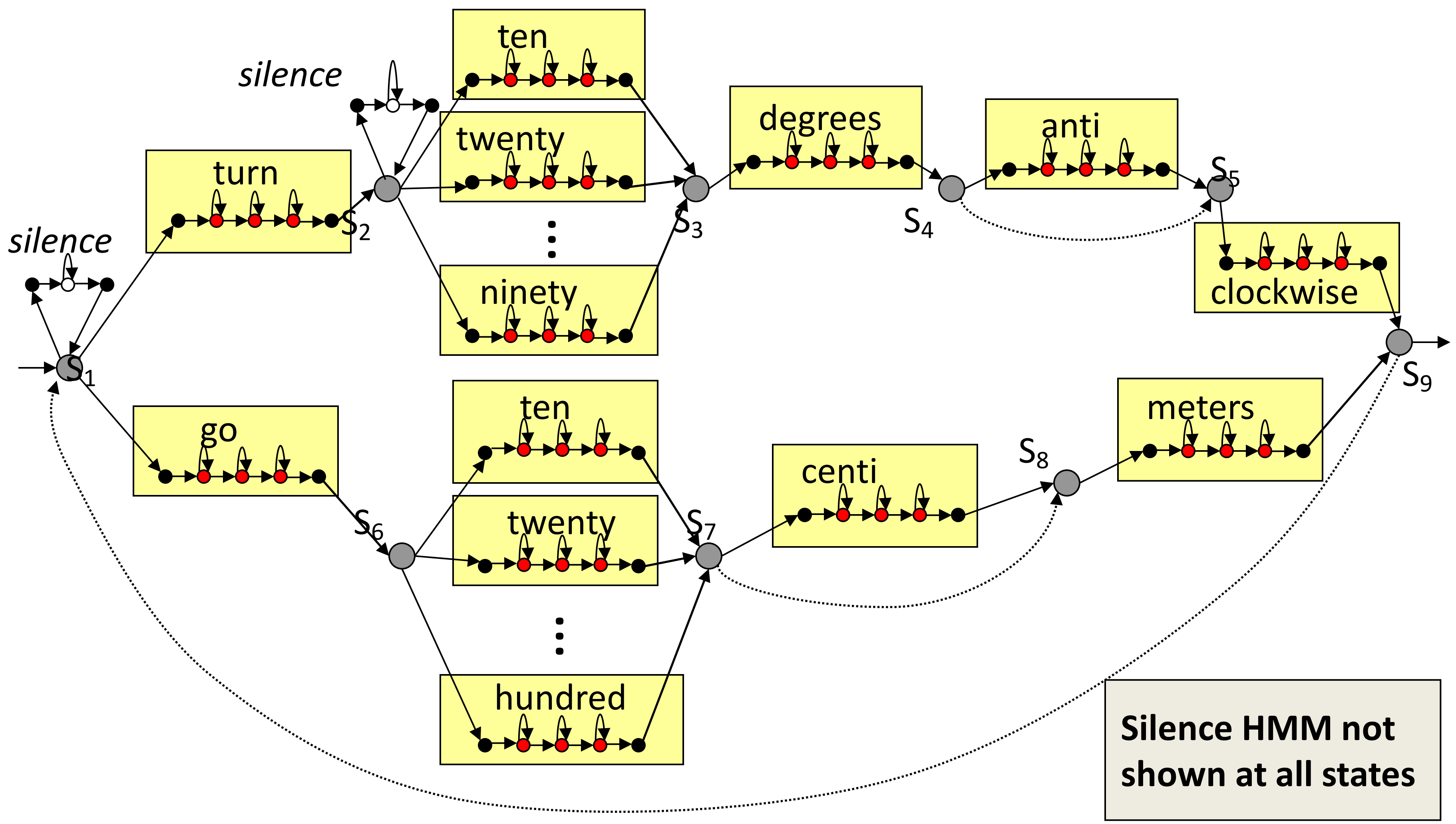
Language HMMs from FSGs (contd.)

- People may pause between words
  - Unpredictably

- Solution: Add optional silence HMM at each sentence HMM state:



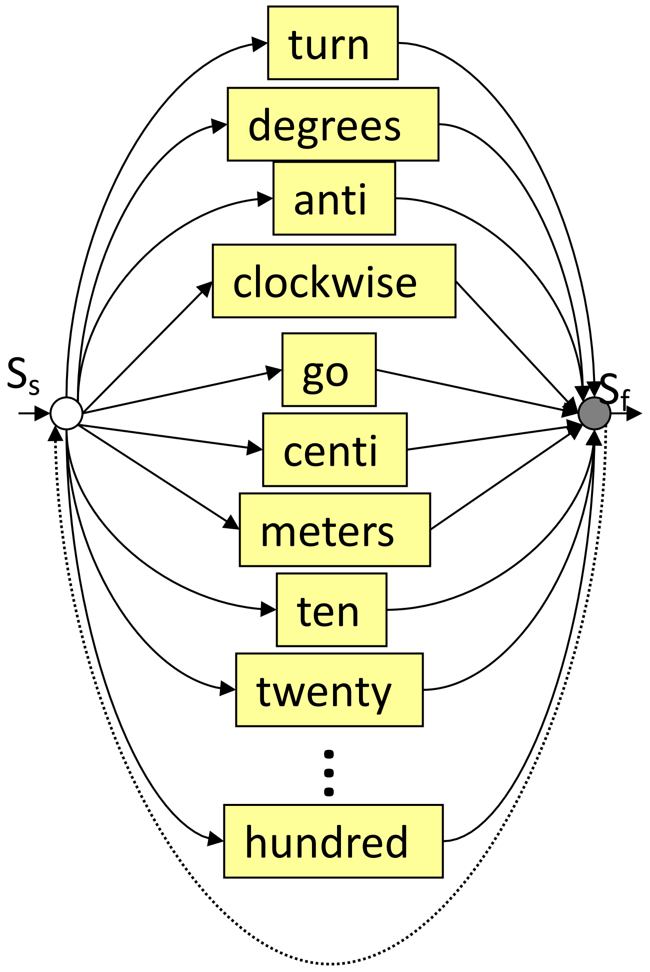
ROBOT1 with Optional Silences



Silence HMM not shown at all states

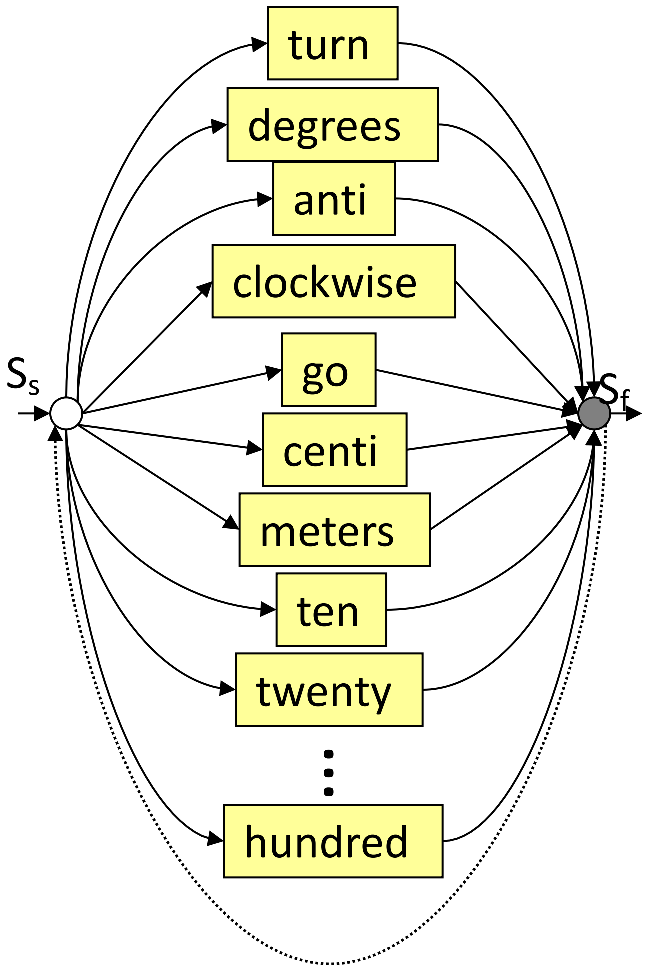
Trellis Construction for *ROBOT0*

- How many rows does a trellis constructed from *ROBOT0* language HMM have?
  - Assume 3 emitting states + 1 non-emitting start state + 1 non-emitting final state, for each word HMM

