

E9 261

09-03-2016

Recap ...

Solution to HMM-GMM re-estimation

$$\pi_i = \frac{\sum_{e=1}^E \gamma_i^e(1)}{E}$$

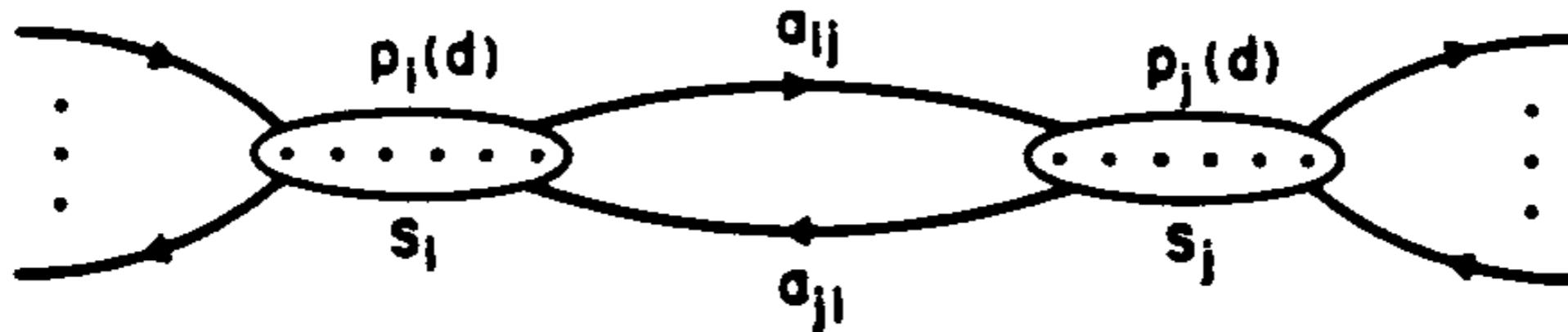
$$c_{il} = \frac{\sum_{e=1}^E \sum_{t=1}^{T_e} \gamma_{il}^e(t)}{\sum_{e=1}^E \sum_{t=1}^{T_e} \gamma_i^e(t)}$$

$$\mu_{il} = \frac{\sum_{e=1}^E \sum_{t=1}^{T_e} \gamma_{il}^e(t) o_t^e}{\sum_{e=1}^E \sum_{t=1}^{T_e} \gamma_{il}^e(t)}$$

Left to right versus Ergodic HMMs

Other Considerations

- Implementation issues
- Scaling
- Explicit duration modeling in HMM



Forward Recursion in Duration Model HMM

$$\begin{aligned}\alpha_t(i) = & \sum_q \sum_d \pi_{q_1} \cdot p_{q_1}(d_1) \cdot P(\mathbf{o}_1 \mathbf{o}_2 \dots \mathbf{o}_{d_1} | q_1) \\ & \cdot a_{q_1 q_2} p_{q_2}(d_2) P(\mathbf{o}_{d_1+1} \dots \mathbf{o}_{d_1+d_2} | q_2) \dots \\ & \cdot a_{q_{r-1} q_r} p_{q_r}(d_r) P(\mathbf{o}_{d_1+d_2+\dots+d_{r-1}+1} \dots \mathbf{o}_t | q_r)\end{aligned}\quad (6.67)$$

where the sum is over all states q and all possible state durations d . By induction we can write $\alpha_t(j)$ as

$$\alpha_t(j) = \sum_{i=1}^N \sum_{d=1}^D \alpha_{t-d}(i) a_{ij} p_j(d) \prod_{s=t-d+1}^t b_j(\mathbf{o}_s) \quad (6.68)$$

where D is the maximum duration within any state. To initialize the computation of $\alpha_t(j)$ we use

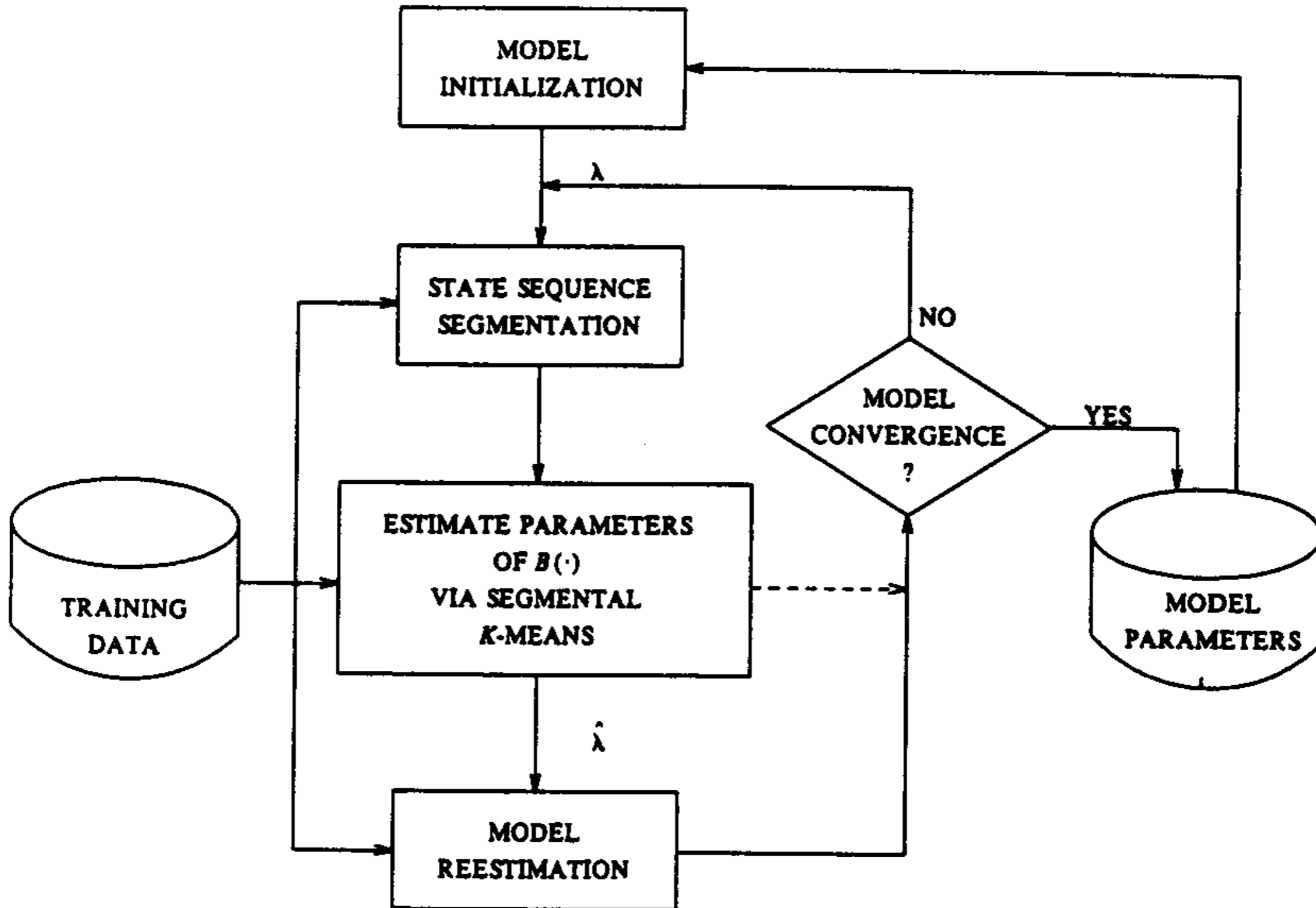
$$\alpha_1(i) = \pi_i p_i(1) \cdot b_i(\mathbf{o}_1) \quad (6.69a)$$

