4.3 Language Model

- 4.3.1 Overview of Language Model
- 4.3.2 N-gram based Language Model
- 4.3.3 Recurrent Neural Network based Language Model

What is Language Models?

- Formal grammars (e.g. regular, context free) give a hard "binary" model of the legal sentences in a language.

- For NLP, a ***probabilistic*** model of a language that gives a probability that a string is a member of a language is more useful.

- To specify a correct probability distribution, the probability of all sentences in a language must sum to 1.

Uses of Language Models

- Speech recognition
  - “I ate a cherry” is a more likely sentence than “Eye eight uh Jerry”
- OCR & Handwriting recognition
  - More probable sentences are more likely correct readings.
- Machine translation
  - More likely sentences are probably better translations.
- Generation
  - More likely sentences are probably better NL generations.
- Context sensitive spelling correction
  - “Their are problems wit this sentence.”

Completion Prediction

- A language model also supports predicting the completion of a sentence.
  - Please turn off your cell _____
  - Your program does not _____

- *Predictive text input* systems can guess what you are typing and give choices on how to complete it.

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N-Gram Models

- Estimate probability of each word given prior context.
  - P(phone | Please turn off your cell)
- Number of parameters required grows exponentially with the number of words of prior context.
- An N-gram model uses only N−1 words of prior context.
  - Unigram: P(phone)
  - Bigram: P(phone | cell)
  - Trigram: P(phone | your cell)
- The ***Markov assumption*** is the presumption that the future behavior of a dynamical system only depends on its recent history. In particular, in a ***kth-order Markov model***, the next state only depends on the *k* most recent states, therefore an N-gram model is a (N−1)-order Markov model.

N-Gram Model Formulas

- Word sequence

$$w_1^n = w_1 \ldots w_n$$

- Chain rule of probability

$$P(w_1^n) = P(w_1)P(w_2 \mid w_1)P(w_3 \mid w_1^2)\ldots P(w_n \mid w_1^{n-1}) = \prod_{k=1}^{n} P(w_k \mid w_1^{k-1})$$

- Bigram approximation

$$P(w_1^n) = \prod_{k=1}^{n} P(w_k \mid w_{k-1})$$

- N-gram approximation

$$P(w_1^n) = \prod_{k=1}^{n} P(w_k \mid w_{k-N+1}^{k-1})$$

Estimating Probabilities

- N-gram conditional probabilities can be estimated from raw text based on the ***relative frequency*** of word sequences.

Bigram: $$P(w_n \mid w_{n-1}) = \frac{C(w_{n-1}w_n)}{C(w_{n-1})}$$

N-gram: $$P(w_n \mid w_{n-N+1}^{n-1}) = \frac{C(w_{n-N+1}^{n-1}w_n)}{C(w_{n-N+1}^{n-1})}$$

- To have a consistent probabilistic model, append a unique start (<s>) and end (</s>) symbol to every sentence and treat these as additional words.

Generative Model & MLE

- An N-gram model can be seen as a probabilistic automata for generating sentences.

  Initialize sentence with N–1 <s> symbols
  Until </s> is generated do:
  Stochastically pick the next word based on the conditional probability of each word given the previous N –1 words.

- Relative frequency estimates can be proven to be ***maximum likelihood estimates*** (MLE) since they maximize the probability that the model *M* will generate the training corpus *T*.

$$\hat{\lambda} = \underset{\lambda}{\operatorname{argmax}} P(T \mid M(\lambda))$$

Example from Textbook

- P(<s> i want english food </s>)

  = P(i | <s>) P(want | i) P(english | want)

  P(food | english) P(</s> | food)

  = .25 x .33 x .0011 x .5 x .68 = .000031

- P(<s> i want chinese food </s>)

  = P(i | <s>) P(want | i) P(chinese | want)

  P(food | chinese) P(</s> | food)

  = .25 x .33 x .0065 x .52 x .68 = .00019

Unknown Words

- How to handle words in the test corpus that did not occur in the training data, i.e. ***out of vocabulary*** (OOV) words?
- Train a model that includes an explicit symbol for an unknown word (<UNK>).
  - Choose a vocabulary in advance and replace other words in the training corpus with <UNK>.
  - Replace the first occurrence of each word in the training data with <UNK>.

