Cairo University
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# Natural Language Processing

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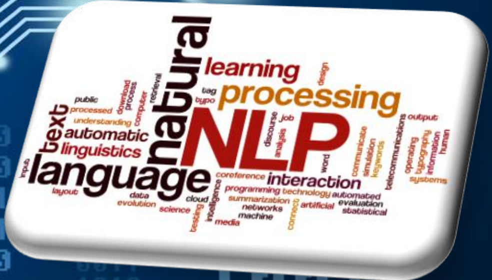
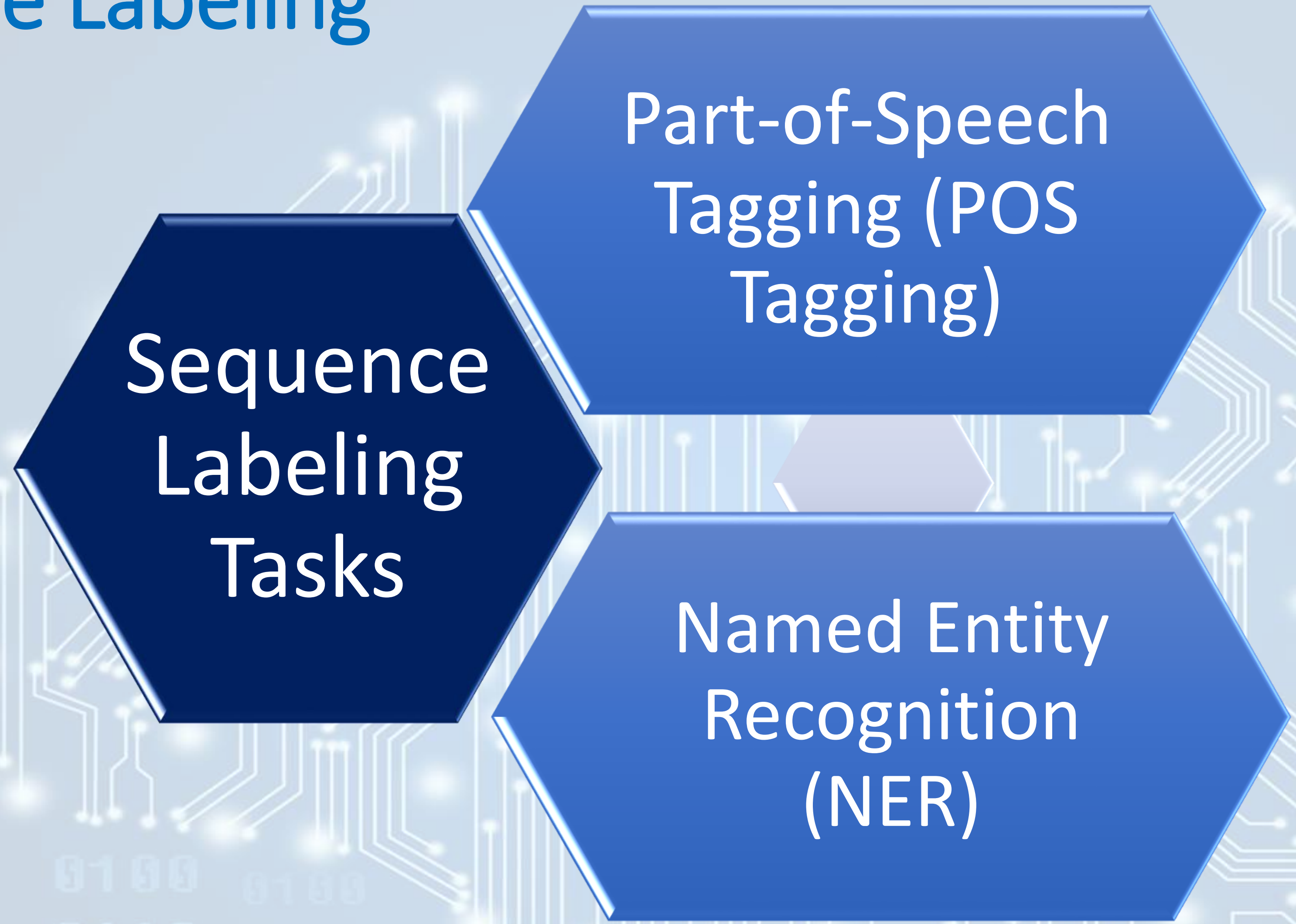