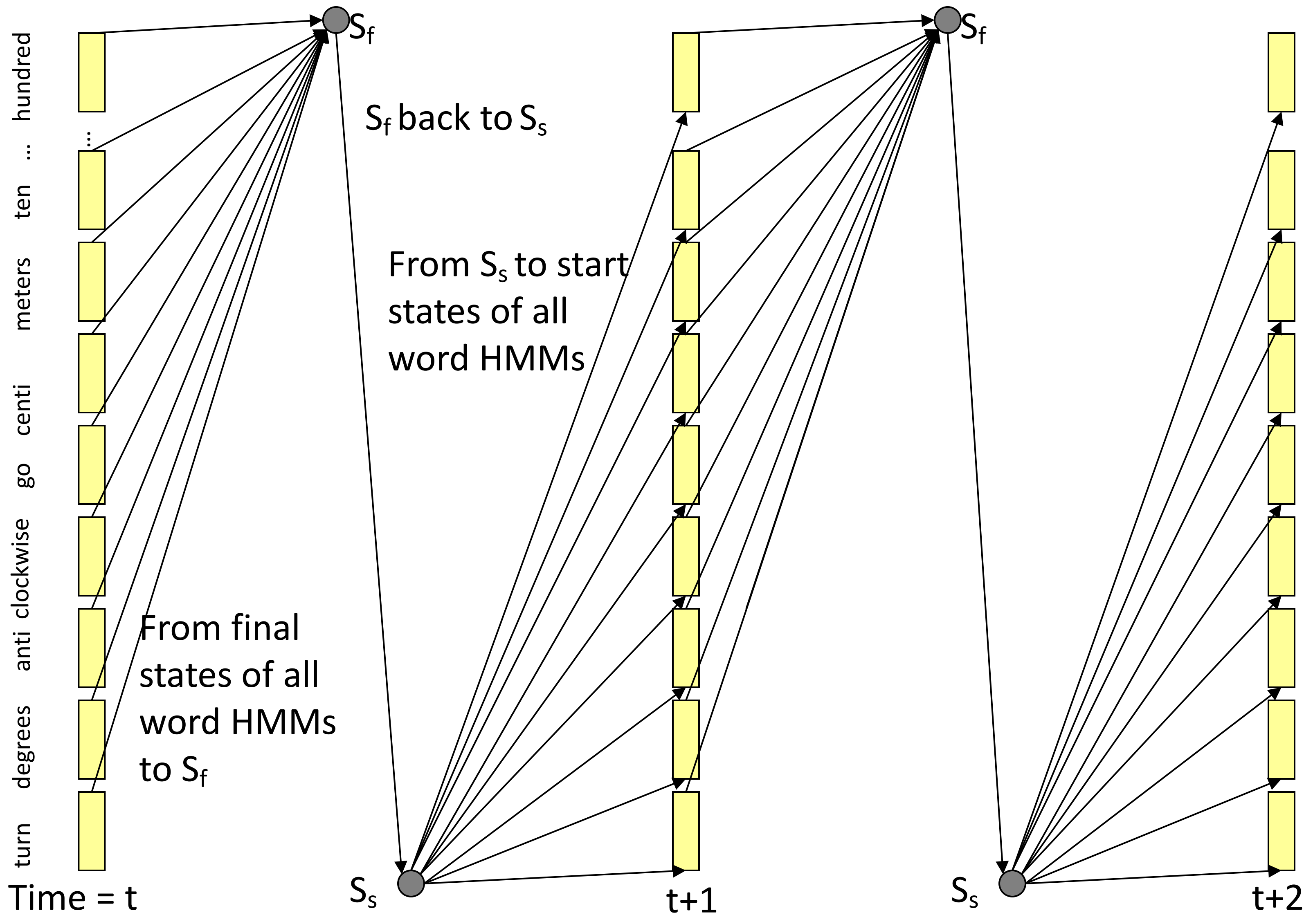


Trellis Construction for *ROBOT0*

- What are the *cross-word transitions* in the trellis?
  - (More accurately, word-exit and word-entry transitions)

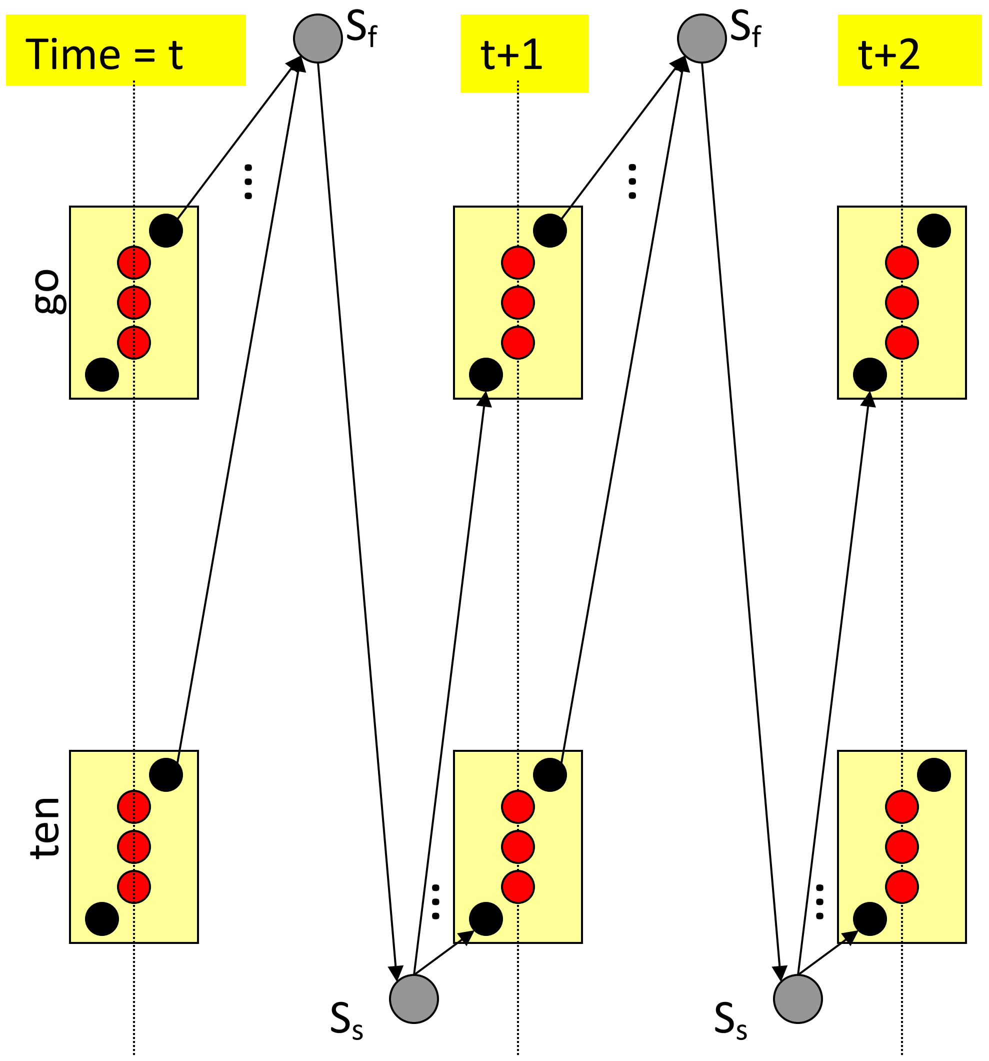


ROBOT0 Cross Word Transitions



ROBOT0 Cross Word Transitions

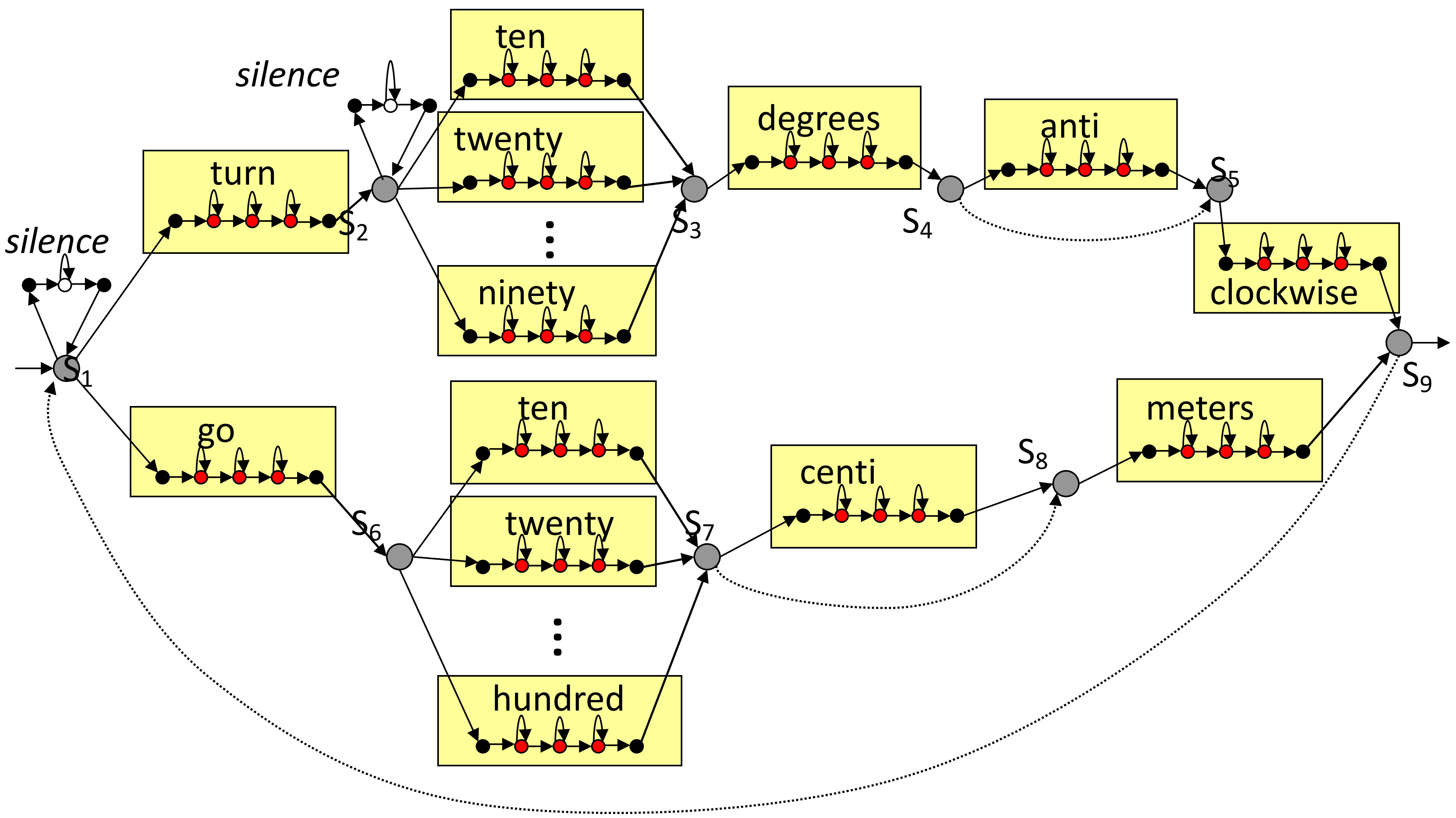
- A portion of trellis shown between time *t* and *t*+2
- Similar Transitions happen from final states of all 17 words to start states of all 17 words
- Non-emitting states shown "between frames"
  - Order them as follows:
    - Find all null state sequences
    - Make sure there are no cycles
    - Order them by dependency
- Other trellis details not shown



Trellis Construction for *ROBOT1*

- How many rows does a trellis constructed from *ROBOT1* language HMM have?
  - Assume 3 emitting states + 1 non-emitting start state + 1 non-emitting final state, for each word HMM, as before