$$P(\mathbf{O} | \lambda) = \sum_{i=1}^N \alpha_T(i)$$

Other Considerations

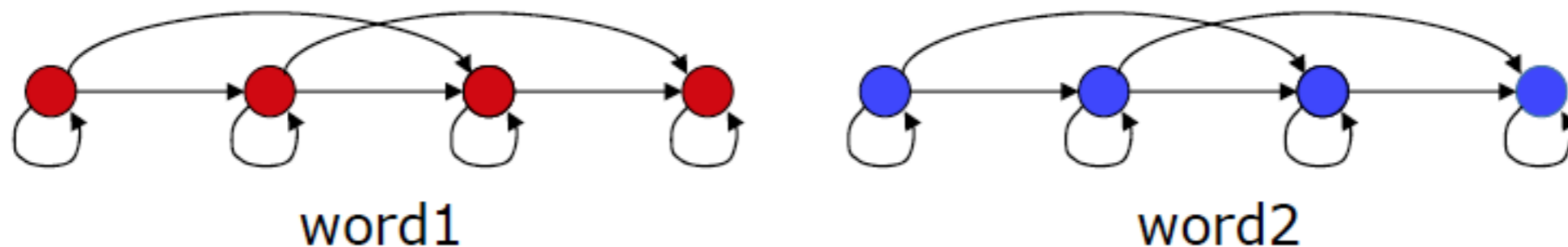
- Implementation issues
 - Scaling
- Explicit duration modeling in HMM
- Comparison of HMMs
- ML versus Bayesian Estimation
- Multiple observation sequence
- Initialization - Flat start

Segmental k-means Algorithm

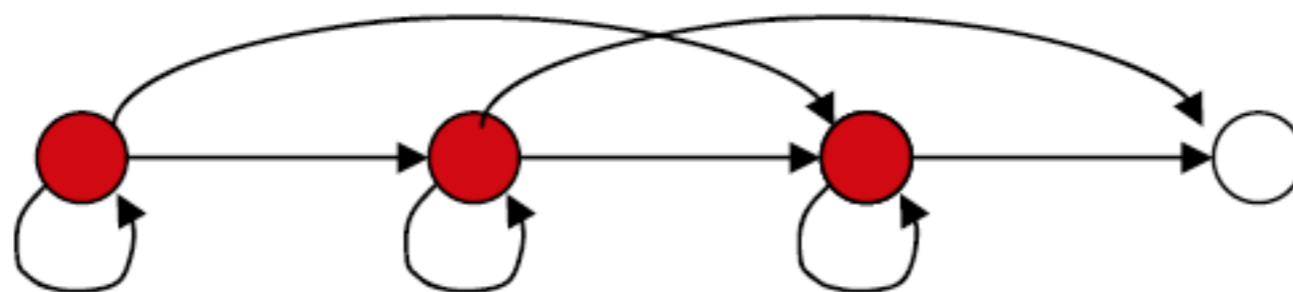


Dealing with Continuous Speech

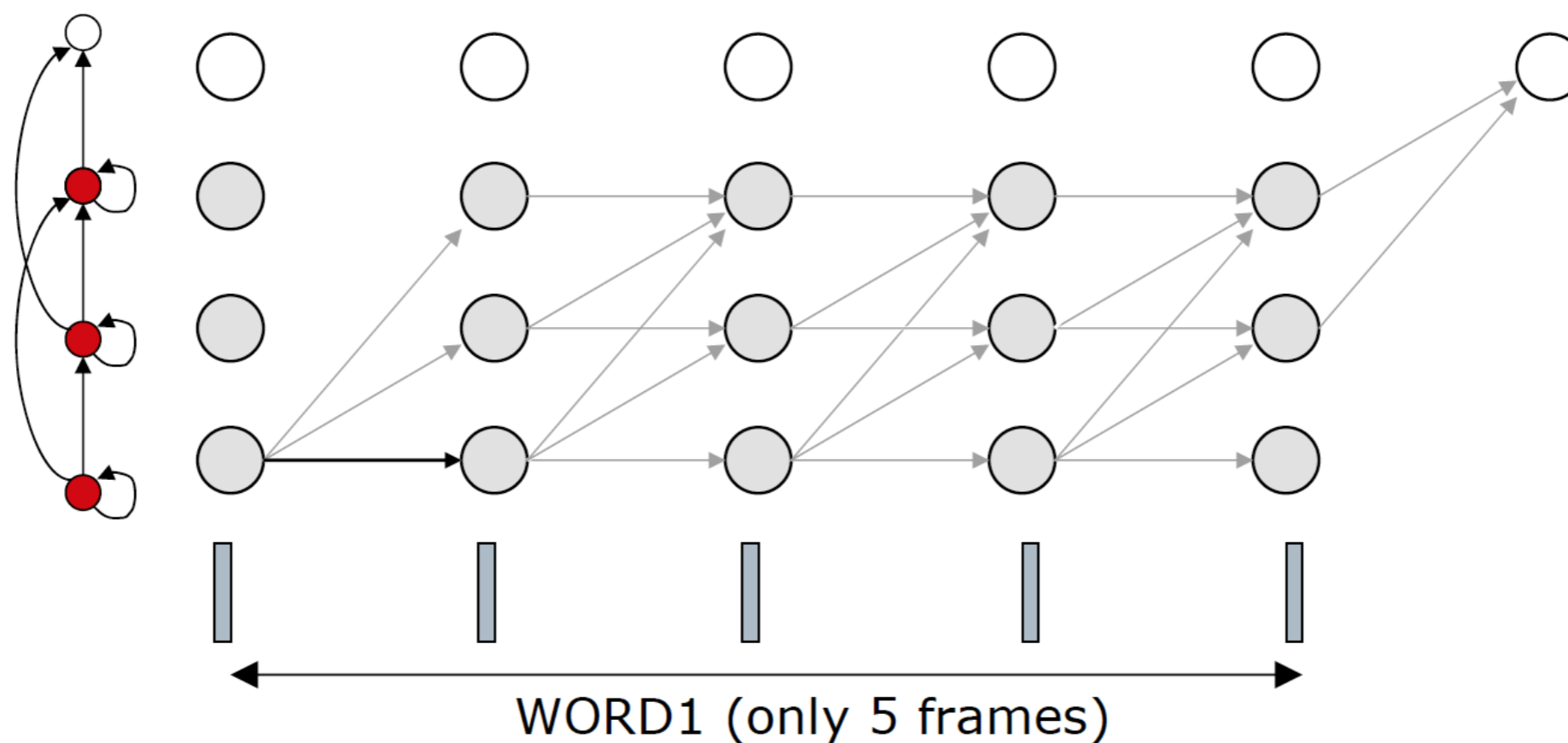
- Isolated Word Recognition is limited
 - Need to deal with string of words
- Word sequences modeled with HMMs which are composed of word HMMs
- Given two words which are both Bakis topology