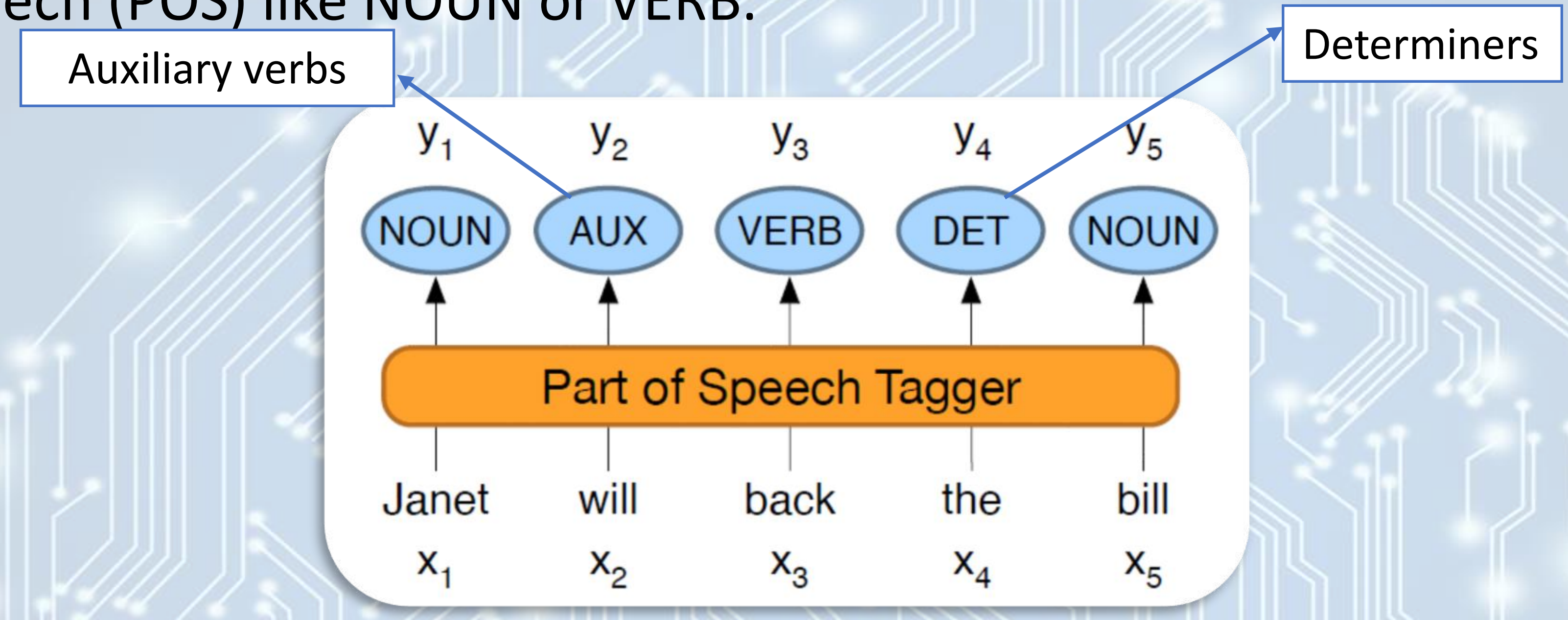
# Sequence Labeling




- Tasks in which we assign, to each word $x_i$ in an input word sequence, a label $y_i$, so that the output sequence $Y$ has the same length as the input sequence $X$ are called **sequence labeling tasks.**

# Part-of-Speech Tagging (POS Tagging)

- Part-of-speech tagging: is the task of taking a sequence of words and assigning each word a part of speech (POS) like NOUN or VERB.




The task of part-of-speech tagging: mapping from input words x1,x2,…,xn to output POS tags y1,y2,…,yn

- Tagging is a **disambiguation task:** words are ambiguous—have more than one possible part-of-speech—the goal of POS-tagging is to resolve these ambiguities, choosing the proper tag for the context.
  - For example, book can be a **verb** (book that flight) or a **noun** (hand me that book).
- POS tagging is a useful first step in lots of natural language processing tasks: Named Entity Recognition (NER), sentiment analysis, machine translation and word sense disambiguation.

# Part-of-Speech Tagging (POS Tagging)

- Parts of speech fall into two broad categories:
  - closed class
  - open class
- **Open classes:** (such as nouns, verbs and adjectives) acquire new members constantly. New nouns and verbs like *iPhone* or *to fax* are continually being created or borrowed.
- **Closed classes:** (such as pronouns, prepositions and conjunctions) acquire new members infrequently, if at all. These are generally function words like *of, it, and,* or *you*, which tend to be very short, occur frequently, and often have structuring uses in grammar.

- The accuracy of part-of-speech tagging algorithms is extremely high, reaches *97%* which is also the human performance on this task.

- **Most Frequent Class Baseline**: Always compare a classifier against a baseline at least as good as the most frequent class baseline (assigning each token to the class it occurred in most often in the training set)→The most-frequent-tag baseline has an accuracy of about *92%*. The baseline thus differs from the state-of-the-art and human ceiling (*97%*) by only *5%*.

- **Penn Treebank** is a famous English-specific part-of-speech **tagset** that has been used to label many syntactically annotated corpora like the Penn Treebank corpora.

# Named Entity Recognition (NER)

- NER: is the task of assigning words or phrases tags like PERSON, LOCATION, or ORGANIZATION.

Citing high fuel prices, [ORG **United Airlines**] said [TIME **Friday**] it has increased fares by [MONEY **$6**] per round trip on flights to some cities also served by lower-cost carriers. [ORG **American Airlines**], a unit of [ORG **AMR Corp.**], immediately matched the move, spokesman [PER **Tim Wagner**] said. [ORG **United**], a unit of [ORG **UAL Corp.**], said the increase took effect [TIME **Thursday**] and applies to most routes where it competes against discount carriers, such as [LOC **Chicago**] to [LOC **Dallas**] and [LOC **Denver**] to [LOC **San Francisco**].

- NER is a useful first step in lots of natural language processing tasks: sentiment analysis (want to know a consumer's sentiment toward a particular entity), question answering and information extraction.

- Unlike part-of-speech tagging, where there is no **segmentation** problem since each word gets one tag.
- NER is to find and label spans of text, it is partly difficult due to:
  - **Segmentation ambiguity**: need to decide what's an entity and what isn't, and where the **boundaries** are. Indeed, most words in a text will not be named entities.
  - **Type ambiguity:** for example *Kentucky* is a restaurant, person or location.