ROBOT1 Language HMM

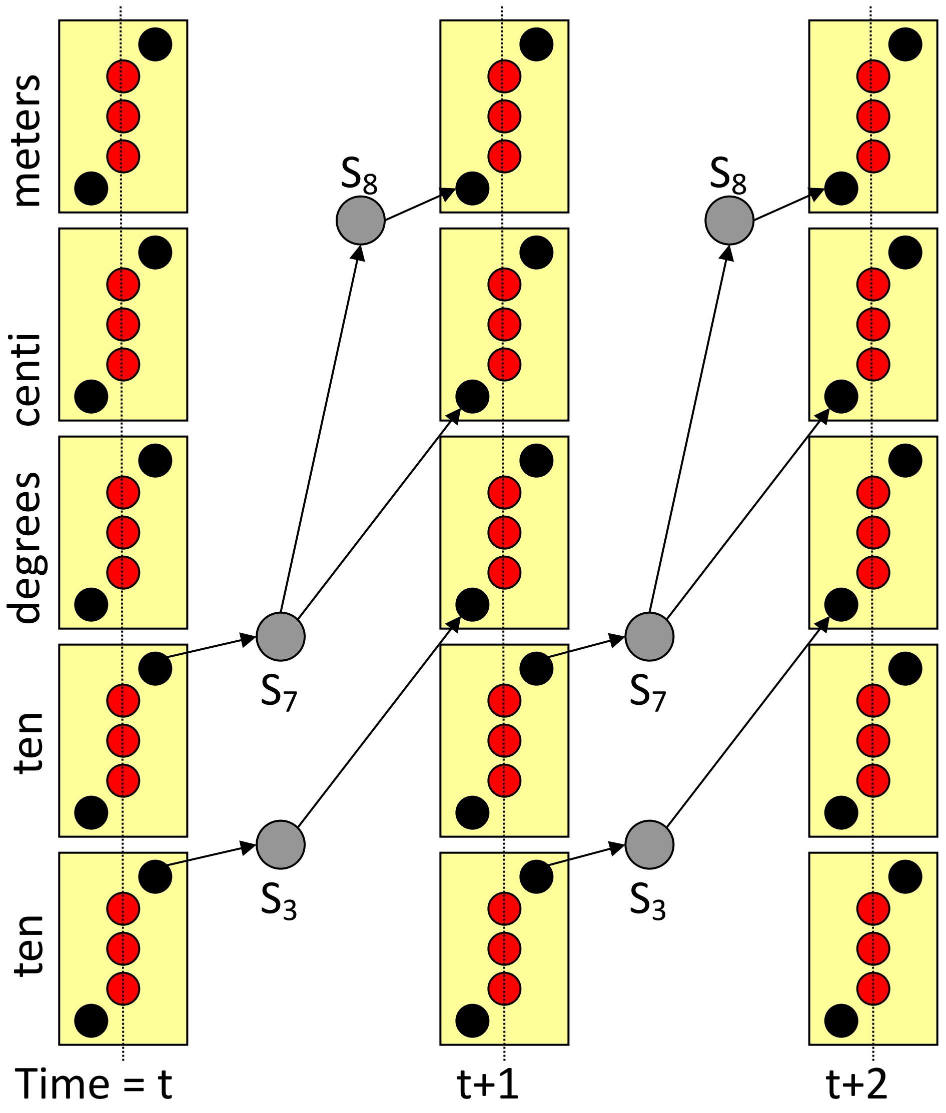


Trellis Construction for *ROBOT1*

- No. of trellis rows = No. of states in Language HMM
  - 26 x 5 word HMM states
    - Note: words “ten” through “ninety” have two copies since they occur between different FSG states! (More on this later)
  - The 9 FSG states become sentence HMM non-emitting states
  - 9 x 3 silence HMM states, one at each FSG state
  - = 130 + 9 + 27 = 166 states or 166 rows
- Often it is possible to reduce the state set, but we won’t worry about that now
- What about word exit and entry transitions?

ROBOT1 Cross Word Transitions

- A portion of trellis shown between time *t* and *t*+2
- Note the FSG-constrained cross word transitions; no longer fully connected
- Note there are two instances of "ten"!
  - From different portions of the graph



Words and Word Instances

- Key points from illustration:
  - FSG states (LM states in general) are distinct, and need to be preserved during decoding
  - If the same word is emitted by multiple different transitions (*i.e.* either the source or destination states are different), there are actually ***multiple*** copies of the word HMM in the sentence HMM

Creation of Application FSGs

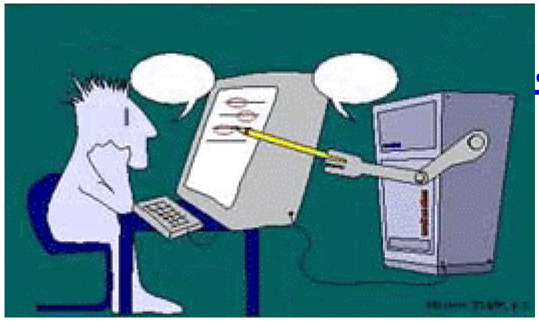
- While FSGs can be trained from training data, they can be easily handcrafted from prior knowledge of expected inputs
  - Suitable for situations where little or no training data available
  - Small to medium vocabulary applications with well structured dialog

- Example applications:
  - Command and control (*e.g.* robot control or GUI control)
  - Form filling (*e.g.* making a train reservation)

- Constraints imposed by an FSG lead to very efficient search implementation
  - FSGs rules out many improbable or illegal word sequences outright
  - Parts of the full NxT search trellis are *a priori* ruled out

Example Application: A Reading Tutor

- Project LISTEN: A reading tutor for children learning to read



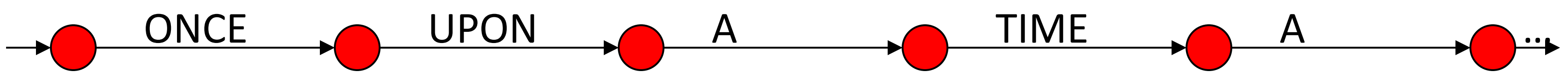
Example Application: Reading Tutor

- A child reads a story aloud, one sentence at a time
- The automated tutor "listens" to the child and tries to help if it has any difficulty
  - Pausing too long at a word
  - Misreading a word
  - Skipping a word

- The child should be allowed to have "normal" reading behavior
  - Repeat a word or phrase, or the entire sentence
  - Partially pronounce a word one or more times before reading it correctly
- Hence, the tutor should account for both normal and incorrect reading
- We do this by building an FSG for the current sentence, as follows

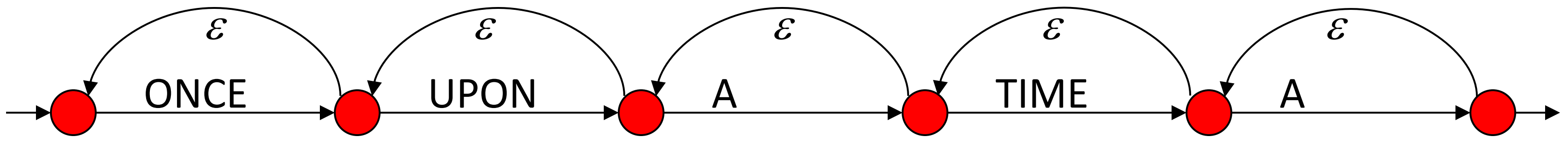
Example Application: Reading Tutor

- For each sentence, the tutor builds a new FSG
- An typical sentence:
  - ONCE UPON A TIME A BEAUTIFUL PRINCESS …
- First we have the "backbone" of the FSG:
  - The backbone models straight, correct reading
    - (Only part of the FSG backbone is shown)
  - FSG states mark positions in text



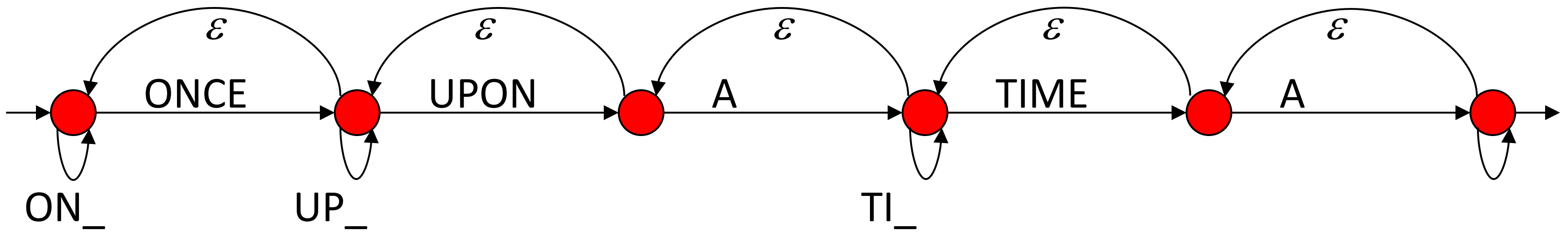
Example Application: Reading Tutor

- We add backward null transitions to allow repetitions
  - Models jumps back to anywhere in the text
  - It is not necessary to add long backward transitions!