Evaluation of Language Models

- Ideally, evaluate use of model in end application (***extrinsic***, ***in vivo***)
  - Realistic
  - Expensive
- Evaluate on ability to model test corpus (***intrinsic***).
  - Less realistic
  - Cheaper
- Verify at least once that intrinsic evaluation correlates with an extrinsic one.

Perplexity

- Measure of how well a model “fits” the test data.
- Uses the probability that the model assigns to the test corpus.
- Normalizes for the number of words in the test corpus and takes the inverse.

$$PP(W) = \sqrt[N]{\frac{1}{P(w_1 w_2 ... w_N)}}$$

- Measures the weighted average branching factor in predicting the next word (lower is better).

Example of Perplexity Evaluation

- Models trained on 38 million words from the Wall Street Journal (WSJ) using a 19,979 word vocabulary.
- Evaluate on a disjoint set of 1.5 million WSJ words.

	Unigram	Bigram	Trigram
Perplexity	962	170	109

Smoothing

- Since there are a combinatorial number of possible word sequences, many rare (but not impossible) combinations never occur in training, so MLE incorrectly assigns zero to many parameters (a.k.a. ***sparse data***).

- If a new combination occurs during testing, it is given a probability of zero and the entire sequence gets a probability of zero (i.e. infinite perplexity).

- In practice, parameters are ***smoothed*** (a.k.a. ***regularized***) to reassign some probability mass to unseen events.
  - Adding probability mass to unseen events requires removing it from seen ones (***discounting***) in order to maintain a joint distribution that sums to 1.

Smoothing Methods

- Many techniques have been developed to improve smoothing for language models.
  - Add-one smoothing
  - Good-Turing
  - Interpolation
  - Back-off
  - Kneser-Ney
  - Class-based (cluster) N-grams

Laplace (Add-One) Smoothing

- "Hallucinate" additional training data in which each possible N-gram occurs exactly once and adjust estimates accordingly.

Bigram: $$P(w_n \mid w_{n-1}) = \frac{C(w_{n-1}w_n)+1}{C(w_{n-1})+V}$$

N-gram: $$P(w_n \mid w_{n-N+1}^{n-1}) = \frac{C(w_{n-N+1}^{n-1}w_n)+1}{C(w_{n-N+1}^{n-1})+V}$$

where V is the total number of possible (N–1)-grams (i.e. the vocabulary size for a bigram model).

- Tends to reassign too much mass to unseen events, so can be adjusted to add $0<\delta<1$ (normalized by δV instead of V).

Model Combination

- As N increases, the power (expressiveness) of an N-gram model increases, ***but*** the ability to estimate accurate parameters from sparse data decreases (i.e. the smoothing problem gets worse).

- A general approach is to combine the results of multiple N-gram models of increasing complexity (i.e. increasing N).

Interpolation

- Linearly combine estimates of N-gram models of increasing order.

  Interpolated Trigram Model:

$$\hat{P}(w_n \mid w_{n-2,} w_{n-1}) = \lambda_1 P(w_n \mid w_{n-2,} w_{n-1}) + \lambda_2 P(w_n \mid w_{n-1}) + \lambda_3 P(w_n)$$

  Where: $\sum_i \lambda_i = 1$

- Learn proper values for λ_i by training to (approximately) maximize the likelihood of an independent ***development*** (a.k.a. ***tuning***) corpus.

Back-off

- Only use lower-order model when data for higher-order model is unavailable (i.e. count is zero).
- Recursively back-off to weaker models until data is available.

$$P_{katz}(w_n \mid w_{n-N+1}^{n-1}) = \begin{cases} P^*(w_n \mid w_{n-N+1}^{n-1}) & \text{if } C(w_{n-N+1}^{n}) > 1 \\ \alpha(w_{n-N+1}^{n-1}) P_{katz}(w_n \mid w_{n-N+2}^{n-1}) & \text{otherwise} \end{cases}$$

Where P* is a discounted probability estimate to reserve mass for unseen events and α's are back-off weights (see text for details).