# Named Entity Recognition (NER)

- The standard approach to sequence labeling for a span-recognition problem like NER is **“BIO tagging”** and its variants: **“IO tagging”** and **“BIOES tagging”.**
  - BIO tagging: we label any token that **begins** a span of interest with the label **B**, tokens that occur **inside** a span are tagged with an **I**, and any tokens **outside** of any span of interest are labeled **O**.
  - IO tagging: loses some information by eliminating the B tag.
  - BIOES tagging: adds an end tag **E** for the **end** of a span, and a span tag **S** for a span consisting of only **one** word.

[PER **Jane Villanueva** ] of [ORG **United**] , a unit of [ORG **United Airlines Holding**] , said the fare applies to the [LOC **Chicago** ] route.

I-Per, enta btdy tag lel entity y3ny hya aslha person msln w el tag bta3ha enha inside.

mynf34 t2ol I w temshy fahem?

| Words | IO Label | BIO Label | BIOES Label |
|---|---|---|---|
| Jane | I-PER | B-PER | B-PER |
| Villanueva | I-PER | I-PER | E-PER |
| of | O | O | O |
| United | I-ORG | B-ORG | B-ORG |
| Airlines | I-ORG | I-ORG | I-ORG |
| Holding | I-ORG | I-ORG | E-ORG |
| discussed | O | O | O |
| the | O | O | O |
| Chicago | I-LOC | B-LOC | S-LOC |
| route | O | O | O |
| . | O | O | O |

- This way the NER is a sequence labeling task same as part-of-speech tagging assigning a single label yi to each input word xi: a sequence labeler is trained to label each token in a text with tags that indicate the presence (or absence) of particular kinds of named entities.

# Sequence Labeling Approaches

- Hidden Markov Model: HMM

ay sequence labeling task, ana a2dr a7lha b wa7da mn el approaches de.

- Conditional Random Field: CRF
- Recurrent Neural Networks: RNN
- Transformers

msh hnshofhom, lakn enta dwr feh, 34an da haga mohema awy.

- Others

# Hidden Markov Model (HMM)

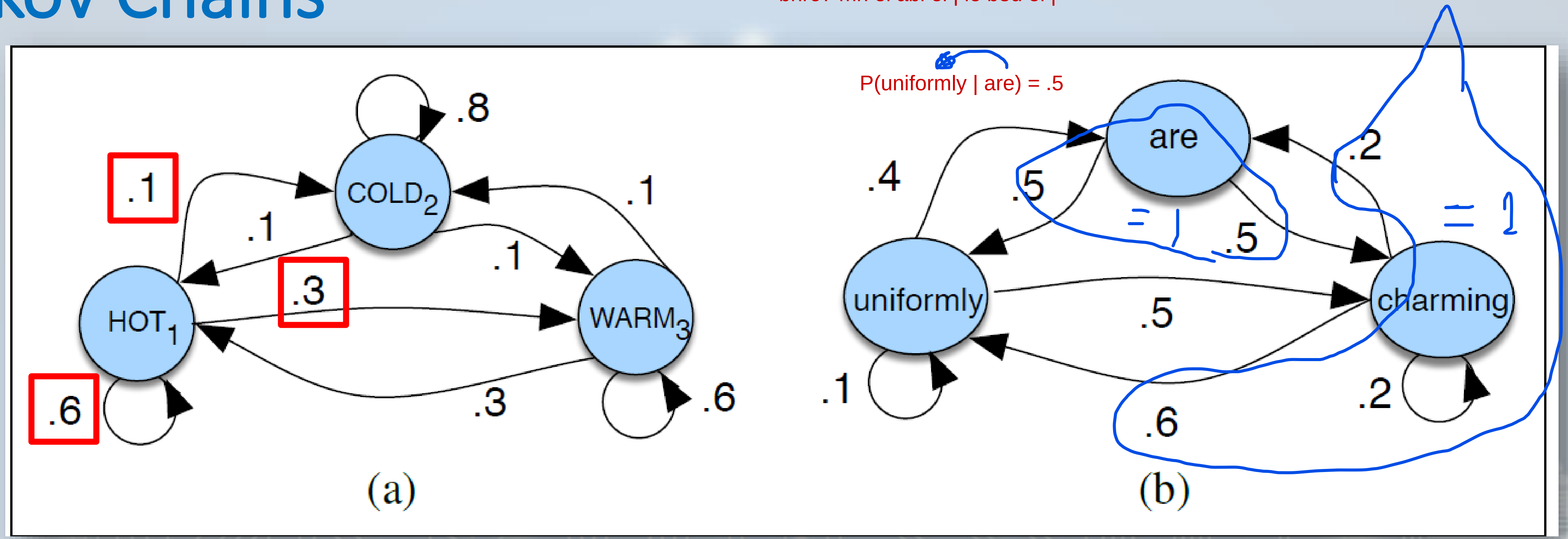
- HMM is a **generative** approach.
- An HMM is a **probabilistic** sequence model: given a sequence of units (words, letters, morphemes, sentences, …), it computes a probability distribution over possible sequences of labels and chooses the best label sequence.

- HMM is based on augmenting the Markov chain.
- A **Markov chain** is a model that tells us something about the probabilities of sequences of random variables/states, each of which can take on values from some set.
  - These sets can be words, or tags, or symbols representing anything, for example the weather.
- A Markov chain makes a very strong assumption that if we want to predict the future in the sequence, all that matters is the **current state**.
  - To predict tomorrow's weather, you could examine today's weather but you weren't allowed to look at yesterday's weather.

$$\textbf{Markov Assumption:} \quad P(q_i = a | q_1 \ldots q_{i-1}) = P(q_i = a | q_{i-1})$$

# Markov Chains

bnro7 mn el abl el | le b3d el |




mgmo3 el probability elly kharga mn ay state lazm y sum up to one.

