Computational Linguistics

Sequence Modeling: HMM, MEMM, and CRF

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- Models used:
  - **Hidden Markov Model (HMM)**
  - **Maximum Entropy Markov Model (MEMM)**
  - **Conditional Random Field (CRF)**

1. Hidden Markov Models (HMM)

- A Hidden Markov Model (HMM) is used to model systems where we observe outputs but not the underlying states.
- In the context of POS tagging:
  - **Hidden States:** The sequence of POS tags (NN, VB, etc.) that we aim to predict.
  - **Observable Symbols:** The actual words in the sentence.

HMM in POS Tagging

Example Sentence: *"Secretariat is expected to race tomorrow"*

- The goal is to assign the correct POS tag to each word.
- Words are observable symbols; POS tags are hidden states.
- HMM helps us determine the most likely sequence of POS tags given the sentence.

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  - *Example:* $P(\text{NN})$, i.e., the probability that the first word in a sentence is a Noun.

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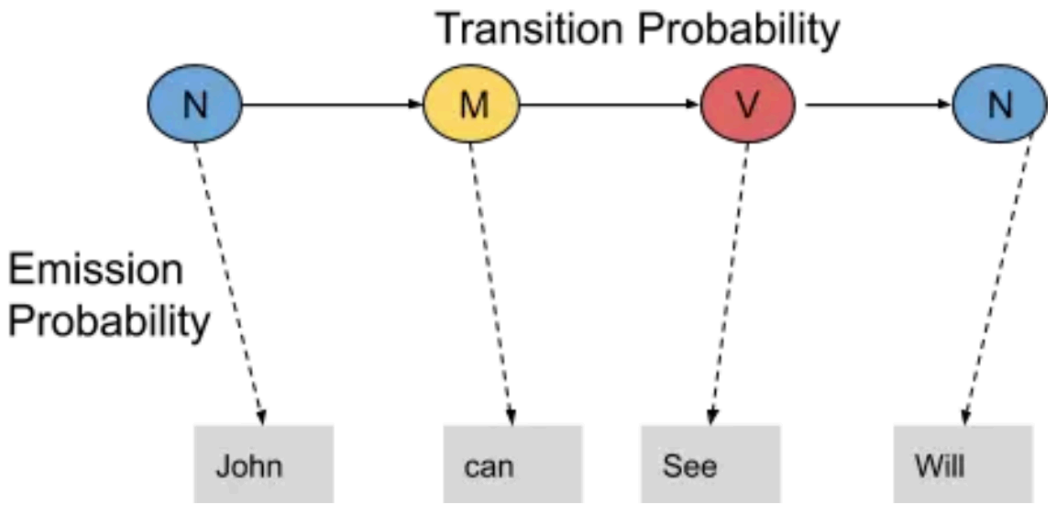
- HMM finds the most likely sequence of POS tags that could produce the observed sequence of words.