Introducing Non-emitting states

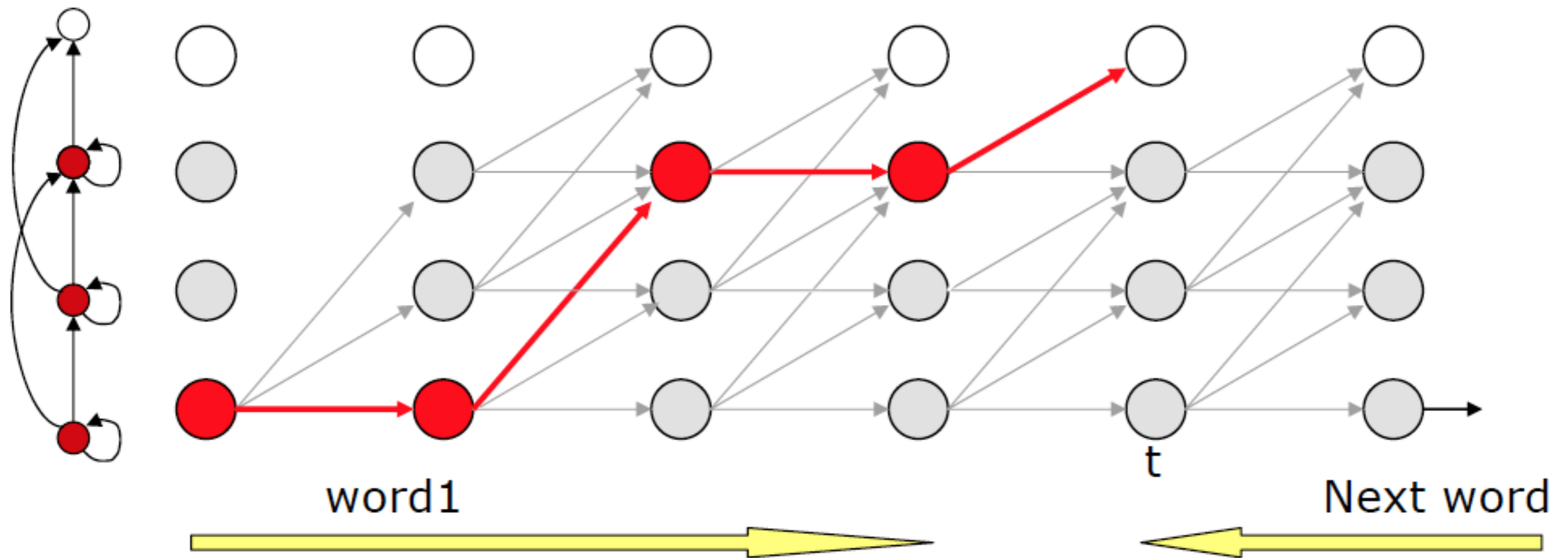


- Non-emitting or null states where no observation is emitted



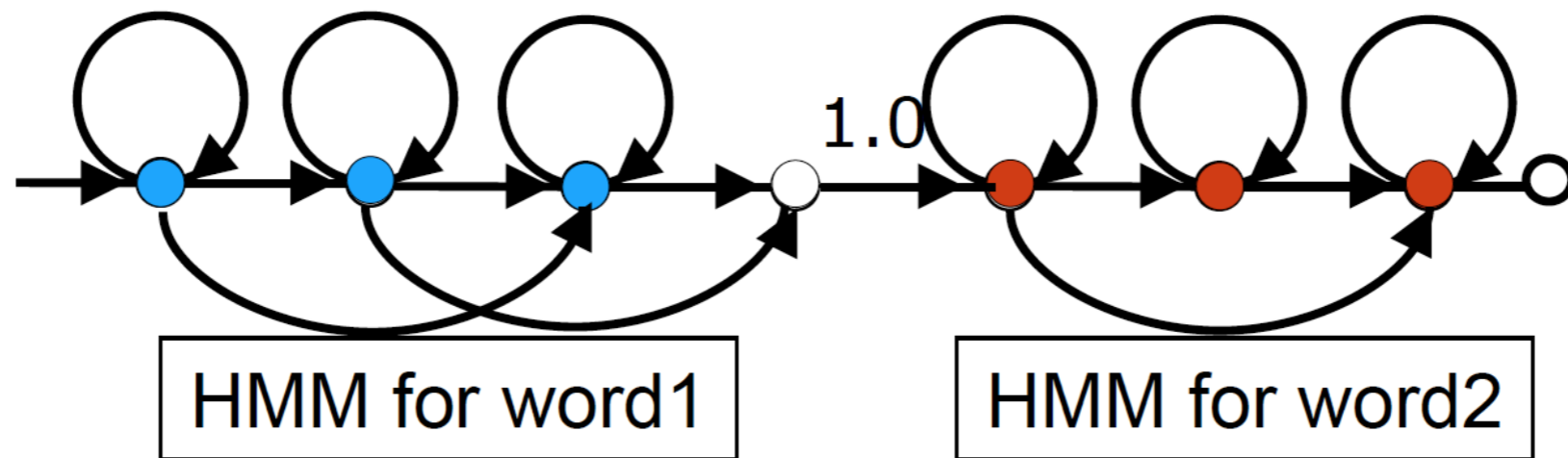
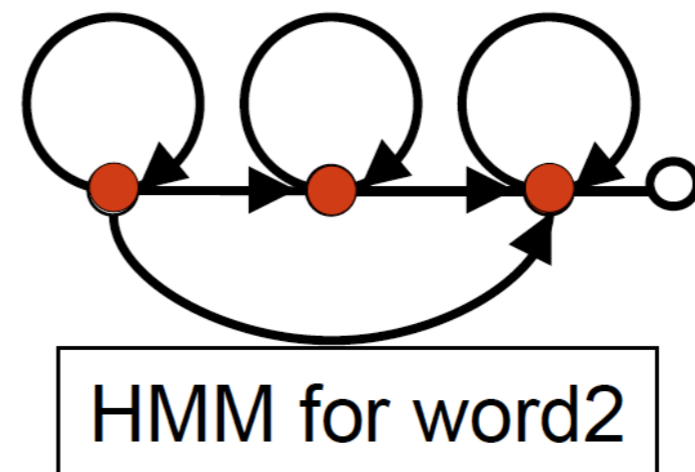
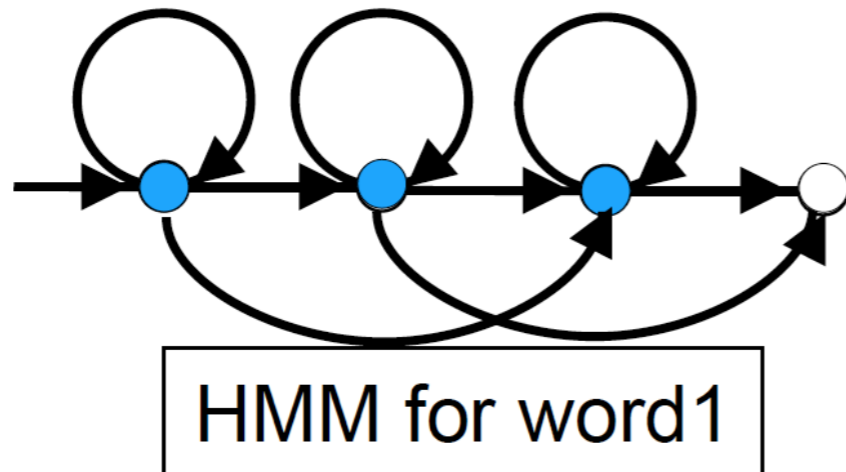
Introducing Non-emitting states