(a) A Markov chain for weather

(b) A Markov chain for words

- The graph consists of nodes and edges:
  - **Nodes→ states**
  - **Edges→ the transitions, with their probabilities**
- The values of arcs leaving a given state must **sum to 1**.
- (a) shows a Markov chain for assigning a probability to a sequence of weather events, for which the vocabulary consists of *HOT*, *COLD*, and *WARM*.
- (b) shows a Markov chain for assigning a probability to a sequence of words w1...wt .
  - This Markov chain should be familiar: it represents a **bigram language model**, with each edge expressing the probability p(wi|wj)

# Markov Chains

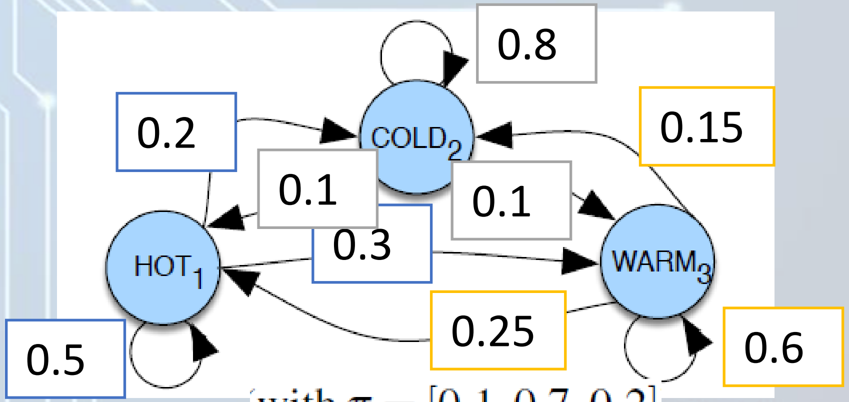
- Formally, a Markov chain is specified by the following components:

| | |
|---|---|
| $Q = q_1 q_2 \ldots q_N$ | a set of $N$ **states** |
| $A = a_{11} a_{12} \ldots a_{N1} \ldots a_{NN}$ | a **transition probability matrix** $A$, each $a_{ij}$ representing the probability of moving from state $i$ to state $j$, s.t. $\sum_{j=1}^{n} a_{ij} = 1 \quad \forall i$ |
| $\pi = \pi_1, \pi_2, \ldots, \pi_N$ | an **initial probability distribution** over states. $\pi_i$ is the probability that the Markov chain will start in state $i$. Some states $j$ may have $\pi_j = 0$, meaning that they cannot be initial states. Also, $\sum_{i=1}^{n} \pi_i = 1$ |

- Example: compute the probability of each of the following sequences:

Can you prove these calculations mathematically??

- hot hot hot hot:
  P(hot)*P(hot|hot)*P(hot|hot)*P(hot|hot)
  =0.1*0.5*0.5*0.5= 0.0215
- cold hot cold hot:
  P(cold)*P(hot|cold)*(cold|hot)*P(hot|cold)
  =0.7*0.1*0.2*0.1= 0.0014




with $\pi = [0.1, 0.7, 0.2]$

# Hidden Markov Model

- A **Markov chain** is useful when we need to compute a probability for a sequence of **observable events**.

- In many cases, however, the events we are interested in are **hidden**: we don't observe them directly.

- For example, we don't normally observe part-of-speech tags in a text. Rather, we see words, and must infer the tags from the word sequence.
  - We call the tags hidden because they are not observed.

why?

- A hidden Markov model (**HMM**) allows us to talk about both **observed events** (like **words** that we see in the input) and **hidden events** (like part-of-speech **tags**).

# Hidden Markov Model

el 7aga elly bhtm eny agblha probability hya elly b3tbr enaha state.

- An HMM is specified by the following components:

| | |
|---|---|
| $Q = q_1 q_2 \ldots q_N$ | a set of $N$ **states** |
| $A = a_{11} \ldots a_{ij} \ldots a_{NN}$ | a **transition probability matrix** $A$, each $a_{ij}$ representing the probability of moving from state $i$ to state $j$, s.t. $\sum_{j=1}^{N} a_{ij} = 1 \quad \forall i$ |
| $\boxed{O = o_1 o_2 \ldots o_T}$ | a sequence of $T$ **observations**, each one drawn from a vocabulary $V = v_1, v_2, \ldots, v_V$ |
| $\boxed{B = b_i(o_t)}$ | a sequence of **observation likelihoods**, also called **emission probabilities**, each expressing the probability of an observation $o_t$ being generated from a state $q_i$ |
| $\pi = \pi_1, \pi_2, \ldots, \pi_N$ | an **initial probability distribution** over states. $\pi_i$ is the probability that the Markov chain will start in state $i$. Some states $j$ may have $\pi_j = 0$, meaning that they cannot be initial states. Also, $\sum_{i=1}^{n} \pi_i = 1$ |

- A first-order hidden Markov model instantiates two simplifying assumptions:

1. probability of a particular state depends only on the previous state:

$$\textbf{Markov Assumption:} \quad P(q_i | q_1, \ldots, q_{i-1}) = P(q_i | q_{i-1})$$