HMM in Pos tagging



POS Tagging Example

- `John can see Will`
- In this example, we consider three POS tags: Noun, Model, and Verb.
- Let the sentence be tagged as **Noun, Model, Verb, Noun**.
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  - **Transition Probabilities:** The likelihood of a particular sequence of tags. For example:
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    - How likely is it that a Model is followed by a Verb?
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    - How likely is it that a Model is followed by a Verb?
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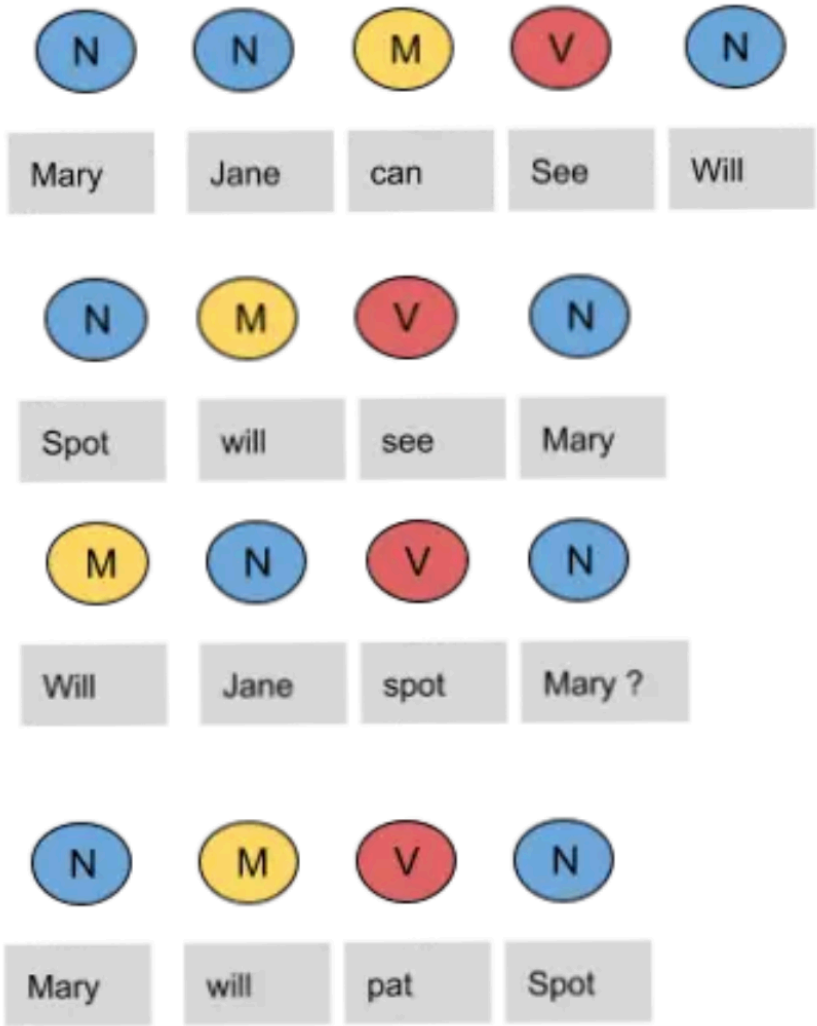
  - **Emission Probabilities:** The likelihood of each word given its tag. For example:
    - The probability that "John" is a Noun.
    - The probability that "can" is a Model.
    - The probability that "see" is a Verb.
    - The probability that "Will" is a Noun.
- For accurate tagging, both transition and emission probabilities should be high for the given sequence.

More Examples



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- To calculate the emission probabilities, we create a counting table as follows:

Words	**Noun**	**Model**	**Verb**
Mary	4	0	0
Jane	2	0	0
Will	1	3	0
Spot	2	0	1
Can	0	1	0
See	0	0	2
pat	0	0	1

Table: Counting Table for Emission Probabilities

Normalized Emission Probabilities

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- For example, 'Noun' appears 9 times, so we divide each value in the 'Noun' column by 9.

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Mary	$\frac{4}{9}$	0	0
Jane	$\frac{2}{9}$	0	0
Will	$\frac{1}{9}$	$\frac{3}{4}$	0
Spot	$\frac{2}{9}$	0	$\frac{1}{4}$
Can	0	$\frac{1}{4}$	0
See	0	0	$\frac{2}{4}$
pat	0	0	1

Table: Normalized Emission Probabilities

Calculating Transition Probabilities

- To calculate transition probabilities, we introduce two additional tags: <S> and <E>, <S> is placed at the beginning of each sentence and <E> is placed at the end of each sentence.