- Slight modifications to forward and backward recursion



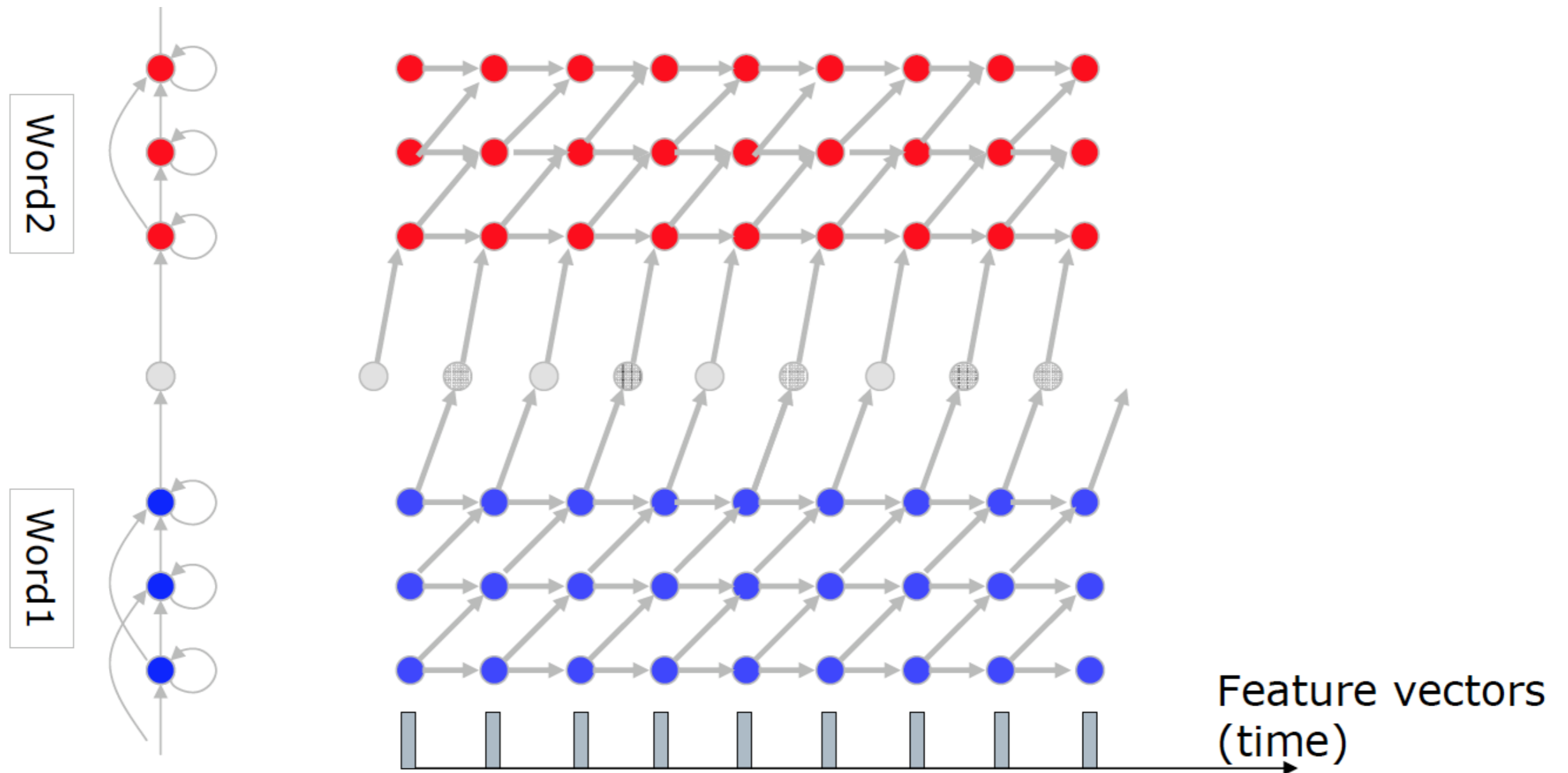
- Probability of reaching state $N+1$ at time t is equivalent to the probability of exiting word1 at time t

Connecting Word HMMs



- One can also introduce the probability of word2 following word1 in this case.