2. probability of an output observation oi depends only on the state that produced the observation qi and not on any other states or any other observations:

$$\textbf{Output Independence:} \quad P(o_i | q_1, \ldots q_i, \ldots, q_T, o_1, \ldots, o_i, \ldots, o_T) = P(o_i | q_i)$$ = bi (Ot)

# HMM Tagger

An HMM has two components, the A and B probabilities:

- The **A** matrix contains the tag transition probabilities **P(ti|ti-1)** which represent the probability of a tag occurring given the previous tag.
  - For example, modal verbs (MD) like *will* are very likely to be followed by a verb in the base form (VB) like *learn* →we expect this probability to be high.
  - We compute the **maximum likelihood estimate** of this transition probability by **counting**: out of the times we see the first tag in a labeled corpus, how often the first tag is followed by the second:

$$\boxed{P(t_i|t_{i-1}) = \frac{C(t_{i-1},t_i)}{C(t_{i-1})}}$$

nfs el fekra baa, dayman bfdal a3ed.

$$P(VB|MD) = \frac{C(MD,VB)}{C(MD)} = \frac{10471}{13124} = .80$$

- The **B** emission probabilities **P(wi|ti)** represent the probability, given a tag (say *MD*), that it will be associated with a given word (say *will*).
  - The MLE of the emission probability is:

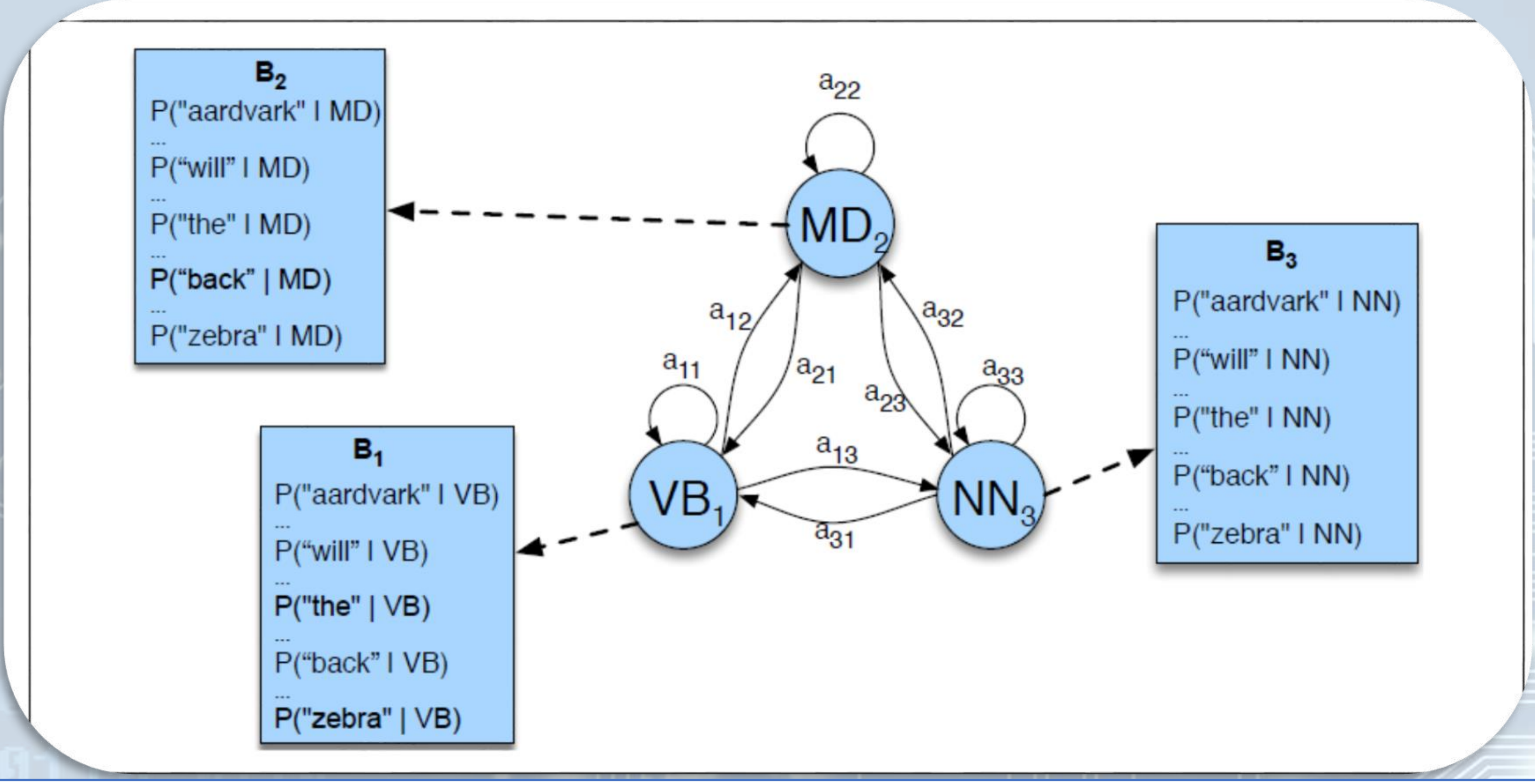
$$\boxed{P(w_i|t_i) = \frac{C(t_i,w_i)}{C(t_i)}}$$

$$P(will|MD) = \frac{C(MD,will)}{C(MD)} = \frac{4046}{13124} = .31$$

This likelihood term is NOT asking:
“which is the most likely tag for the word will?”
→ the posterior P(MD|will).
Instead, P(will|MD) answers the question:
“If we were going to generate a MD, how likely is it that this modal would be will?”