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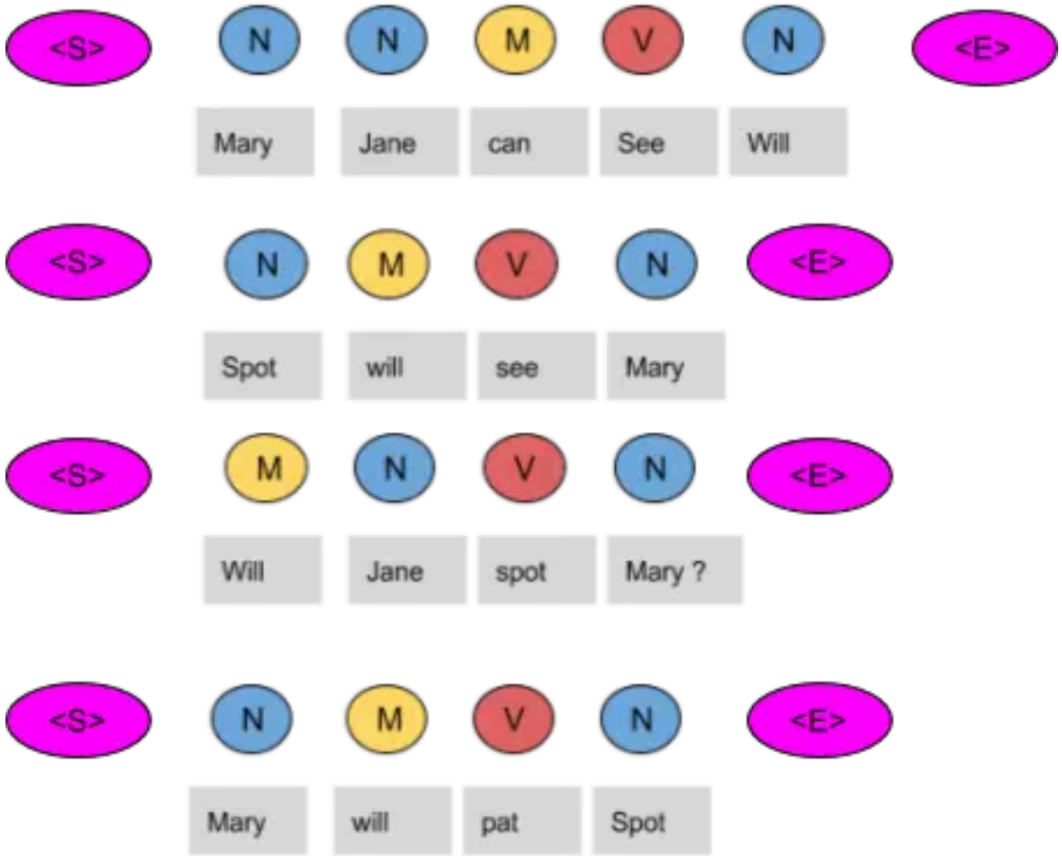
- These tags help to define the boundaries of the sentences and manage transitions between POS tags.



Transition Probability Table

- Let us create a table and fill it with the co-occurrence counts of the tags:

	N	**M**	**V**	**<E>**
<S>	3	1	0	0
N	1	3	1	4
M	1	0	3	0
V	4	0	0	0

Table: Co-occurrence Counts of POS Tags

- In the table:
  - The <S> tag is followed by the N tag three times, so the first entry is 3.
  - The Model tag follows the <S> once, so the second entry is 1.
  - The rest of the table is filled in a similar manner.

- Next, divide each term in a row by the total number of co-occurrences for that tag.

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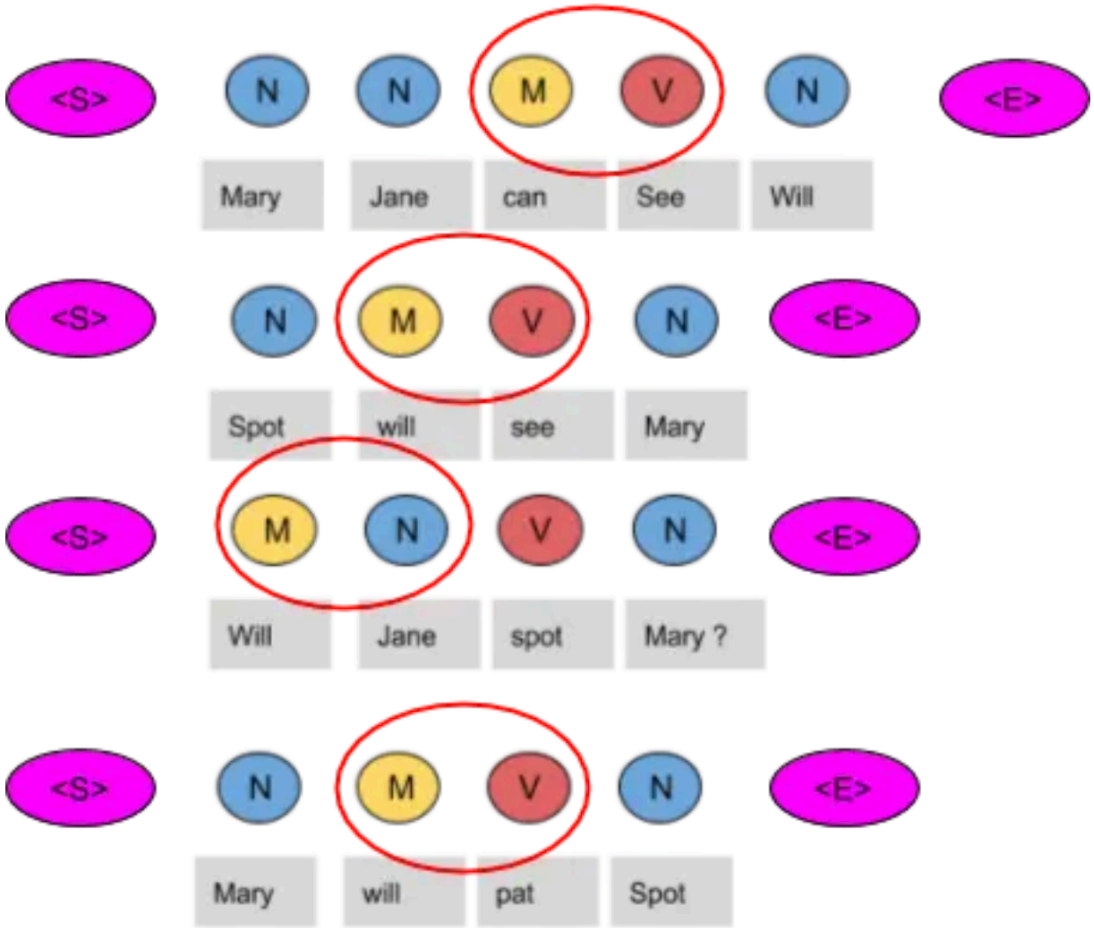
  - For example, the Model tag is followed by any other tag four times.
  - Divide each element in the third row by 4.