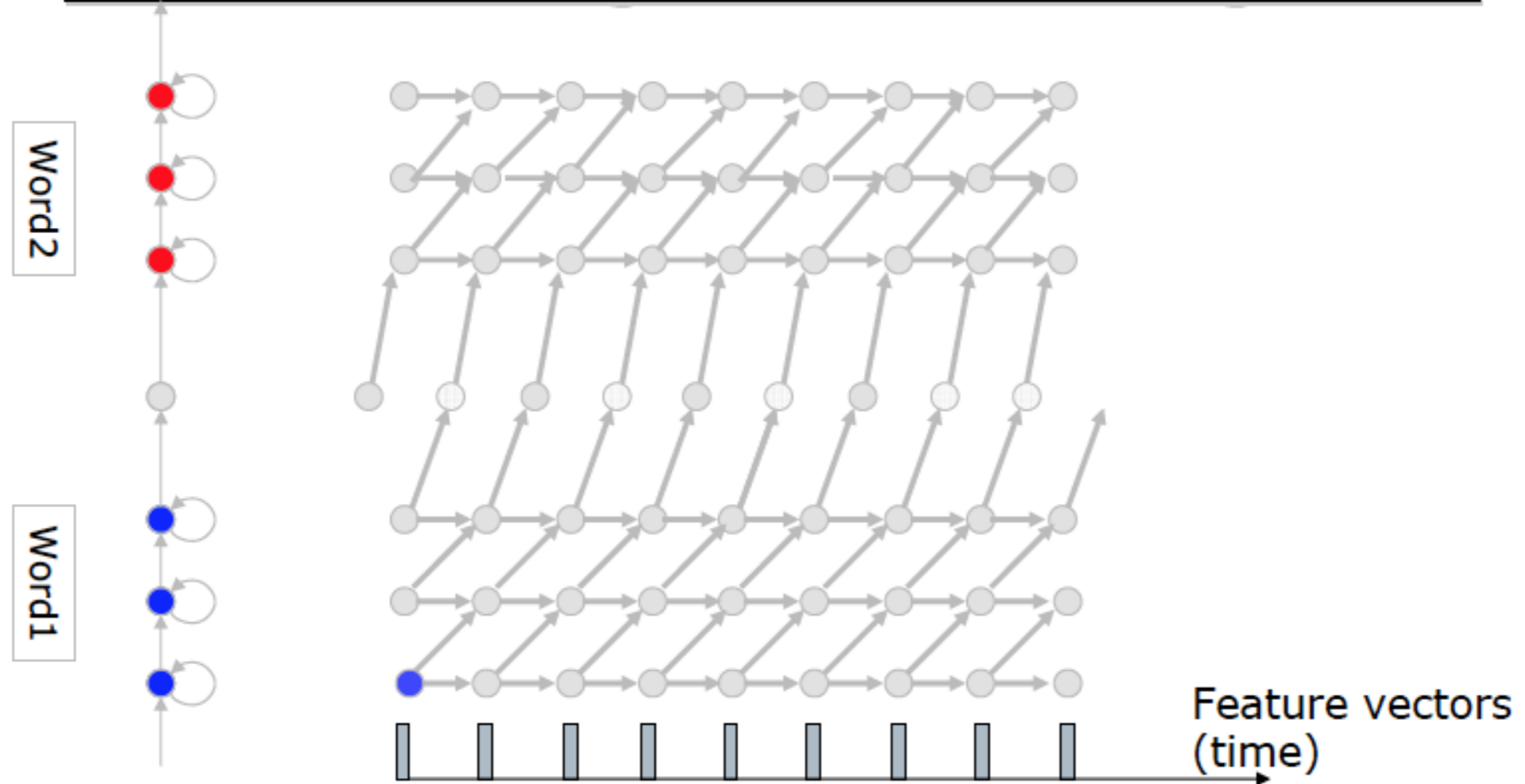
Trellis with connected word models



- Null states don't have time instant associated so they happen between two time instants.