# HMM Tagger

- A three states HMM part-of-speech tagger (the full tagger would have one state for each tag):




An illustration of the two parts of an HMM representation:
- the A transition probabilities.
- the B observation likelihoods that are associated with each state, one likelihood for each possible observation word.

# HMM Tagging as Decoding

- **Decoding:** is the task of determining the hidden variables sequence corresponding to the sequence of observations.

**Decoding**: Given as input an HMM $\lambda = (A, B)$ and a sequence of observations $O = o_1, o_2, ..., o_T$, find the most probable sequence of states $Q = q_1 q_2 q_3 \ldots q_T$.

- For part-of-speech tagging, the goal of HMM decoding is to choose the tag sequence *t1…tn* that is most probable given the observation sequence of *n* words *w1…wn*:

$$\hat{t}_{1:n} = \underset{t_1 \ldots t_n}{\operatorname{argmax}} P(t_1 \ldots t_n | w_1 \ldots w_n)$$

- Using Bayes' rule: $\hat{t}_{1:n} = \underset{t_1 \ldots t_n}{\operatorname{argmax}} \frac{P(w_1 \ldots w_n | t_1 \ldots t_n) P(t_1 \ldots t_n)}{P(w_1 \ldots w_n)}$
- Dropping the denominator: $\hat{t}_{1:n} = \underset{t_1 \ldots t_n}{\operatorname{argmax}} P(w_1 \ldots w_n | t_1 \ldots t_n) P(t_1 \ldots t_n)$
- HMM taggers make two further simplifying assumptions:

$$P(w_1 \ldots w_n | t_1 \ldots t_n) \approx \prod_{i=1}^{n} P(w_i | t_i)$$

probability of a word appearing depends only on its own tag and is independent of neighboring words and tags.

$$P(t_1 \ldots t_n) \approx \prod_{i=1}^{n} P(t_i | t_{i-1})$$

the bigram assumption, is that the probability of a tag is dependent only on the previous tag, rather than the entire tag sequence.

pi 34an homa independent.

nfs el klam baa. enta b2et 5ebra delw2ty.

$$\hat{t}_{1:n} = \underset{t_1 \ldots t_n}{\operatorname{argmax}} P(t_1 \ldots t_n | w_1 \ldots w_n) \approx \underset{t_1 \ldots t_n}{\operatorname{argmax}} \prod_{i=1}^{n} \overbrace{P(w_i | t_i)}^{\text{emission}} \overbrace{P(t_i | t_{i-1})}^{\text{transition}}$$