	N	**M**	**V**	**<E>**
<S>	$\frac{3}{4}$	$\frac{1}{4}$	0	0
N	$\frac{1}{9}$	$\frac{3}{9}$	$\frac{1}{9}$	$\frac{4}{9}$
M	$\frac{1}{4}$	0	$\frac{3}{4}$	0
V	$\frac{4}{4}$	0	0	0

Table: Normalized Transition Probabilities

- These are the respective transition probabilities for the given sentences.
- Now, how does the HMM determine the appropriate sequence of tags for a new sentence using these probabilities?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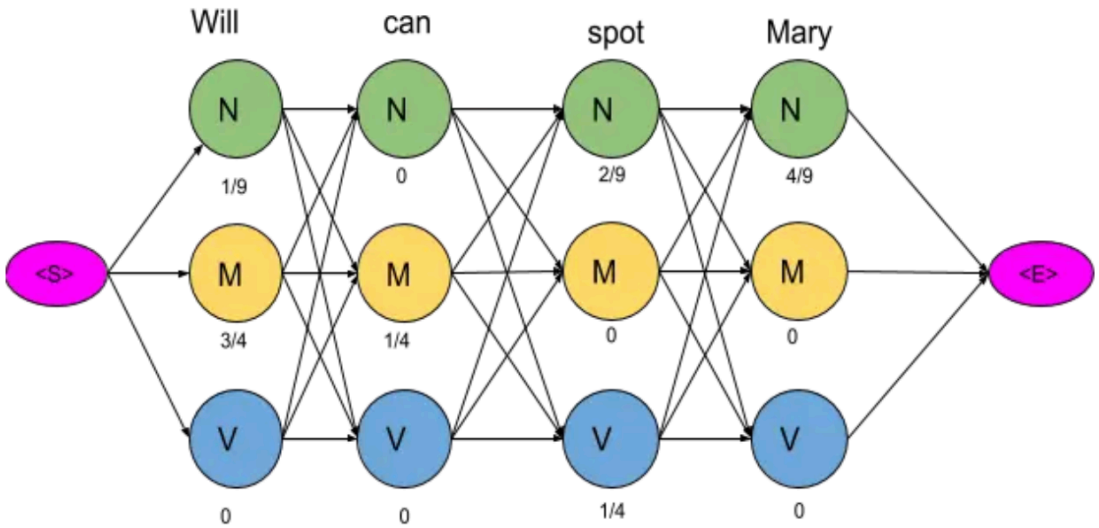
Example Sentence