Trellis with connected word models

Forward Through a non-emitting State

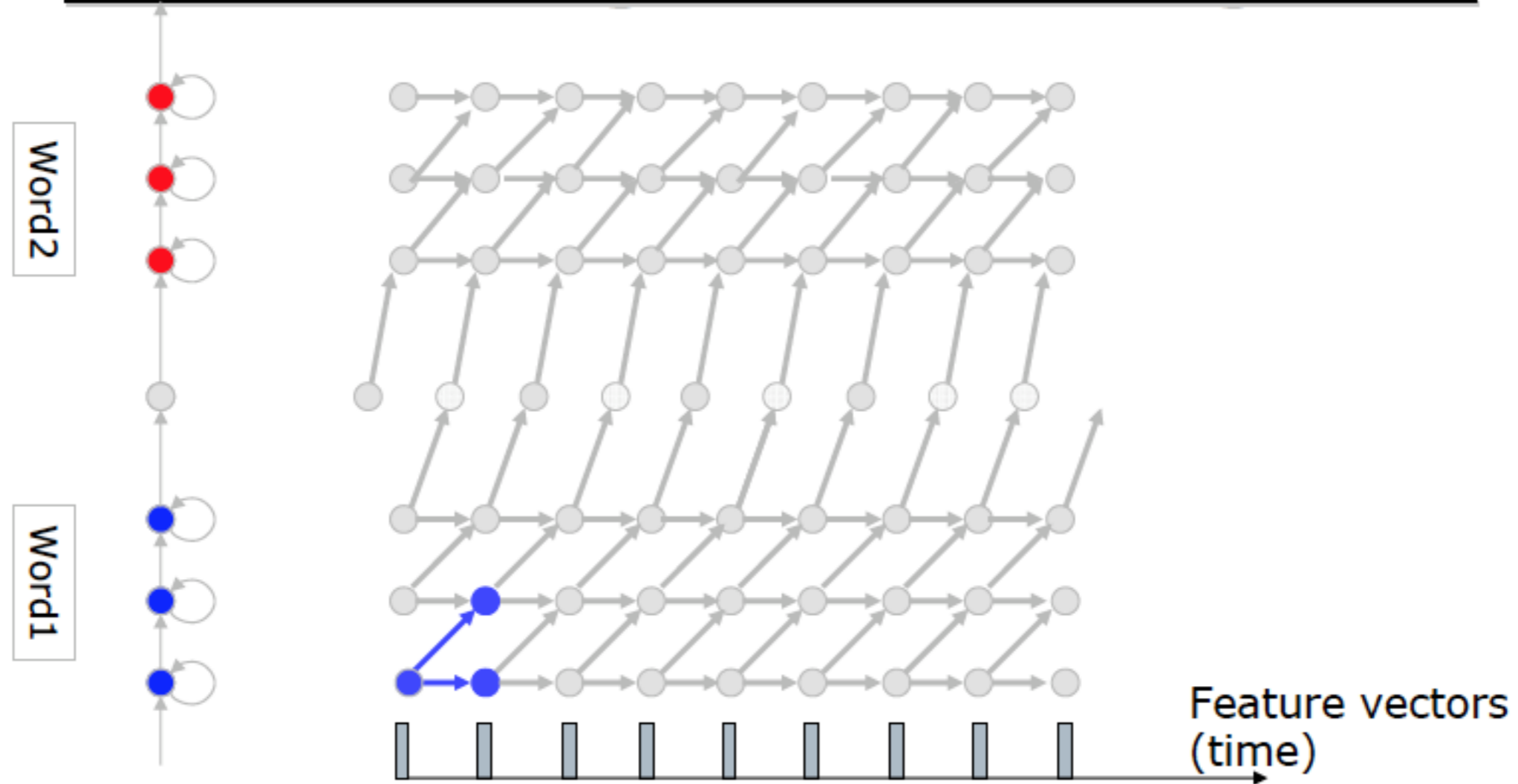


- At the first instant only one state has a non-zero forward probability

t

Trellis with connected word models

Forward Through a non-emitting State

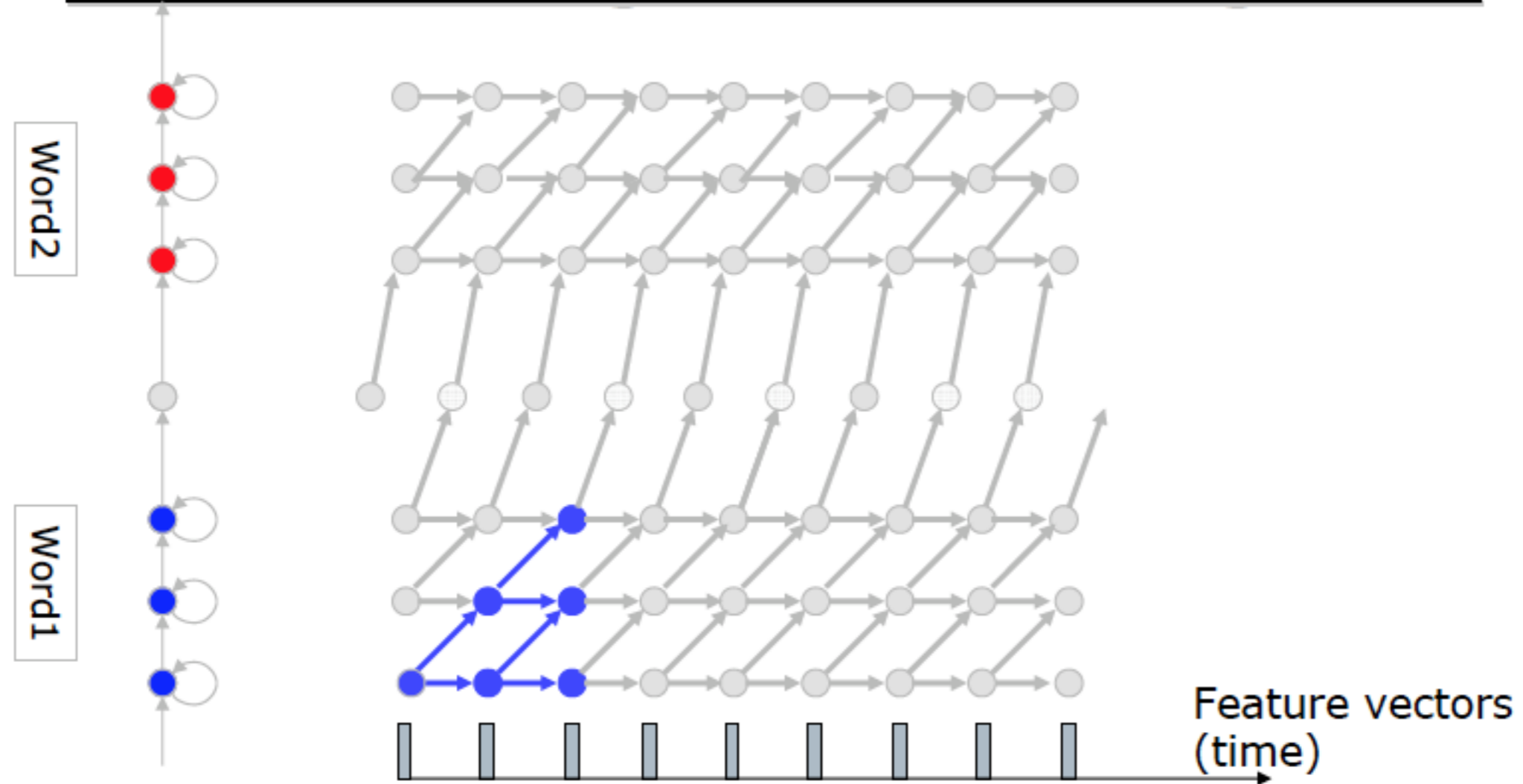


- From time 2 a number of states can have non-zero forward probabilities
- Non-zero alphas