enta btdwr 3la kol el permutations, da very computationally expensive,

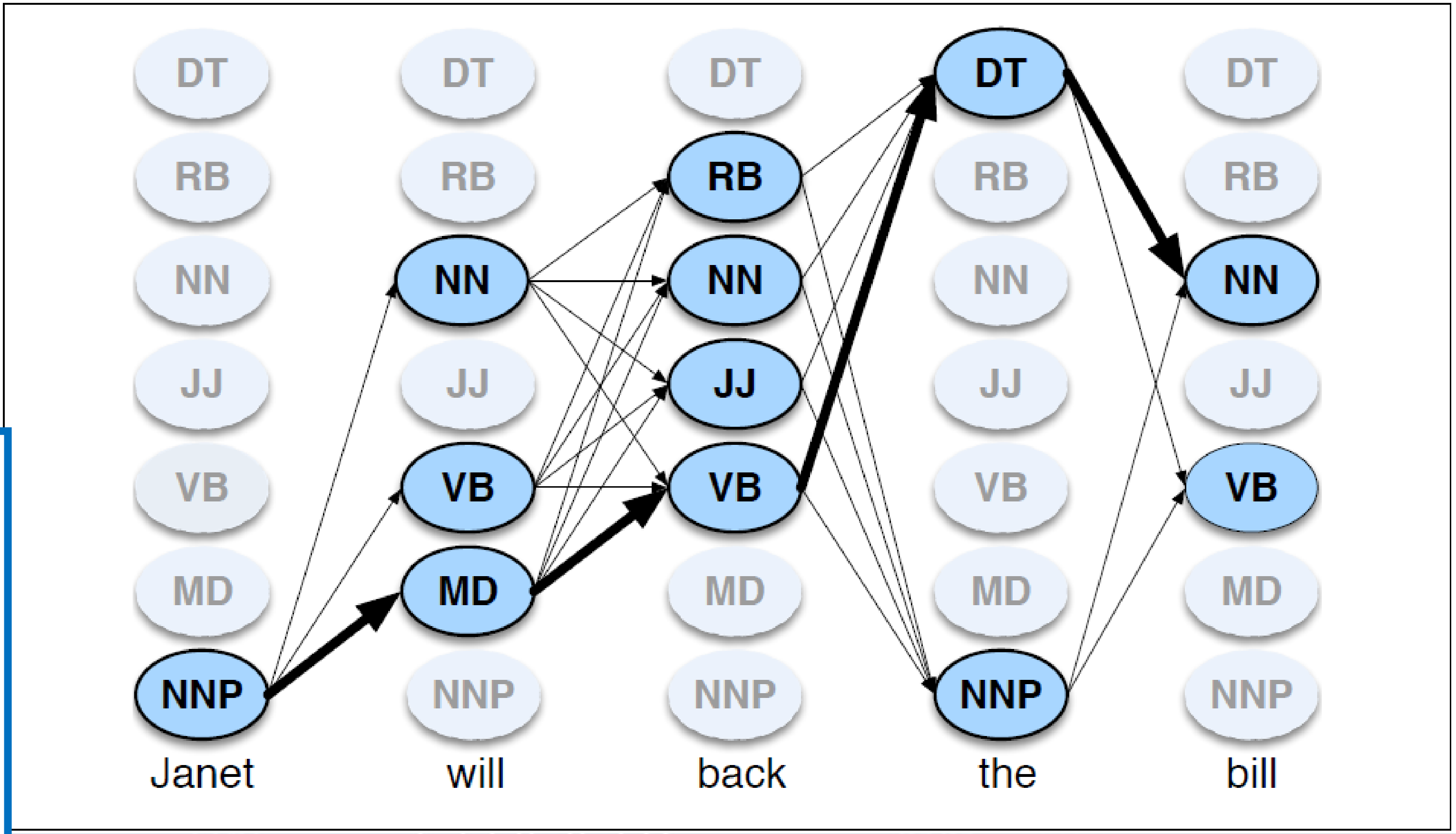
# The Viterbi Algorithm

- The decoding algorithm for HMMs is the Viterbi algorithm, it is an instance of dynamic programming.
- The algorithm first sets up a **probability matrix or lattice**, with one column for each observation *ot* and one row for each state *qi* in the state graph.

- DT: determiner
- RB: adverb
- NN: singular or mass noun
- JJ: adjective
- VB: verb base
- MD: modal
- NNP: proper noun, singular

A sketch of the lattice for *Janet will back the bill:*

- The possible tags (qi) for each word.
- The path corresponding to the correct tag sequence is highlighted.
- States (parts of speech) which have a zero probability of generating a particular word according to the B matrix such as P(Janet|DT) are greyed out.




ay 7aga fade out, m3naha en el probability bta3tha given el kelma de = 0.

# The Viterbi Algorithm

- Each cell of the lattice, $v_t(j)$, represents the probability that the HMM is in state $j$ after seeing the first $t$ observations and passing through the most probable state sequence $q_1,\ldots,q_{t-1}$, given the HMM λ.
- The value of each cell $v_t(j)$ is computed by recursively taking the most probable path that could lead us to this cell:

$$v_t(j) = \max_{i=1}^{N} \boxed{v_{t-1}(i)\, a_{ij}}\, b_j(o_t)$$

enta m5zn el result, fa hena baa bntb2 el dp logic ....

| | |
|---|---|
| $v_{t-1}(i)$ | the **previous Viterbi path probability** from the previous time step |
| $a_{ij}$ | the **transition probability** from previous state $q_i$ to current state $q_j$ |
| $b_j(o_t)$ | the **state observation likelihood** of the observation symbol $o_t$ given the current state $j$ |

# The Viterbi Algorithm Example

- Let's tag the sentence *Janet will back the bill*
- The gold answer: *Janet/NNP will/MD back/VB the/DT bill/NN*
- The **A transition probabilities P(ti|ti-1)** computed from the WSJ corpus without smoothing *(ONLY part is shown).* Rows are labeled with the conditioning event:
  - E.g.: $\boxed{\text{P(VB|MD)=0.7968}}$, $\boxed{P(NNP|\langle s\rangle)=\pi_{NNP} = 0.2767}$

el rows homa el given

el column hya el 7aga elly bdwr 3leha.

el table da given 3ndk.

| | NNP | MD | VB | JJ | NN | RB | DT |
|---|---|---|---|---|---|---|---|
| $<s>$ | 0.2767 | 0.0006 | 0.0031 | 0.0453 | 0.0449 | 0.0510 | 0.2026 |
| **NNP** | 0.3777 | 0.0110 | 0.0009 | 0.0084 | 0.0584 | 0.0090 | 0.0025 |
| **MD** | 0.0008 | 0.0002 | 0.7968 | 0.0005 | 0.0008 | 0.1698 | 0.0041 |
| **VB** | 0.0322 | 0.0005 | 0.0050 | 0.0837 | 0.0615 | 0.0514 | 0.2231 |
| **JJ** | 0.0366 | 0.0004 | 0.0001 | 0.0733 | 0.4509 | 0.0036 | 0.0036 |
| **NN** | 0.0096 | 0.0176 | 0.0014 | 0.0086 | 0.1216 | 0.0177 | 0.0068 |
| **RB** | 0.0068 | 0.0102 | 0.1011 | 0.1012 | 0.0120 | 0.0728 | 0.0479 |
| **DT** | 0.1147 | 0.0021 | 0.0002 | 0.2157 | 0.4744 | 0.0102 | 0.0017 |

# The Viterbi Algorithm Example

- The **observation likelihoods B (Emission probability matrix)** computed from the WSJ corpus without smoothing (*simplified slightly*).
  - E.g.: P(back|JJ)=0.000340
  - The word *Janet* only appears as an *NNP*, *back* has *4* possible parts of speech, and the word *the* can appear as a *determiner* or as an *NNP*.