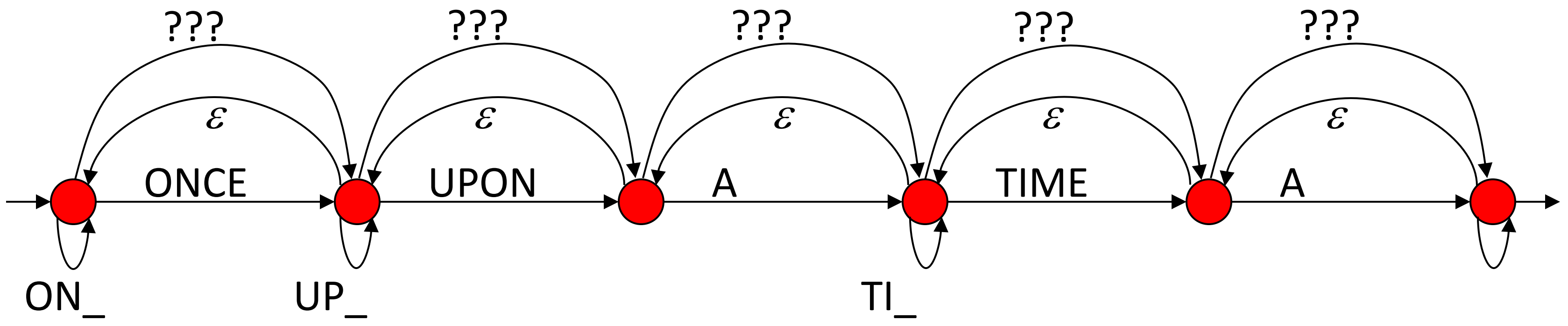
Example Application: Reading Tutor

- We add truncated word models to allow partial reading of a word (shown with an _; *e.g.* ON_)
  - There may be more than one truncated form; only one is shown
  - Partial reading is assumed to mean the child is going to attempt reading the word again, so we do not change state
  - Short words do not have truncated models



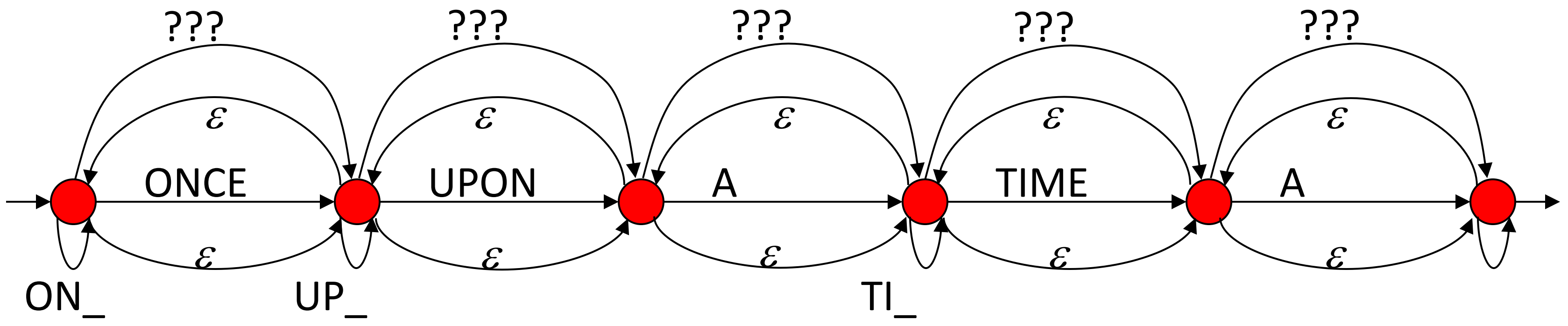
Example Application: Reading Tutor

- We add transitions parallel to each correct word, to model misreading, labeled with a *garbage model* (shown as ???)
  - How we obtain the garbage model is not important right now
  - It essentially models any *unexpected* speech; *e.g.*
    - Misreading, other than the truncated forms
    - Talking to someone else



Example Application: Reading Tutor

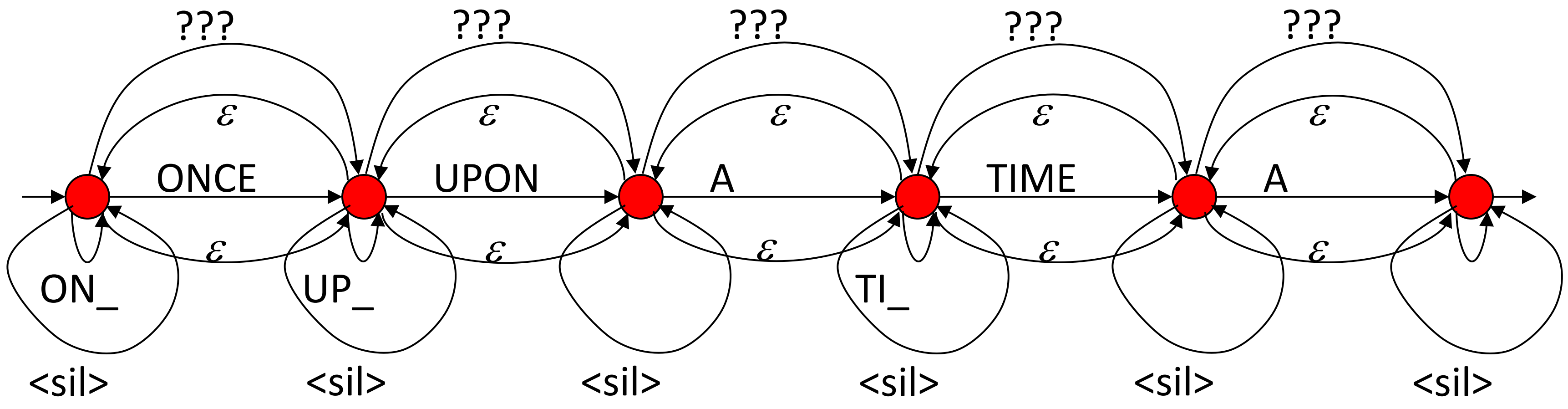
- We add forward null transitions to model one or more words being skipped
  - It is not necessary to add long forward transitions!



Example Application: Reading Tutor

- Not to forget! We add optional silences between words
  - Silence transitions (labeled <sil>) from a state to itself
    - If the child pauses between words, we should not change state

- Finally, we add transition probabilities estimated from actual data recorded with children using the reading tutor



Example Application: Reading Tutor

- The FSG is crafted from an "expert's" mental model of how a child might read through text
- The FSG does *not* model the student getting stuck (too long a silence)
  - There is no good way to model durations with HMMs or FSGs
  - Instead, the application specifically uses word segmentation information to determine if too long a silence has elapsed

- The application creates a new FSG for each new sentence, and destroys old ones
- Finally, the FSG module even allows dynamic fine-tuning of transition probabilities and modifying the FSG start state
  - To allow the child to continue from the middle of a sentence
  - To adapt to a child's changing reading behavior

FSG Representation

- A graphical representation is perfect for human visualization of the system

- However, difficult to communicate to a speech recognizer!
  - Need a textual representation
  - Two possibilities: tabular, or rule-based
    - Commonly used by most real ASR packages that support FSGs

Tabular FSG Representation Example

- Example FSG from Sphinx-2 / Sphinx-3

```
FSG_BEGIN
NUM_STATES    5
START_STATE   0
FINAL_STATE   4
TRANSITION  0 1  0.9   ONCE
TRANSITION  0 0  0.01  ONCE
TRANSITION  1 2  0.9   UPON
TRANSITION  1 1  0.01  UPON
TRANSITION  2 3  0.9   A
TRANSITION  2 2  0.01  A
TRANSITION  3 4  0.9   TIME
TRANSITION  3 3  0.01  TIME
TRANSITION  0 1  0.01
TRANSITION  1 2  0.01
TRANSITION  2 3  0.01
TRANSITION  3 4  0.01
TRANSITION  1 0  0.017
TRANSITION  2 0  0.017
TRANSITION  3 0  0.017
TRANSITION  4 0  0.017
TRANSITION  2 1  0.01
TRANSITION  3 2  0.01
TRANSITION  4 3  0.01
FSG_END
```

Table of transitions

Tabular FSG Representation

- Straightforward conversion from graphical to tabular form:
  - List of states (*e.g.* states may be named or numbered)
    - *E.g.* Sphinx-2 uses state numbers
  - List of transitions, of the form:

    Origin-state, destination state, emitted word, transition probability
    - Emitted word is optional; if omitted, implies a null transition
    - Transition probability is optional
      - All unspecified transition probabilities from a given state are equally likely
  - Set of start states
  - Set of final states

Rule-Based FSG Representation

- Before we talk about this, let us consider something else first

Recursive Transition Networks

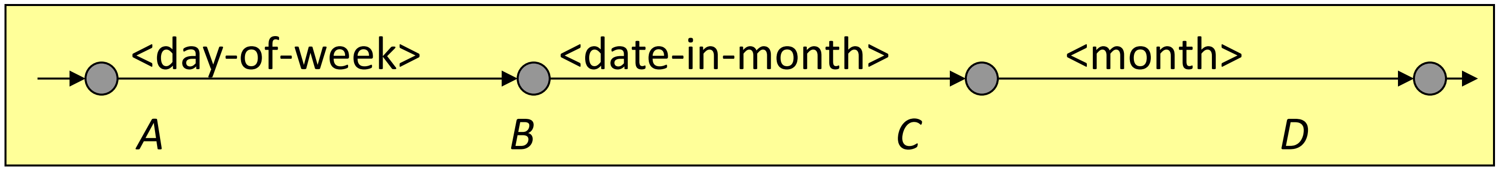
- What happens if we try to "compose" an FSG using other FSGs as its components?
  - *Key idea*: A transition in an FSG-like model can be labeled with an entire FSG, instead of a single word
    - When the transition is taken, it can emit any one of the *sentences* in the *language* of the label FSG

- Such networks of nested grammars are called *recursive transition networks* (RTNs)
  - Grammar definitions can be *recursive*

- But first, let us consider such composition *without* any recursion
  - Arbitrary networks composed in this way, that include recursion, turn out not to be FSGs at all

Nested FSGs

- *E.g.* here is a <*date*> FSG:

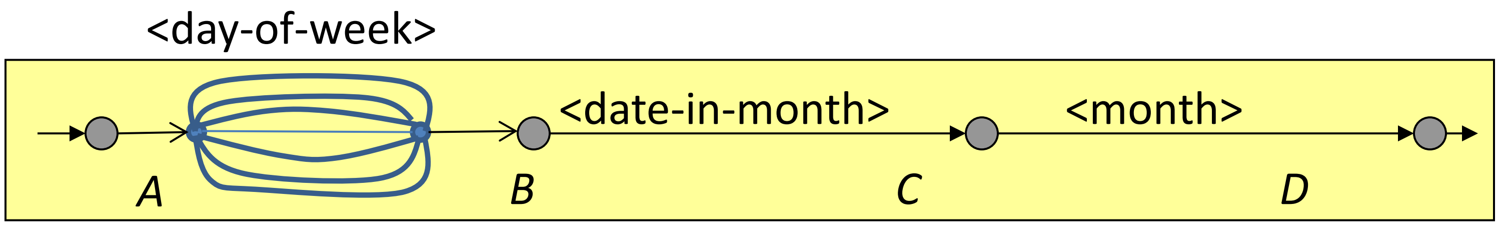


  – Where, <day-of-week>, <date-in-month> and <month> are the FSGs defined earlier

- *Exercise*: Include <year> into this specification, and allow reordering the components