t

Trellis with connected word models

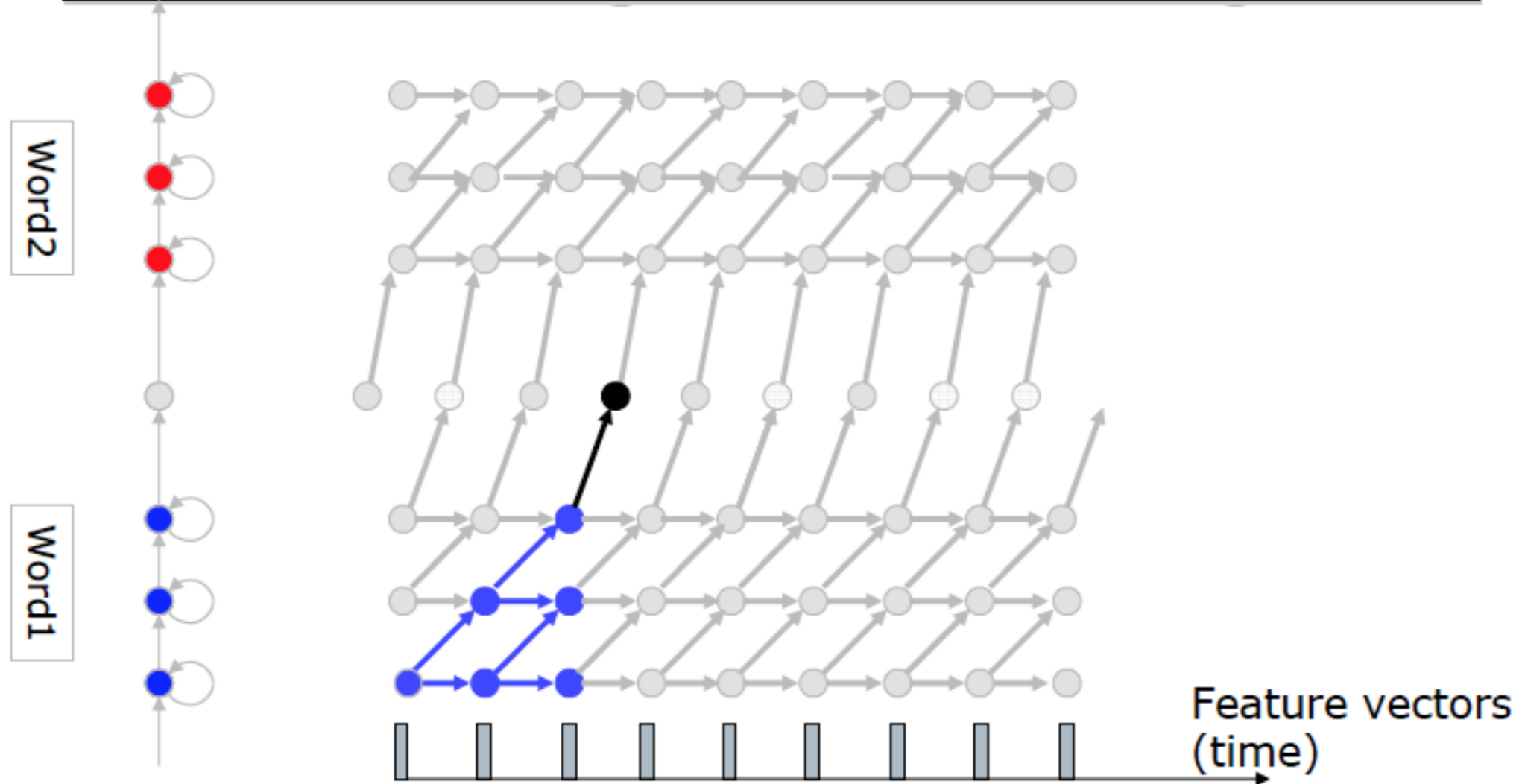
Forward Through a non-emitting State



- From time 2 a number of states can have non-zero forward probabilities
- Non-zero alphas

Trellis with connected word models

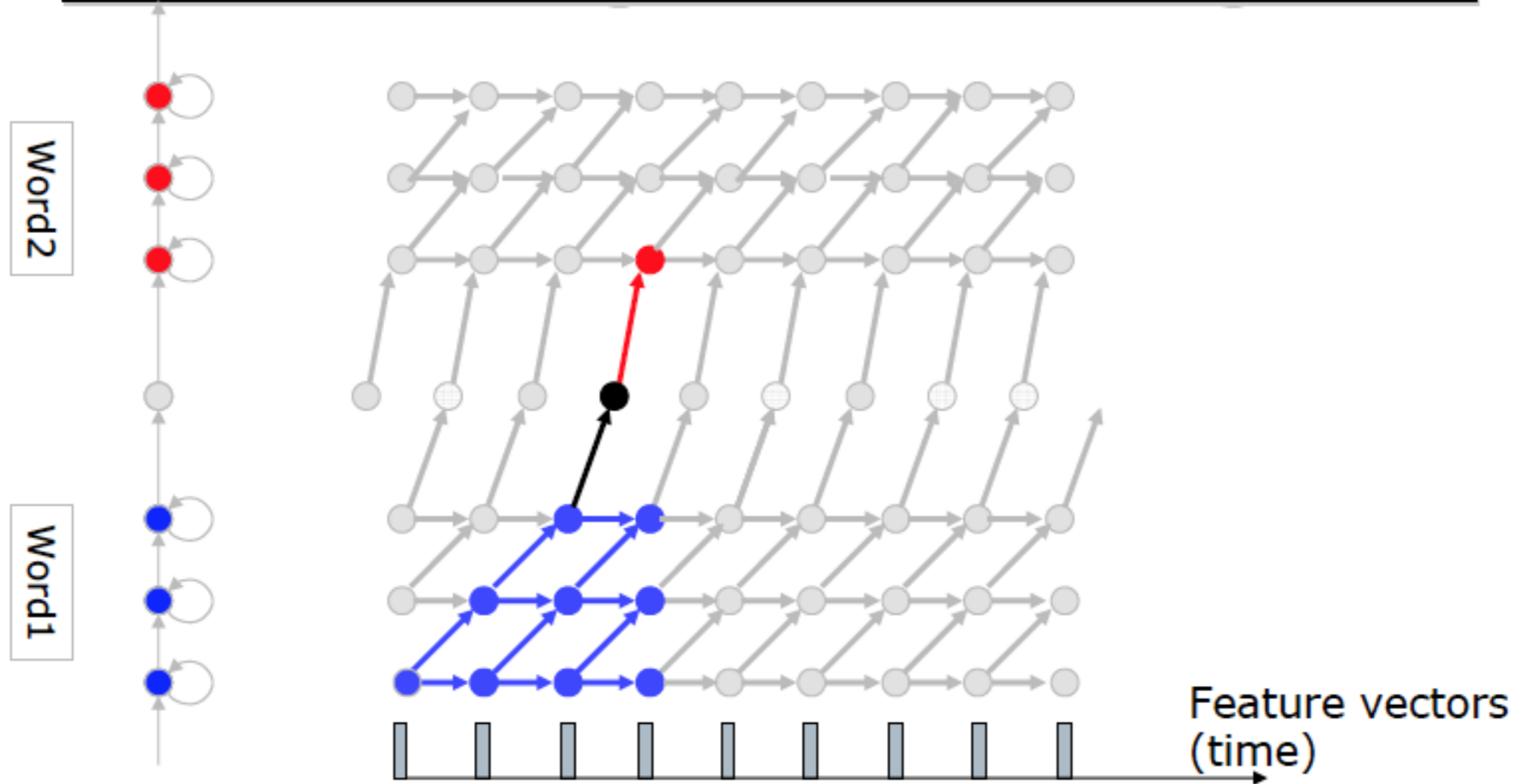
Forward Through a non-emitting State



- Between time 3 and time 4 (in this trellis) the non-emitting state gets a non-zero alpha