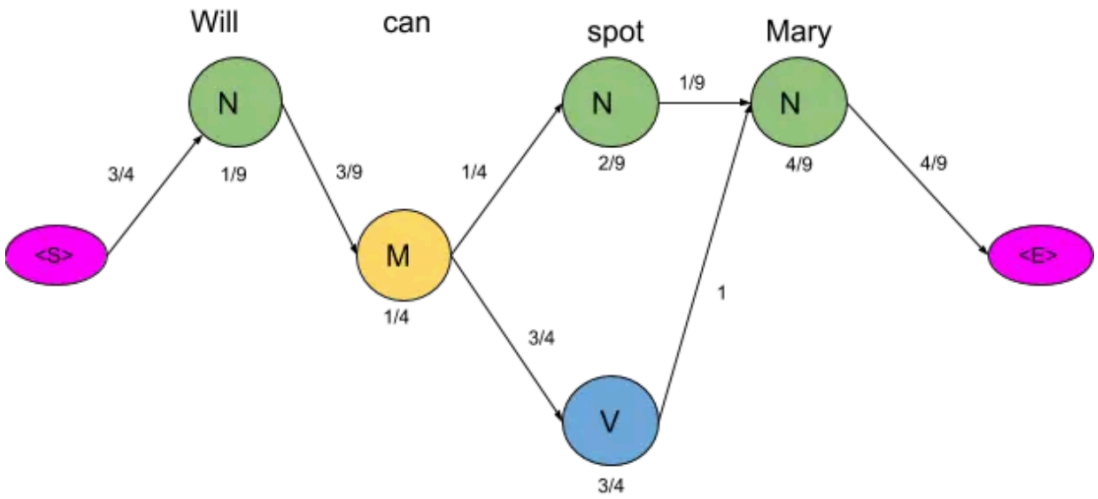
Consider the sentence: *"Will can spot Mary"*

- Suppose the sentence is tagged incorrectly as follows:
  - **Will** as a **Model**
  - **Can** as a **Verb**
  - **Spot** as a **Noun**
  - **Mary** as a **Noun**

81 possible combinations for the sentence 'Will can spot Mary'



Delete all the vertices and edges with probability zero and also include transition probability



Path 1

<S> → N → M → N → N → <E>

$$\text{Probability} = \frac{3}{4} \times \frac{1}{9} \times \frac{3}{9} \times \frac{1}{4} \times \frac{1}{4} \times \frac{2}{9} \times \frac{1}{9} \times \frac{4}{9} \times \frac{4}{9} = 0.00000846754$$

Path 2

<S> → N → M → V → N → <E>

$$\text{Probability} = \frac{3}{4} \times \frac{1}{9} \times \frac{3}{9} \times \frac{1}{4} \times \frac{3}{4} \times \frac{1}{4} \times 1 \times \frac{4}{9} \times \frac{4}{9} = 0.00025720164$$

- Clearly, the probability of the second sequence is much higher
- Hence the HMM tags each word in the sentence according to this sequence.