Nested FSGs

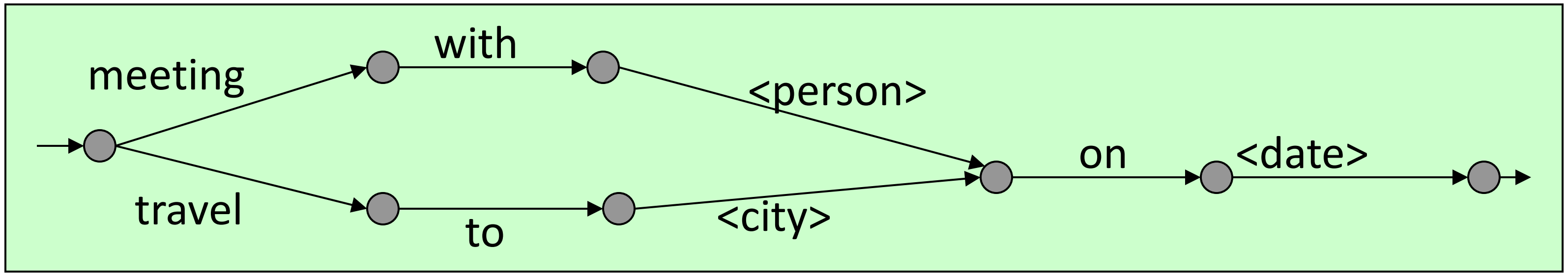
- *E.g.* here is a <*date*> FSG:



  – Each edge in day of week sub-graph represents the HMM for one of “Sunday”, “Monday”, … “Saturday”
  – Note: Insertion of language HMM for day of week similar to insertion of word HMMs

More Nested FSGs

- *Example*: Scheduling task
  - (Transition labels with <> actually refer to other FSGs)



  - The <date> FSG above is further defined in terms of other FSGs
  - Thus, FSG references can be *nested* arbitrarily deeply

- As usual, we have not shown transition probabilities, but they are nevertheless there, at least implicitly
  - *E.g.* meetings are much more frequent than travels (for most office-workers!)

Flattening Composite FSGs for Decoding

- In the case of the above scheduling task FSG, it is possible to flatten it into a regular FSG (*i.e.* without references to other FSGs) simply by embedding the target FSG in place of an FSG transition
  - Very similar to generation of sentence HMMs from FSGs

- At this point, the flattened FSG can be directly converted into the equivalent sentence HMM for decoding

Flattening Composite FSGs for Decoding

- However, not all composite “FSGs” can be flattened in this manner, if we allow recursion!
  – As mentioned, these are really RTNs, and not FSGs

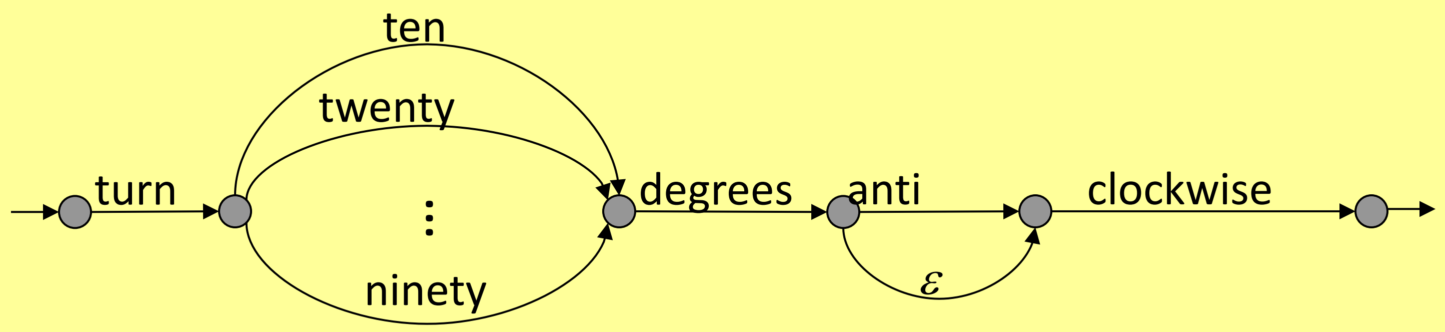
- The grammars represented by them are called *context free grammars* (CFGs)

- Let us consider this recursion in some detail

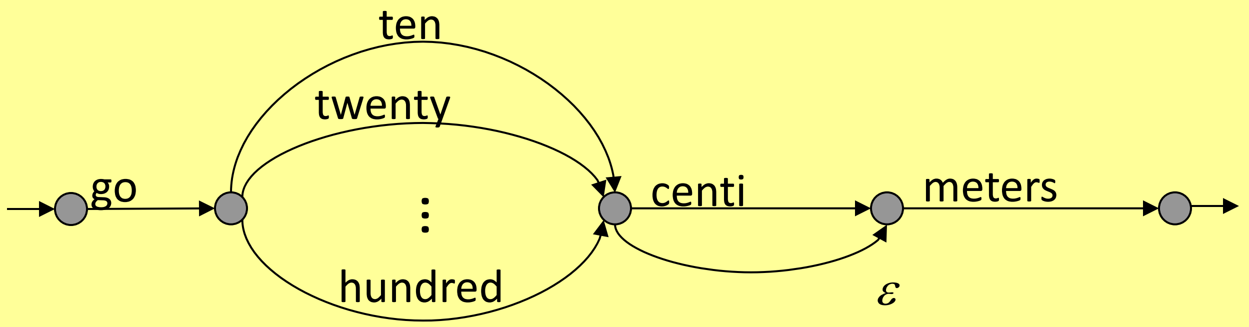
Recursion in Grammar Networks

- It is possible for a grammar definition to refer to *itself*
- Let us consider the following two basic FSGs for robot control:

  - <Turn-command> FSG:

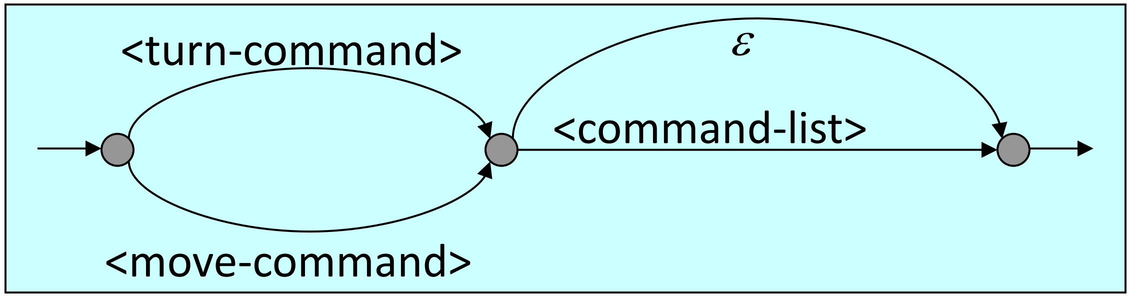


  - <Move-command> FSG:



Recursion in Grammar Networks (contd.)

- We can rewrite the original robot control grammar using the following *recursive* definition:
  - <command-list> grammar:



  - <command-list> grammar is defined in terms of itself

Recursion in Grammar Networks (contd.)

- Recursion can be *direct*, or *indirect*
  - <command-list> grammar is defined directly in terms of itself
  - Indirect recursion occurs when we can find a sequences of grammars, F_1, F_2, F_3, ..., F_k, such that:
    - F_1 refers to F_2, F_2 refers to F_3, etc., and F_k refers back to F_1

- Problem with recursion:
  - It is not always possible to simply blindly expand a grammar by plugging in the component grammars in place of transitions
    - Leads to infinite expansion

A Little Digression: Grammar Libraries

- It is very useful to have a *library* of reusable grammar components
  - New applications can be designed rapidly by composing together already existing grammars

- A few examples of common, reusable grammars:
  - Date, month, day-of-week, etc.
  - Person names and place name (cities, countries, states, roads)
  - Book, music or movie titles
  - Essentially, almost any *list* is a potentially reusable FSG

RTNs and CFGs

- Clearly, RTNs are a powerful tool for defining structured grammars

- As mentioned, the class of grammars represented by such networks is called the class of *context free grammars* (CFGs)
  - Let us look at some characteristics of CFGs

Context Free Grammars

- Compared to FSGs, CFGs are a more powerful mechanism for defining *languages* (sets of acceptable sentences)
  - "Powerful" in the sense of imposing more structure on sentences
  - CFGs are a superset of FSGs
    - Every language accepted by an FSG is also accepted by some CFG
    - But not every CFG has an equivalent FSG

- Human languages are actually fairly close to CFGs, at least syntactically
  - Many applications use them in structured dialogs

Context Free Grammars

- What is a CFG?
  - Graphically, CFGs are exactly what we have been discussing:
    - The class of grammars that can have *concepts* defined in terms of other grammars (possibly themselves, recursively)
  - They are context free, because the definition of a *concept* is the same, regardless of the *context* in which it occurs
    - *i.e.* independent of where it is embedded in another grammar

- However, unlike FSGs, may not have graphical representations

- In textual form, CFGs are defined by means of *production rules*

Context Free Grammars (contd.)

- Formally, a CFG is defined by the following:
  - A finite set of *terminal* symbols (*i.e.* words in the vocabulary)
  - A finite set of *non-terminal* symbols (the *concepts*, such as <date>, <person>, <move-command>, <command-list> etc.
  - A special non-terminal, usually *S,* representing the CFG
  - A finite set of *production rules*
    - Each rule defines a non-terminal as a *possibly empty sequence* of other symbols, each of which may be a terminal or a non-terminal
      - There may be multiple such definitions for the same non-terminal
    - The empty rule is usually denoted: <non-terminal> ::= *e*

- The language generated by a CFG is the set of all sentences of terminal symbols that can be derived by expanding its special non-terminal symbol *S*, using the production rules

Why Are CFGs Useful?