Trellis with connected word models

Forward Through a non-emitting State

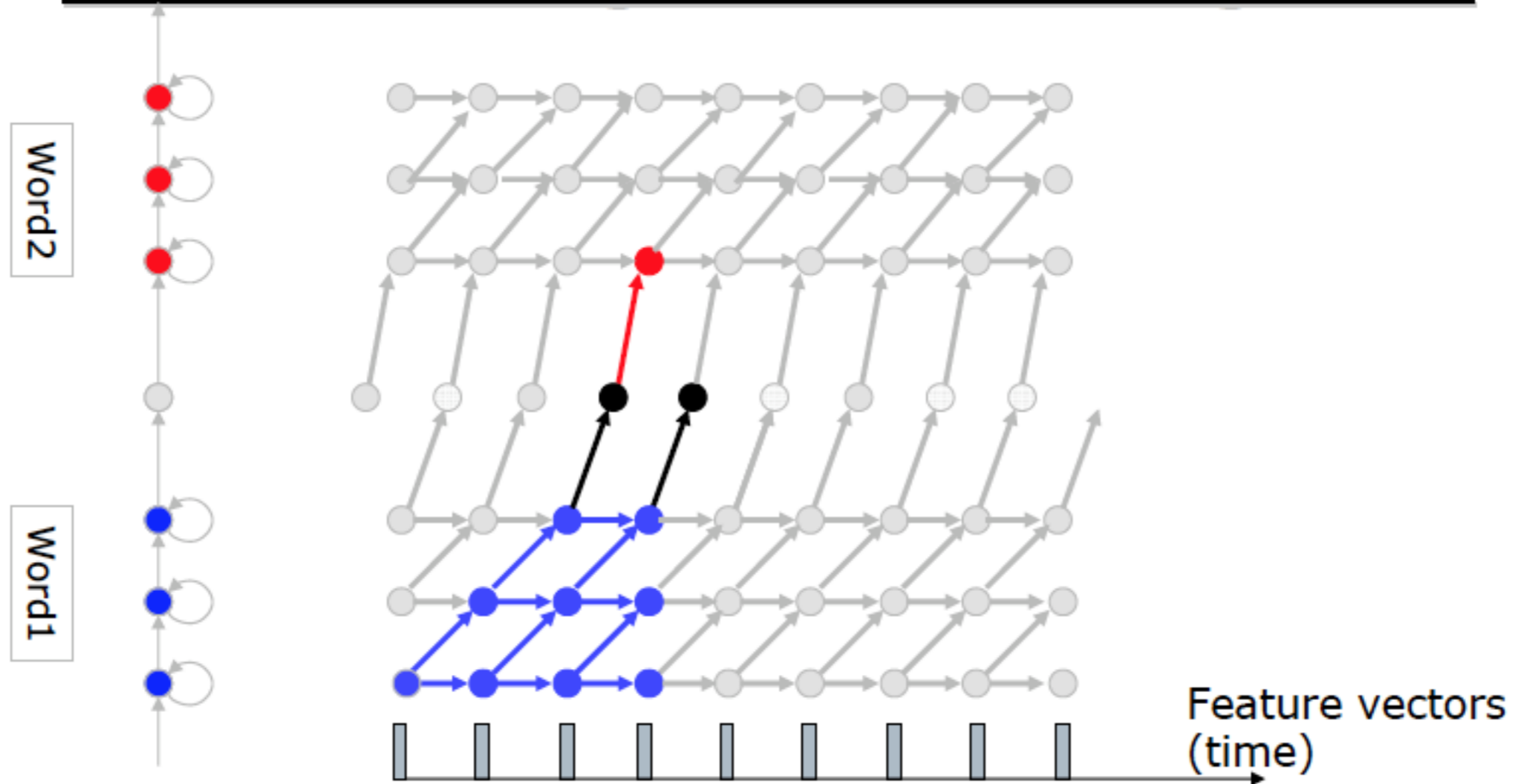


- At time 4, the first state of word2 gets a probability contribution from the non-emitting state

t

Trellis with connected word models

Forward Through a non-emitting State

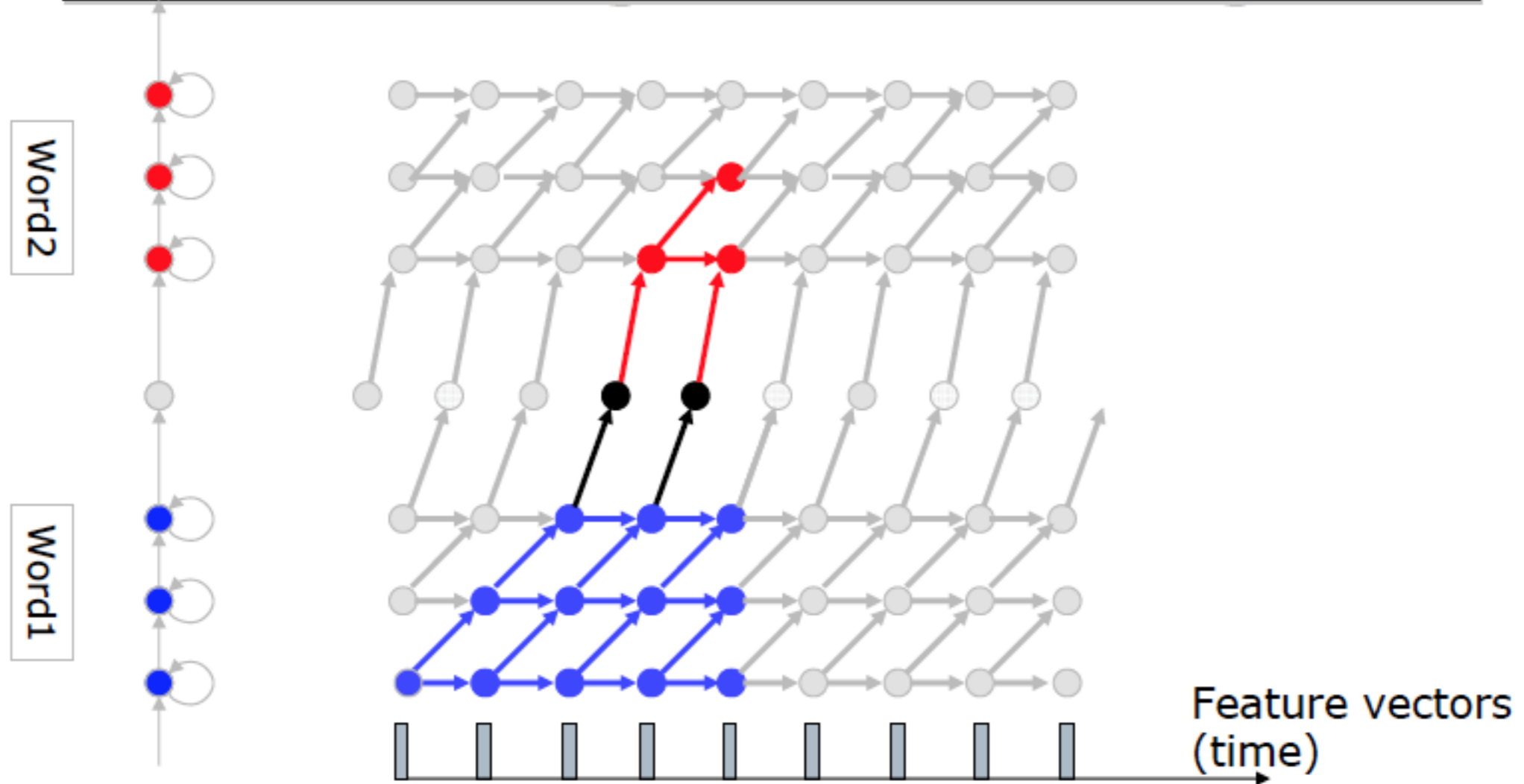


- Between time 4 and time 5 the non-emitting state may be visited

t

Trellis with connected word models

Forward Through a non-emitting State



- At time 5 (and thereafter) the first state of word 2 gets contributions both from an emitting state (itself at the previous instant) and the non-emitting state