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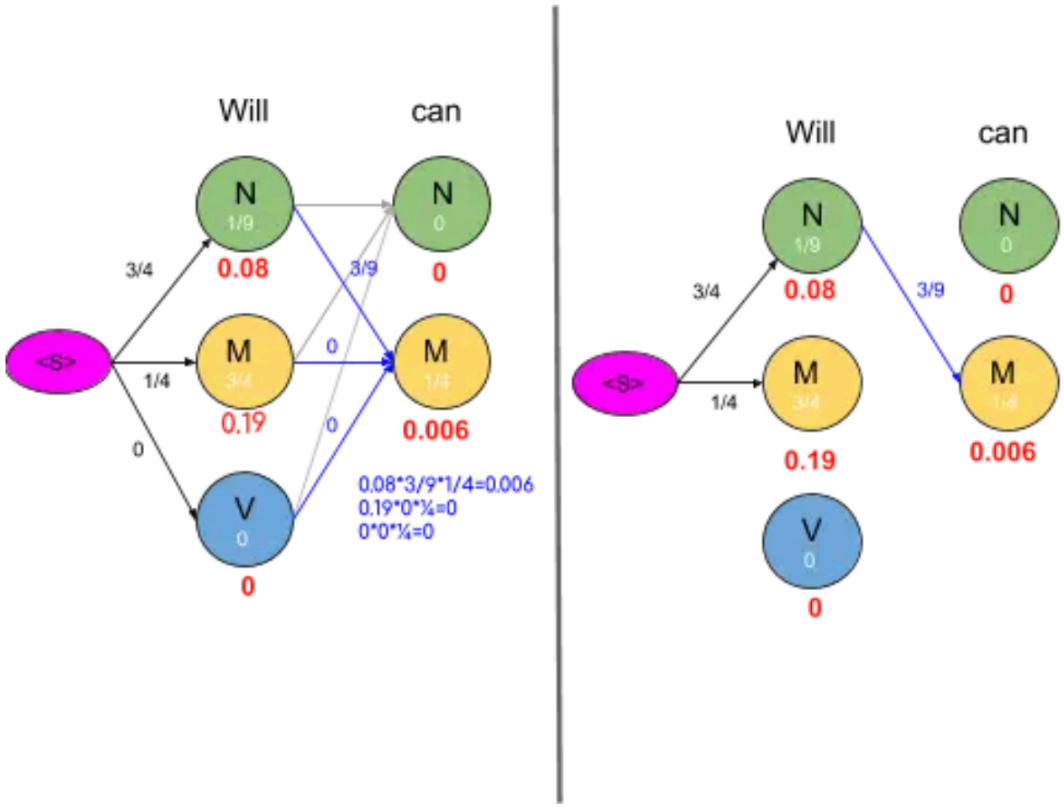
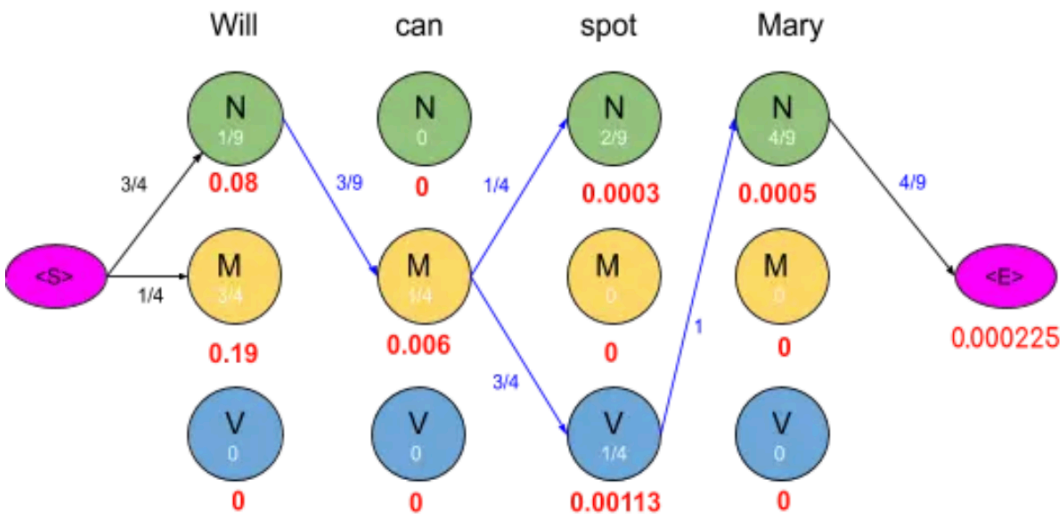
Consider the mini path having the lowest probability.



- **Nodes with Zero Probability:**
  - Some nodes may have a probability of zero.
  - Such nodes have no edges attached, as all paths to them have zero probability.



Key Algorithms in HMM

- **Forward Algorithm:**
  - Calculates the probability of an observation sequence given the model.
  - *Formula:*

$$\alpha_t(i) = P(O_1, O_2, \ldots, O_t, Q_t = S_i \mid \lambda)$$

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- **Baum-Welch Algorithm:**
  - Used for training HMM, updating model parameters using observed data.
  - *Procedure:* Iteratively adjusts transition and emission probabilities to maximize the likelihood of the observed data.

Challenges and Limitations of HMM

Assumption of Markov Property:	• Current state depends only on the previous state.
Fixed Number of States:	• HMMs require a predefined number of states.
Data Sparsity:	• Difficulty in estimating probabilities with limited data.
Long-Range Dependencies:	• HMMs struggle with capturing dependencies beyond the immediate previous state.

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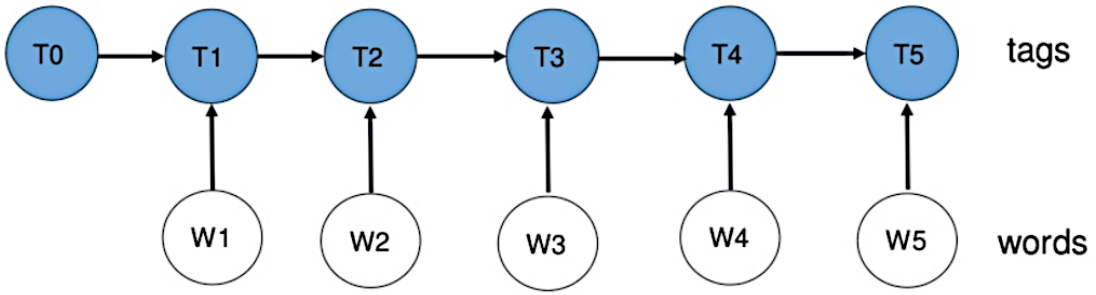