A Problem for N-Grams: Long Distance Dependencies

- Many times local context does not provide the most useful predictive clues, which instead are provided by ***long-distance dependencies***.
  - Syntactic dependencies
    - "The ***man*** next to the large oak tree near the grocery store on the corner **is** tall."
    - "The ***men*** next to the large oak tree near the grocery store on the corner **are** tall."
  - Semantic dependencies
    - "The ***bird*** next to the large oak tree near the grocery store on the corner **flies** rapidly."
    - "The ***man*** next to the large oak tree near the grocery store on the corner **talks** rapidly."
- More complex models of language are needed to handle such dependencies.

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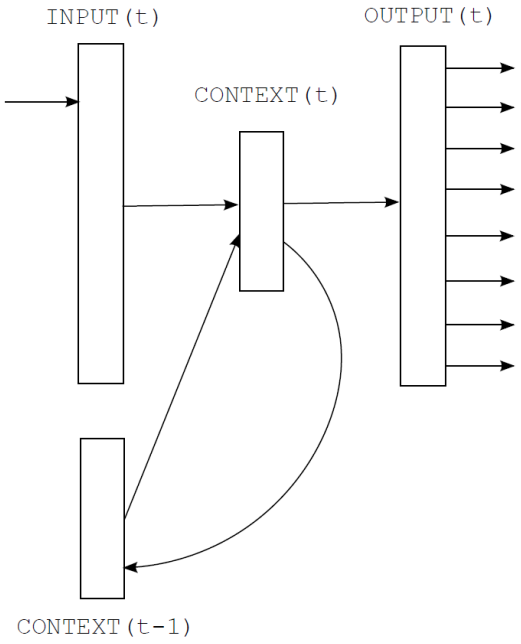
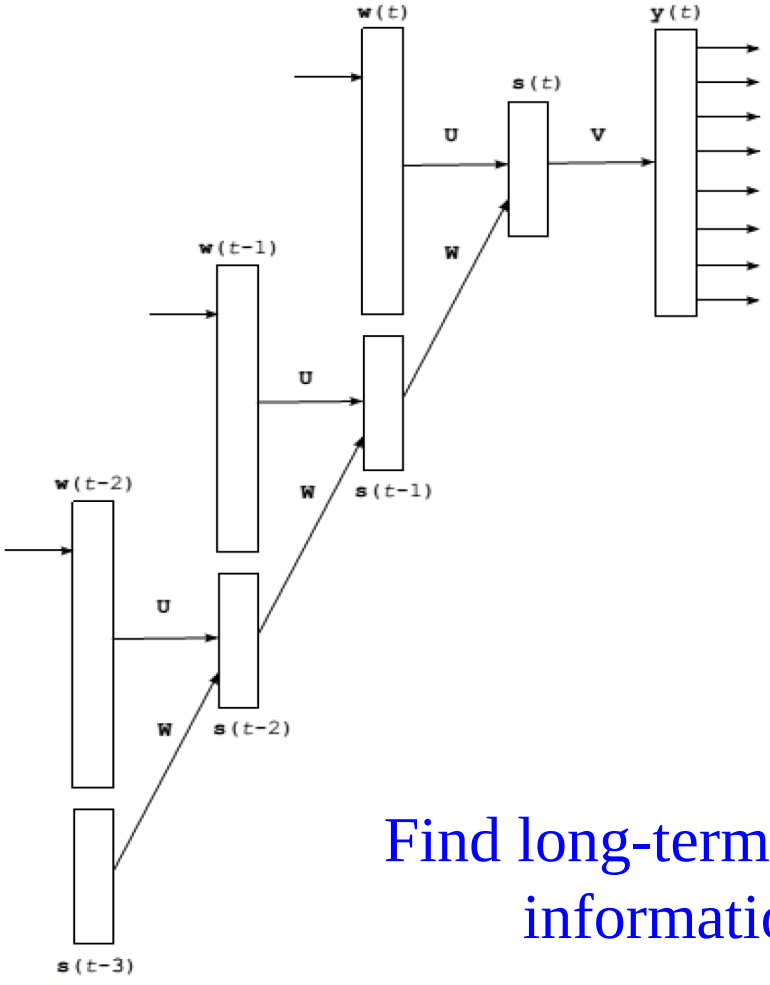
Structure of RNN-based LM