- The syntax of large parts of human languages can be defined using CFGs
  - *e.g.* a simplistic example:

```
<sentence> ::= <noun-phrase> <verb-phrase>
<noun-phrase> ::= <name> | <article> <noun>
<verb-phrase> ::= <verb> <noun-phrase>
<name> ::= HE | SHE | JOHN | ALICE…
<article> ::= A | AN | THE
<noun> ::= BALL | BAT | FRUIT | BOOK …
<verb> ::= EAT | RUN | HIT | READ …
```

- Clearly, the language allows nonsensical sentences:

  JOHN EAT A BOOK

  - But it is syntactically “correct”
  - The grammar defines the syntax, not the semantics

Robot Control CFG

- Example rules for robot control
- <command-list> is the CFG being defined (= *S*):

```
<command-list>   ::=  <turn-command>  |  <move-command>
<command-list>   ::=  <turn-command><command-list>
<command-list>   ::=  <move-command><command-list>

<turn-command>  ::=  TURN <degrees> DEGREES <direction>
<direction>          ::=  clockwise | anti clockwise
<move-command>::=  GO <distance> <distance-units>
<distance-units>   ::=  meters  |  centi meters
<degrees>           ::= TEN | TWENTY | THIRTY | FORTY | … | NINETY
<distance>          ::= TEN | TWENTY | THIRTY | … | HUNDRED
```

Probabilistic Context Free Grammars

- CFGs can be made probabilistic by attaching a probability to each production rule
  - These probabilities are used in computing the overall likelihood of a recognition hypothesis (sequence of words) matching the input speech

- Whenever a rule is used, the rule probability is applied

Context Free Grammars: Another View

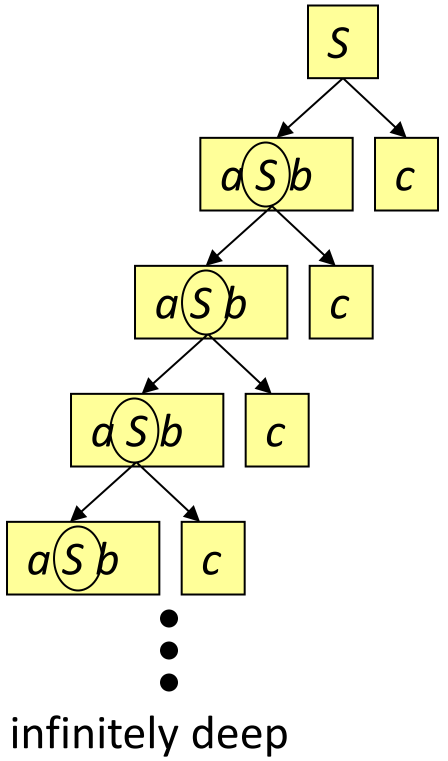
- Non-terminals can be seen as *functions* in programming languages
  - Each production rule defines the function body; as a sequence of statements
  - Terminals in the rule are like ordinary assignment statements
  - A non-terminal within the rule is a *call to a function*
- Thus, the entire CFG is like a program made up of many functions
  - Obviously, program execution can take many paths!
  - Each program execution produces a complete sentence

CFG Based Decoding

- Consider the following simple CFG:
  - *S* is like an *overloaded* function
    - It is also the entire "program"
  - The "call tree" on the right shows all possible "program execution paths"

S ::= aSb | c

- CFG based decoding is equivalent to finding out which rules were used in what sequence, to produce the spoken sentence
  - A general algorithm to determine this is too complex to describe here
  - Instead, we can try to approximate CFGs by FSGs



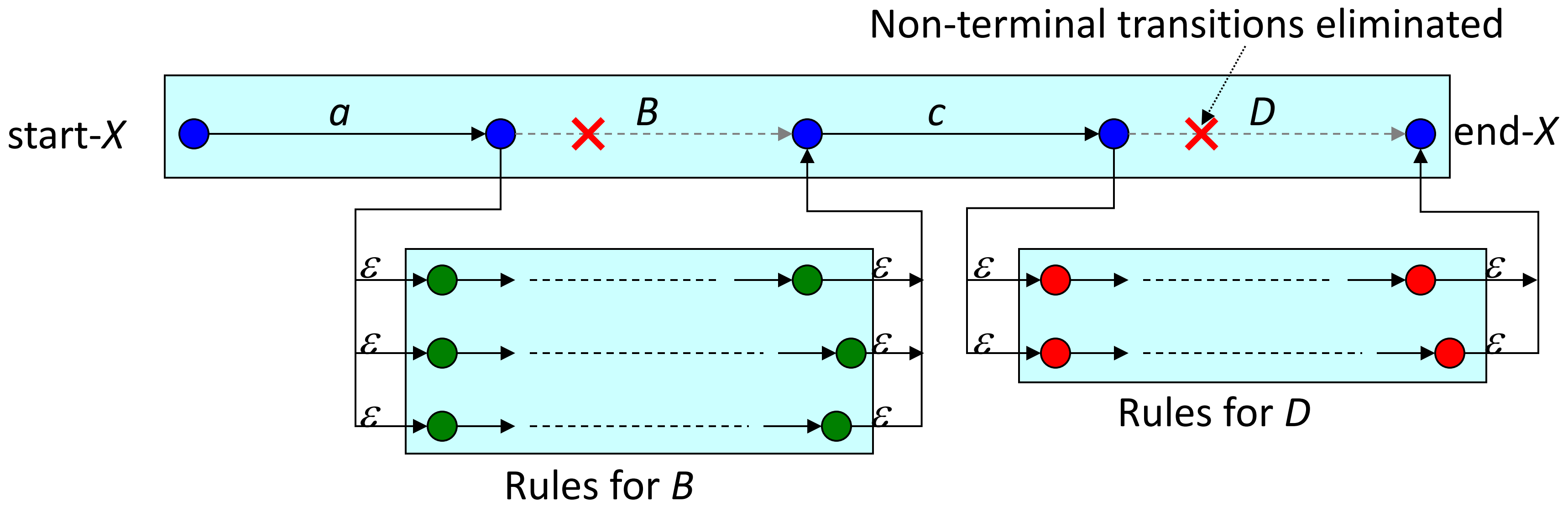
Approximating a CFG by an FSG

- Advantage: back in familiar, efficient decoding territory
- Disadvantage: depends on the approximation method
  - In some, the FSG will allow illegal sentences to become legal
  - In others, the FSG will disallow some legal sentences

- For practical applications, the approximations can be made to work nicely
  - Many applications need only FSGs to begin with
  - The errors committed by the approximate FSG can be made extremely rare

FSG Approximation to CFGs:

- Consider a rule: *X* ::= *aBcD*, where *a* and *c* are terminal symbols (words), and *B* and *D* are non-terminals
- We can create the following FSG for the rule:



- It should be clear that when the above construction is applied to all the rules of the CFG, we end up with an FSG

FSG Approximation to CFGs:

- Example

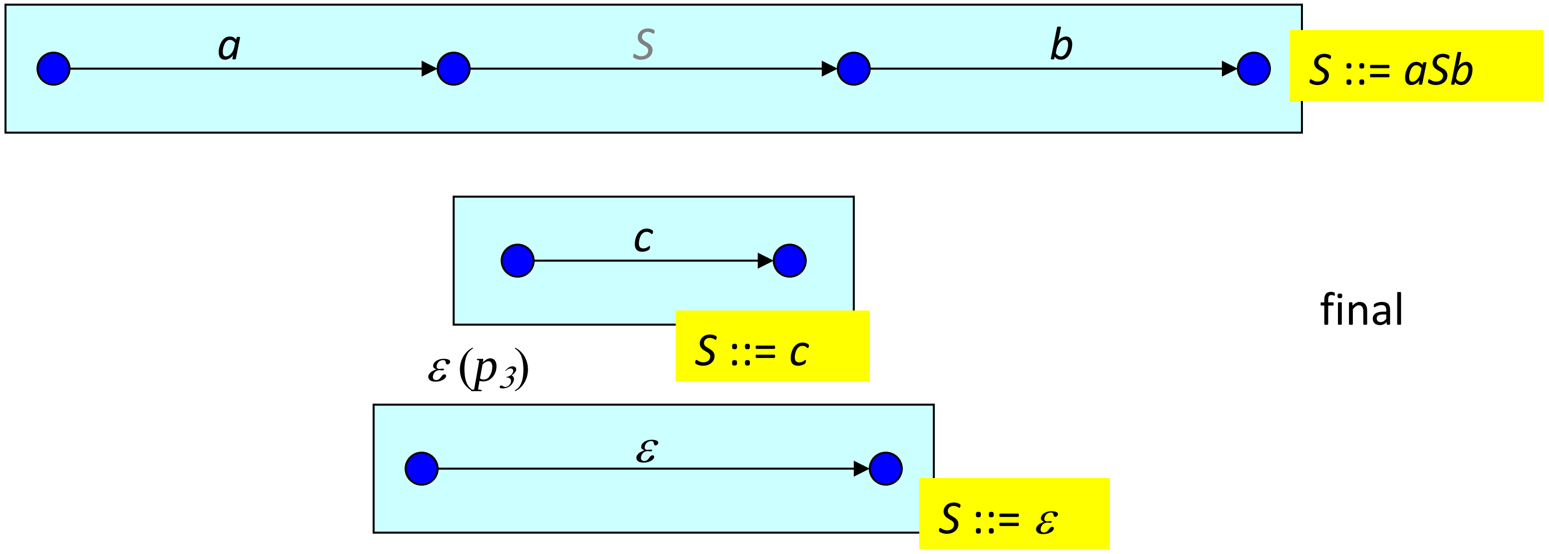
$$\boxed{S ::= aSb \mid c \mid \varepsilon}$$

FSG Approximation to CFGs:

- We can construct an FSG from a CFG as follows:

  $S ::= aSb \mid c \mid \varepsilon$

  - Take each production rule in the CFG as a *sequence* of state transitions, one transition per symbol in the rule
    - The first state is the start state of the rule, and the last the final state of the rule