Discriminative model, model conditional probability Pr(T | W) directly.

$$\Pr(\boldsymbol{T}|\boldsymbol{W}) = \prod_{i=1}^{L} \Pr(t_i|t_{i-1}, w_i) = \prod_{i=1}^{L} \frac{\exp(\sum_j \beta_j f_j(t_{i-1}, w_i))}{Z(t_{i-1}, w_i)}$$

t_0 is a dummy start state.

Example of POS tagging with MEMM. Source: Gui et al. 2019, slide 46.

HMM vs. MEMM: Generative vs. Discriminative Models

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  - Words are modeled as observations generated from hidden states.
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- **MEMM (Maximum Entropy Markov Model): Discriminative Model**
  - Directly models the posterior probability $P(T \mid W)$.
  - Discriminates among possible tag sequences given a word sequence.
  - Uses conditional probability, conditioned on the previous tag and current word.

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  - Directly models the posterior probability $P(T \mid W)$.
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HMM vs. MEMM: Generative vs. Discriminative Models

- **HMM (Hidden Markov Model): Generative Model**
  - Words are modeled as observations generated from hidden states.
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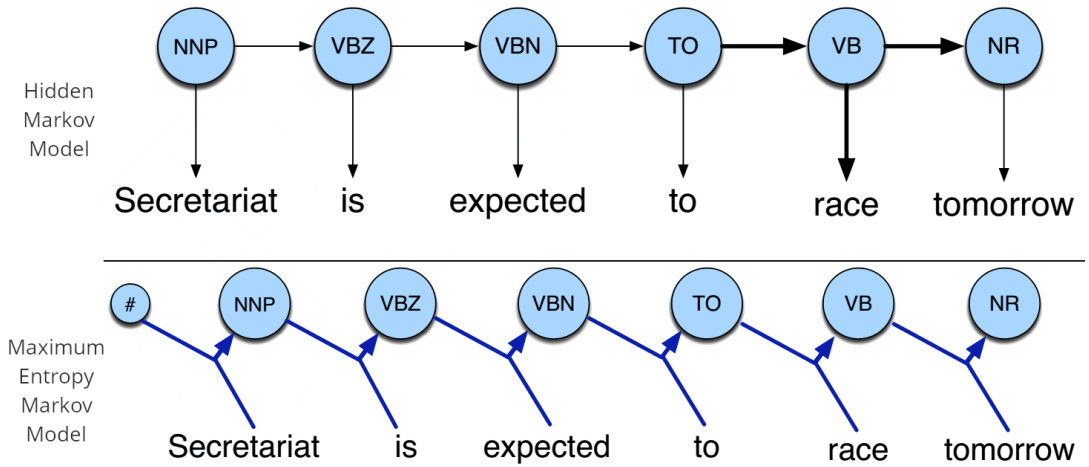
- **Training and Flexibility**
  - **HMM:**
    - Probabilities are obtained by training on a text corpus.
  - **MEMM:**
    - Builds a distribution by adding features (e.g., capitalization, hyphens, word endings).
    - Selects the maximum entropy distribution given the feature constraints.
    - More flexible: Allows for diverse, non-independent features.



Source: Adapted from Jurafsky and Martin 2009, fig. 6.20.

Disadvantages of MEMM and the Need for CRF

- **Disadvantages of MEMM:**
  - **Label Bias Problem:**
    - MEMM assigns probabilities based on local decisions at each state.
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    - States with fewer outgoing transitions (fewer choices) are often favored, regardless of the overall sequence quality.
  - **Limited Global Context:**
    - MEMM only considers the current word and previous tag for prediction.
    - It does not account for the entire sequence context, which may lead to suboptimal tagging.

3. Conditional Random Fields

- CRF is a type of discriminative probabilistic model used for labeling and segmenting structured data.
- Unlike HMM, which is generative, CRF models the conditional probability of the label sequence given the observation sequence.
- Unlike MEMM, CRF models the entire sequence jointly, avoiding the label bias problem associated with locally normalized models like MEMM.