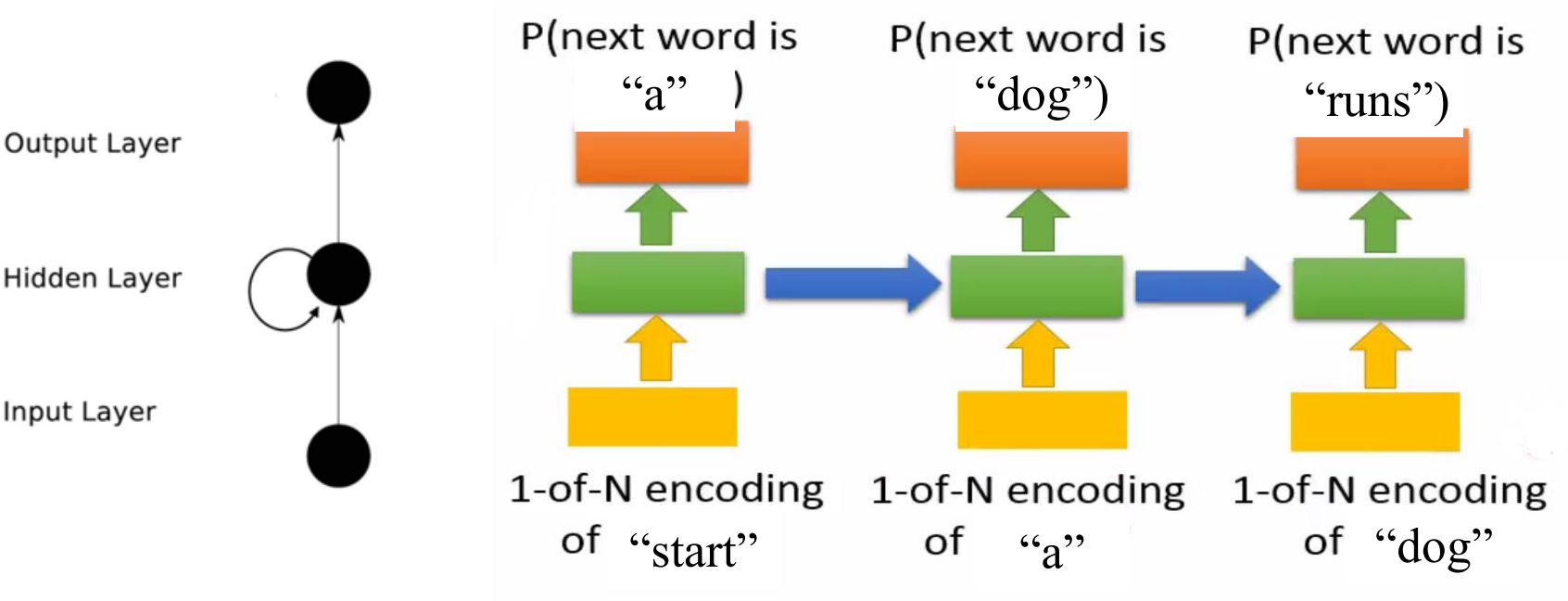


RNN structure



Find long-term history information

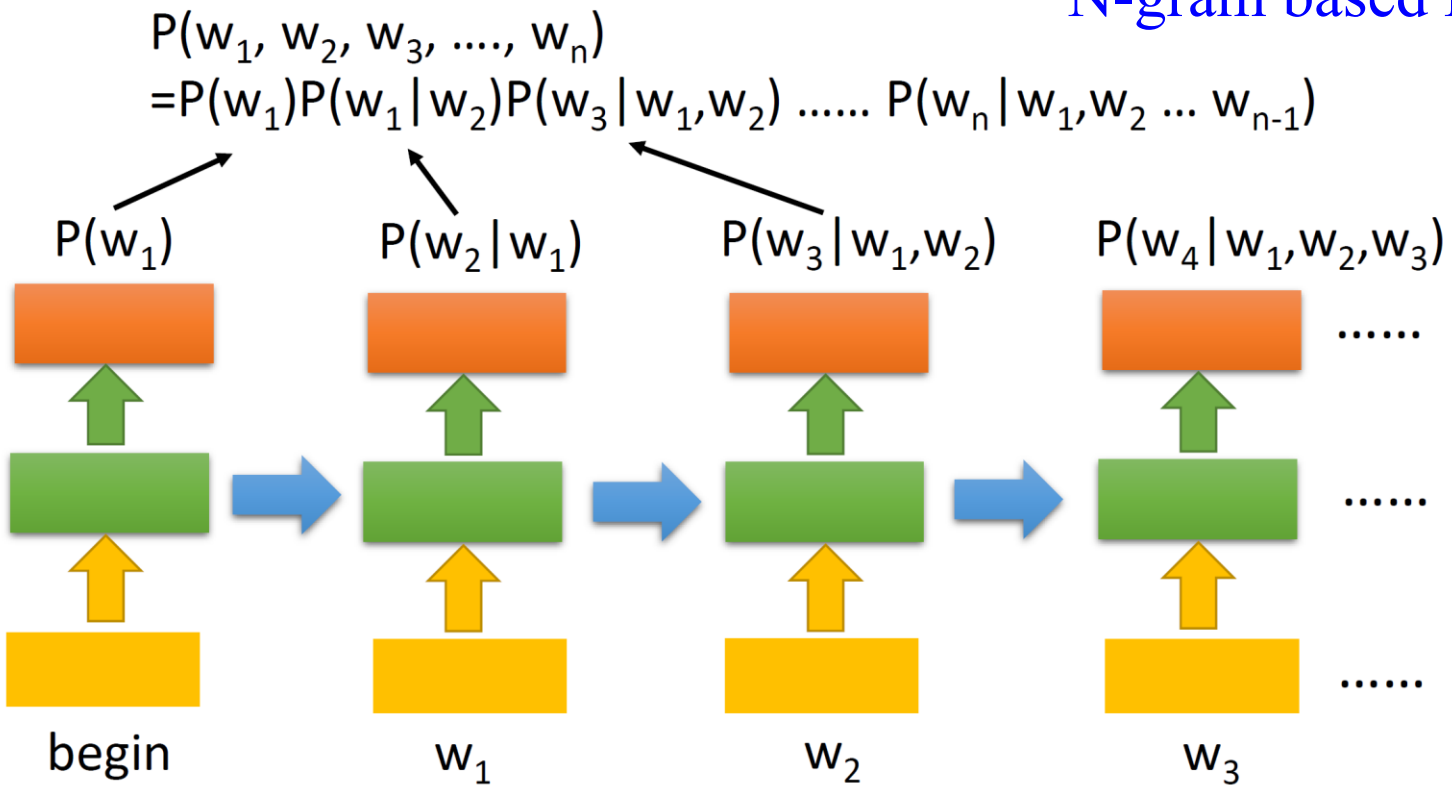
Example of RNN-based LM



Computing RNN-based LM

- To compute P(w_1, w_2, …, w_n) by RNN

Longer context than N-gram based LM



4.4 Decoding Algorithm for ASR

- 4.4.1 Viterbi Based Decoding Algorithm
- 4.4.2 WFST Based Decoding Algorithm

ASR system using Acoustic Model (AM) and N-gram based Language Model (LM)

- Calculation of best hypothesis of word sequence

$$P(W \mid Y) = \arg\max_{\{w_1^N\}\{t_1^N\}} \{ \sum_{n-1}^{N} \log(P_{acoust}(y_{t_{n-1}+1}^{t_n} \mid w_n)) + \lambda \cdot \sum_{n-1}^{N} \log(P_{lang}(w_n \mid w_{n-1}) + \delta) \}$$