FSG Approximation to CFGs:

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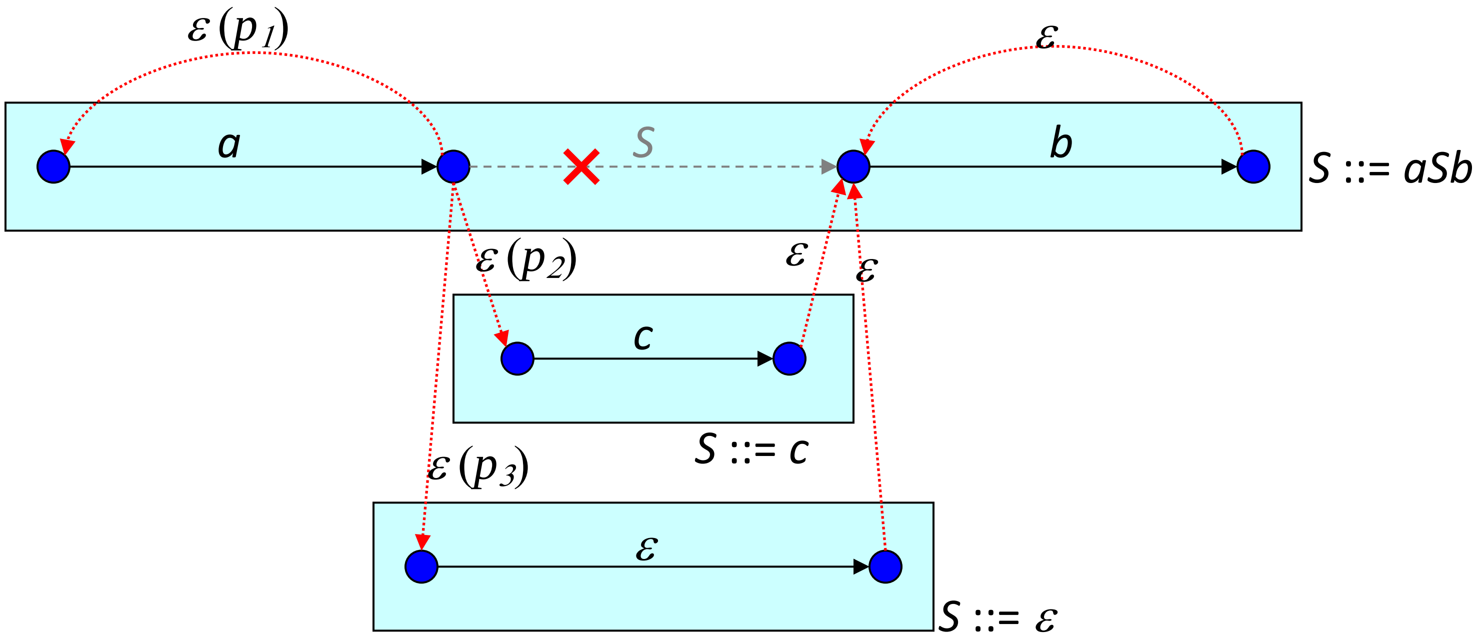
  - Replace each non-terminal in the sequence with null transitions *to* the start, and *from* the end of each rule for that non-terminal



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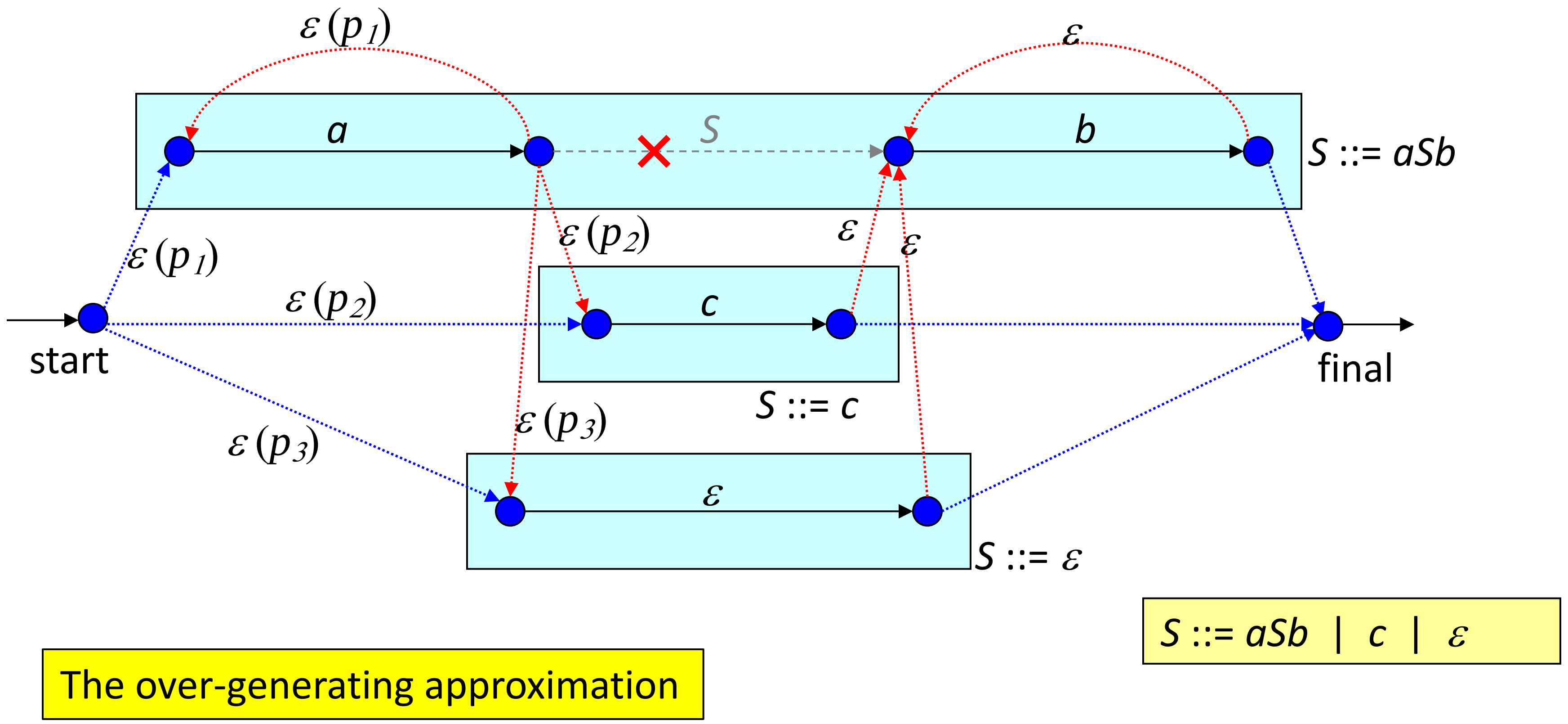
  - Replace each non-terminal in the sequence with null transitions *to* the start, and *from* the end of each rule for that non-terminal
    - (The empty string *e* is considered to be a terminal symbol)
  - Make the start states of all the rules for the distinguished CFG symbol *S* to be the start states of the FSG
  - Similarly, make the final states of the rules for *S* to be the final states of the FSG
    - Or, add new start and final states with null transitions to and from the above
- Since the CFG has a *finite* set of rules of *finite* length, and we remove all non-terminals, we end up with a plain FSG

CFG to FSG Example

- Let's convert the following CFG to FSG:
  - Assume the rules have probabilities p_1, p_2 and p_3 ($p_1+p_2+p_3=1$)
- We get the FSG below:



Why is this FSG an Approximation?

- Consider S :== aSb | c | ε
- Any string *must* have as many "*a*"s as "*b*"s
- The approximate FSG does not guarantee that the number of "*a*"s and "*b*"*s* are the same
  - The FSG behavior is governed entirely by its *current* state, and not how it got there
  - To implement the above requirement, the FSG would have to remember that it took a particular transition a long time ago
- The constructed FSG allows all sentences of the CFG, since the original paths are all preserved
- Unfortunately, it also *allows illegal paths to become legal*

Another FSG Approximation to CFGs

- Another possibility is to eliminate the infinite recursion
  - In most practical applications, one rarely sees recursion depths beyond some small number
- So, we can arbitrarily declare that recursion cannot proceed beyond a certain depth

- We only need to explore a *finite* sized tree
- A finite sized search problem can be turned into an FSG!