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- **Why Use CRF for POS Tagging?**
  - CRF considers the entire sentence when predicting the POS tags, leading to more accurate and context-aware tagging.
  - It overcomes the label bias problem present in models like MEMM.

How CRF Works in POS Tagging

- **Modeling Sequence Data:**
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  - The model uses features from the entire sequence to determine the most likely tag sequence.
- **Feature Functions:**
  - CRF leverages feature functions to capture relevant patterns in the data, such as:
    - Word identity, prefixes, suffixes
    - Previous tags, capitalization, word shapes
  - These features help in making informed decisions about the POS tags.

Advantages of CRF in POS Tagging

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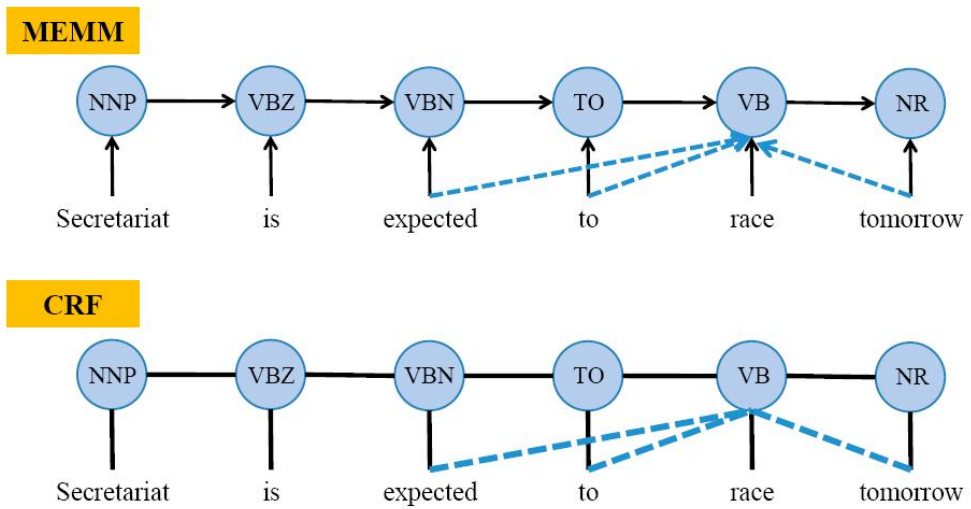
- **Flexibility:**
  - CRF allows for the inclusion of diverse and non-independent features, enhancing its adaptability to different POS tagging challenges.

MEMM v.s. CRF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Conclusion: HMM, MEMM, and CRF

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  - **Type:** Generative Model
  - **Probability:** Models joint probability $P(W, T) = P(W \mid T) \times P(T)$
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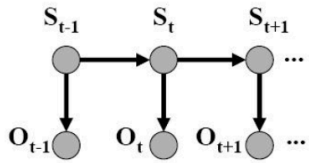
- **CRF (Conditional Random Field):**
  - **Type:** Discriminative Model
  - **Probability:** Models global conditional probability $P(T \mid W)$ across the entire sequence.
  - **Advantages:** Overcomes label bias, handles entire sequences jointly, allows for diverse features.
  - **Disadvantages:** Computationally intensive, complex to implement and train.

Summary

$\vec{s} = s_1, s_2, \ldots s_n \qquad \vec{o} = o_1, o_2, \ldots o_n$

HMM

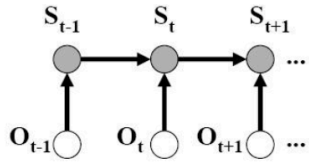
$$P(\vec{s}, \vec{o}) \propto \prod_{t=1}^{|\vec{o}|} P(s_t \mid s_{t-1}) P(o_t \mid s_t)$$



MEMM

$$P(\vec{s} \mid \vec{o}) \propto \prod_{t=1}^{|\vec{o}|} P(s_t \mid s_{t-1}, o_t)$$

$$\propto \prod_{t=1}^{|\vec{o}|} \frac{1}{Z_{s_{t-1}, o_t}} \exp\left(\sum_j \lambda_j f_j(s_t, s_{t-1}) + \sum_k \mu_k g_k(s_t, x_t) \right)$$



CRF

$$P(\vec{s} \mid \vec{o}) \propto \frac{1}{Z_{\vec{o}}} \prod_{t=1}^{|\vec{o}|} \exp\left(\sum_j \lambda_j f_j(s_t, s_{t-1}) + \sum_k \mu_k g_k(s_t, x_t) \right)$$