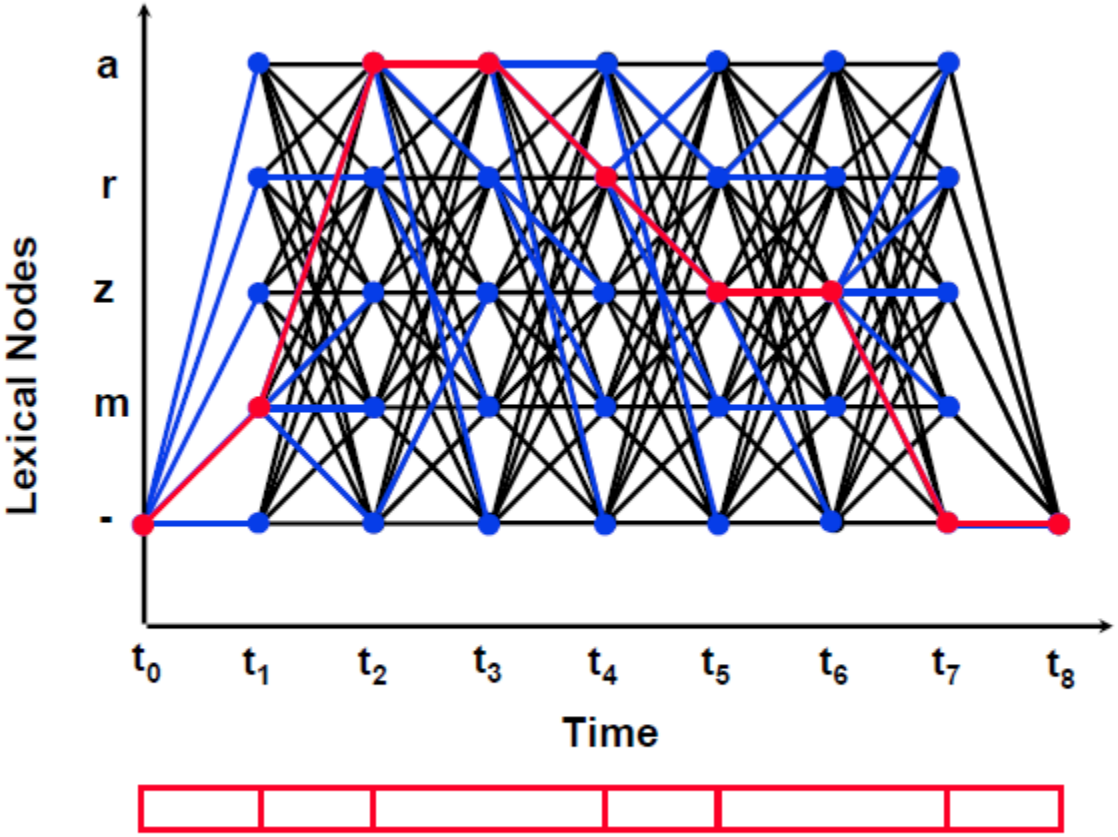
$P_{acoust}(y_{t_{n-1}+1}^{t_n} \mid w_n)$: likelihood of AM