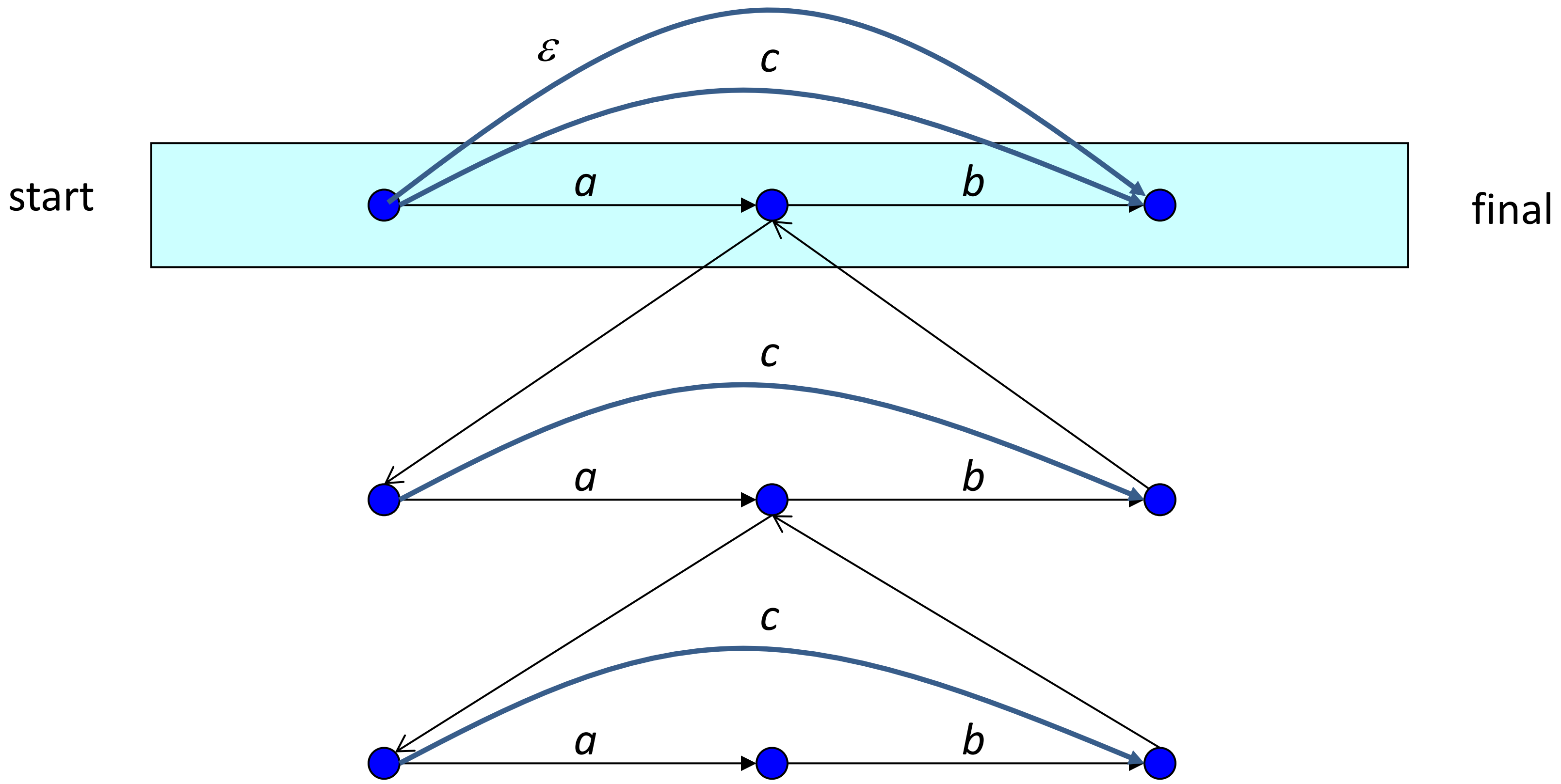
- This FSG will never accept an illegal sentence, but it may reject legal ones (those that exceed the recursion depth limit)
  - The deeper the limit, the less the chance of false rejection

Another Approximation: CFG to FSG Example

- The *under-generating* approximation

S ::= aSb | c | ε

S ::= ab | acb | aabb | aacbb | aaabbb | aaacbbb



FSG Optimization

- In the first version, the FSG created had a large number of null transitions!
- We can see from manual examination that many are redundant
- Blindly using this FSG to create a search trellis would be highly inefficient

- We can use FSG optimization algorithms to reduce its complexity
  - It is possible to eliminate unnecessary (duplicate) states
  - To eliminate unnecessary transitions, usually null-transitions

- Topic of discussion for another day!

The Language Weight

- According to the basic speech recognition equation, we wish to maximize: $P(X|W)\ P(W)$ over all word sequences W

- In practice, it has been found that left in this form, the language model (*i.e.* $P(W)$) has little effect on accuracy
- Empirically, it has been found necessary to maximize: $P(X|W)P(W)^k$, for some $k>1$
  - k is known as the *language weight*
  - Typical values of k are around 10, though they range rather widely
  - When using log-likelihoods, the LM log-likelihoods get multiplied by k

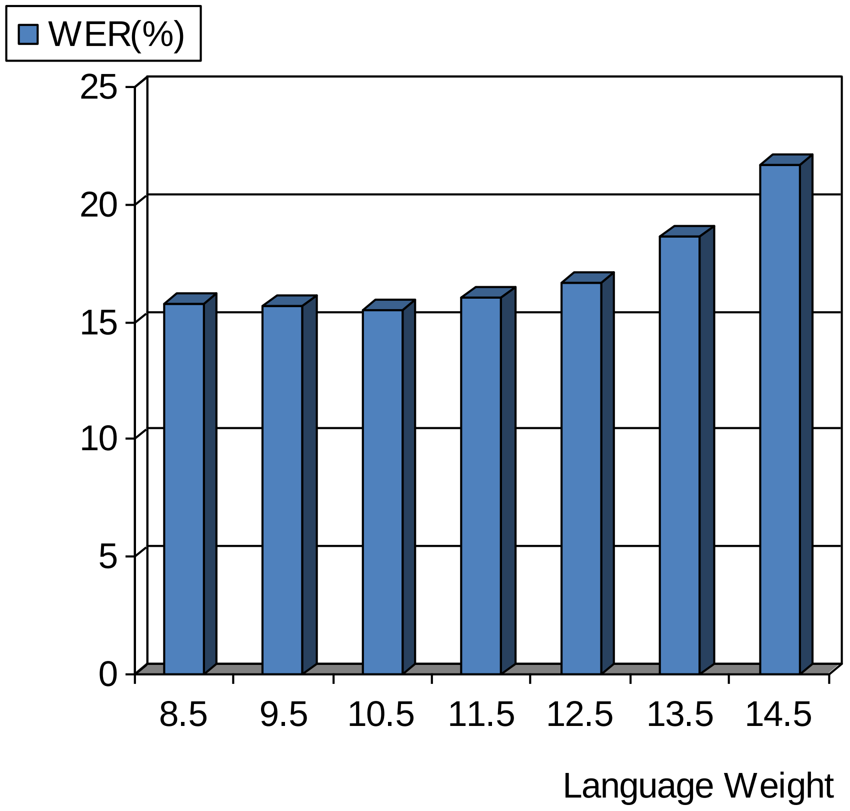
Optimizing Language Weight

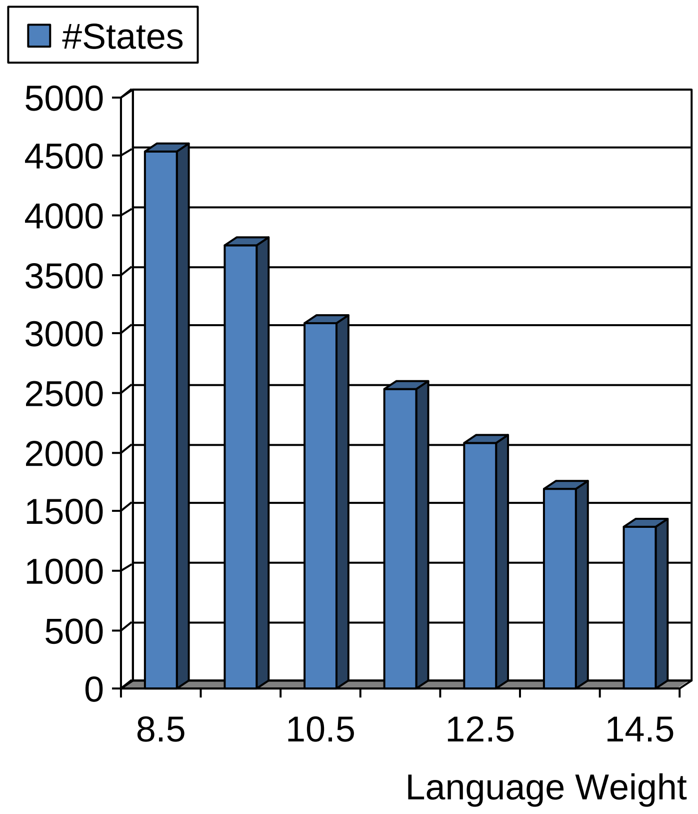
- The optimum setting for the language weight is determined empirically, by trying a range of values on some test data
  - This process is referred to as *tuning* the language weight

- When attempting such tuning, one should keep in mind that changing the language weight changes the range of total path likelihoods
- As a result, beam pruning behavior gets affected
  - As language weight is increased, the LM component of the path scores decreases more quickly (p^k, where $p<1$ and $k>1$)
  - If the beam pruning threshold is kept constant, more paths fall under the pruning threshold and get pruned
- Thus, it is necessary to adjust the beam pruning thresholds while changing language weight
  - Makes the tuning process a little more "interesting"

Optimizing Language Weight: Example

- No. of active states, and word error rate variation with language weight (20k word task)





- Relaxing pruning improves WER at LW=14.5 to 14.8%

Rationale for the Language Weight

- Basically an *ad hoc* technique, but there are arguments for it:
- HMM state output probabilities are usually density values, which can range very widely (*i.e.*, not restricted to the range 0..1)
- LM probabilities, on the other hand, are true probabilities (< 1.0)
- Second, acoustic likelihoods are computed on a frame-by-frame basis as though the frames were completely independent of each other
  - Thus, the acoustic likelihoods tend to be either widely under or over estimated
- In combination, the effect is that the *dynamic range* of acoustic likelihoods far exceeds that of the LM
- The language weight is needed to counter this imbalance between the range of the two scores

CFG Support in ASR Systems and SRGS

- Most commercial systems provide some support for CFG grammars
- May be specified in many formats
  - BNF (Backus Naur format)
  - ABNF (Augmented BNF)

- Many standards
  - SRGS (Speech Recognition Grammar Specification) is a proposed W3C standard
    - Specifies the format in which CFG grammars may be input to a speech recognizer
    - For details: http://www.w3.org/TR/speech-grammar/
  - JSGF (Java speech grammar format)
  - Others

- Need tools to read the CFG in the appropriate format and convert it to the desired internal representation
  - Several open source tools
  - Write your own: YACC / Bison / ..

Summary

- Language models are essential for recognition accuracy
- LMs can be introduced into the decoding framework using the standard speech equation
- The formula for $P(w_1, w_2, w_3, \ldots, w_n)$ naturally leads to the notion of N-gram grammars for language models
- However, N-gram grammars have to be trained
- When little or no training data are available, one can fall back on structured grammars based on expert knowledge
- Structured grammars are of two common types: finite state (FSG) and context free (CFG)
- CFGs obtain their power and appeal from their ability to function as building blocks
- FSGs can be easily converted into sentence HMM for decoding
- CFGs are much harder to decode exactly
- However, CFGs can be approximated by FSGs by making some assumptions

Looking Forward

- It is hard to construct structured grammars for large vocabulary applications

- Our next focus will be large vocabulary and its implications for all aspects of modeling and decoding strategies