$P_{lang}(w_n \mid w_{n-1})$: likelihood of LM

λ : Weighting δ : Penalty of insertion

Viterbi search

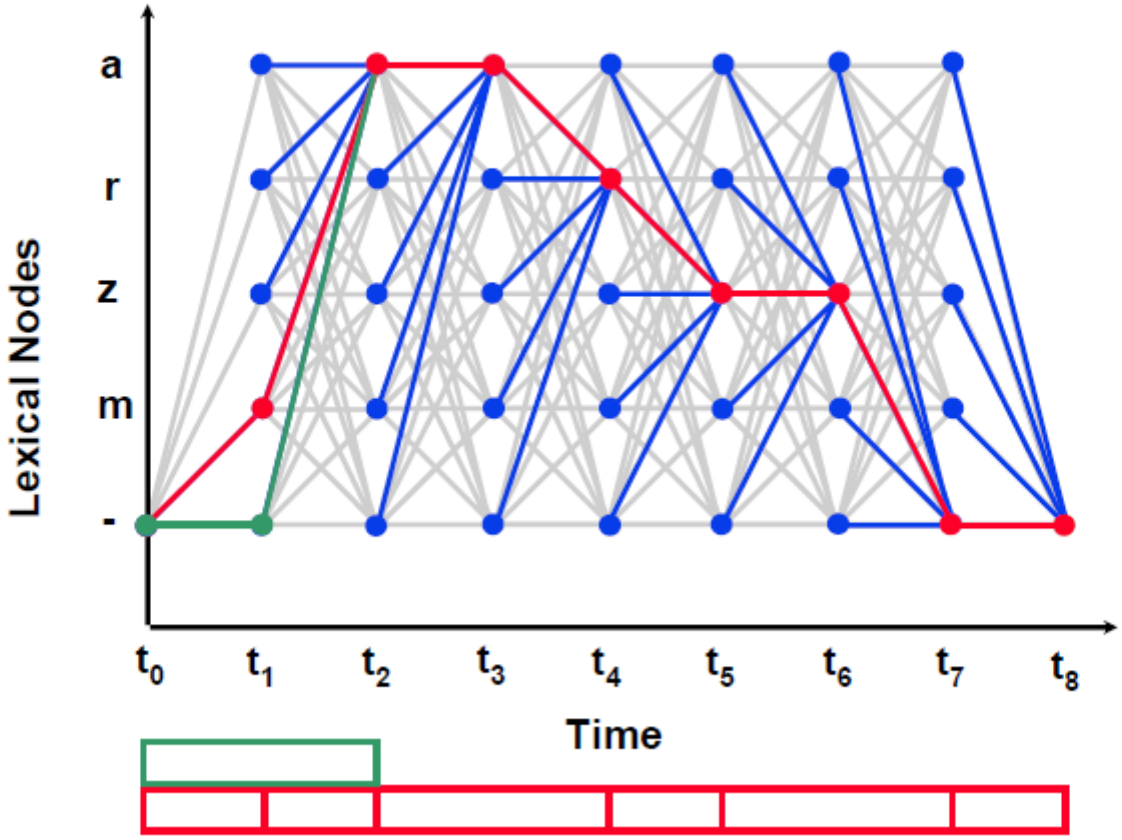
- Viterbi search typically used in first-pass to find best path



- Relative and absolute thresholds used to speed-up search

A* search example

- Second pass uses backwards *A** search to find *N*-best paths
- Viterbi backtrace is used as future estimate for path scores



Search issue

- **Search often uses forward and backward passes, e.g.,**
  - Forward Viterbi search using bigram
  - Backwards A* search using bigram to create a word graph
  - Rescore word graph with trigram (i.e., subtract bigram scores)
  - Backwards A* search using trigram to create *N*-best outputs
- **Search relies on two types of pruning:**
  - Pruning based on relative likelihood score
  - Pruning based maximum number of hypotheses
  - Pruning provides tradeoff between speed and accuracy
- **Multiple searches is a form of successive refinement**
  - More sophisticated models can be used in each iteration

4.4 Decoding Algorithm for ASR

- 4.4.1 Viterbi Based Decoding Algorithm
- 4.4.2 WFST Based Decoding Algorithm

Weighted finite state transducer (WFST)

- exploit several knowledge sources (lexicon, grammar, phonetics) to find most likely spoken word sequence

$$HCLG = H \circ C \circ L \circ G$$

G probabilistic grammar or language model acceptor (word)

L lexicon (phones to words)

C context-dependent relabeling (ctx-dep-phone to phone)

H HMM structure (PDF labels to context-dependent phones)

Create H, C, L, G separately and compose them together

Decoding with WFST

- Solve

$$W' = argmax_W P(X|W)P(W)$$

- Compose recognizer as (H o C o L o G) which maps states to word sequences
- Decode by aligning the feature vectors X with HCLG "

  i.e.,

$$W' = argmax_W X \circ (H \circ C \circ L \circ G)$$