Remember the greyed out nodes in the graph →Prob=0

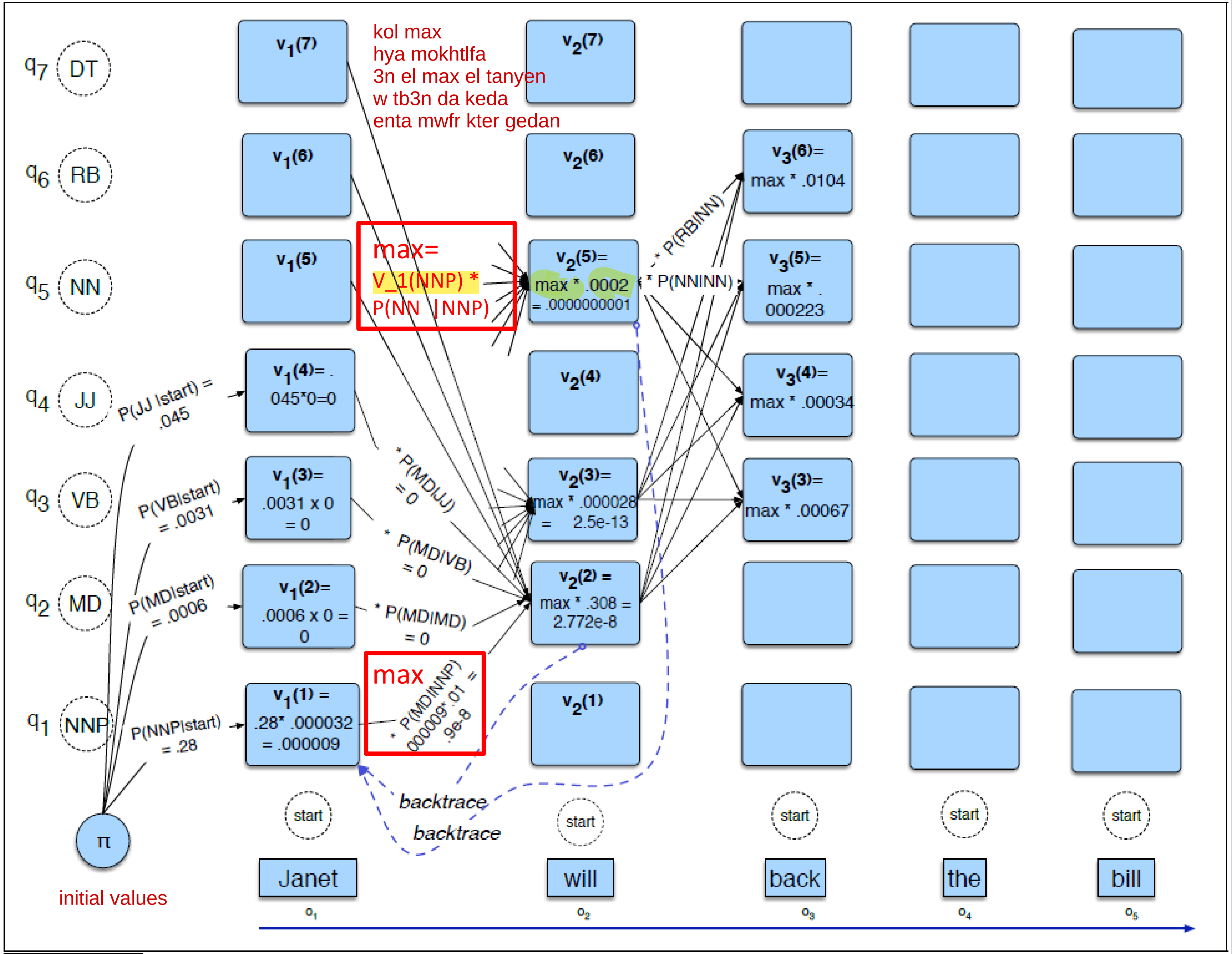
| | Janet | will | back | the | bill |
|---|---|---|---|---|---|
| NNP | 0.000032 | 0 | 0 | 0.000048 | 0 |
| MD | 0 | 0.308431 | 0 | 0 | 0 |
| VB | 0 | 0.000028 | 0.000672 | 0 | 0.000028 |
| JJ | 0 | 0 | 0.000340 | 0 | 0 |
| NN | 0 | 0.000200 | 0.000223 | 0 | 0.002337 |
| RB | 0 | 0 | 0.010446 | 0 | 0 |
| DT | 0 | 0 | 0 | 0.506099 | 0 |

dol homa el emission probabilities.

# The Viterbi Algorithm Example

$$v_t(j) = \max_{i=1}^{N} v_{t-1}(i)\, a_{ij}\, b_j(o_t)$$

- We begin in column 1 (for the word *Janet*) by setting the Viterbi value in each cell to the product of the $\pi$ transition probability and the observation likelihood of the word *Janet* given the tag for that cell.
- Next, each cell in the *will* column gets updated. For each state, we compute the value viterbi[s,t] by taking the maximum over the extensions of all the paths from the previous column that lead to the current cell.
- Each cell keeps the probability of the best path so far and a pointer to the previous cell along that path.
- Termination: take the max value from the last column of the Viterbi matrix selecting its tag and then use the pointer to go back (selecting tags) until reach the 1rst word.



# The Viterbi Algorithm

**function** VITERBI(*observations* of len *T*,*state-graph* of len *N*) **returns** *best-path*, *path-prob*

create a path probability matrix *viterbi[N,T]*
**for** each state *s* **from** 1 **to** *N* **do** ; initialization step
$viterbi[s,1] \leftarrow \pi_s * b_s(o_1)$
$backpointer[s,1] \leftarrow 0$
**for** each time step *t* **from** 2 **to** *T* **do** ; recursion step
**for** each state *s* **from** 1 **to** *N* **do**
$viterbi[s,t] \leftarrow \max_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$
$backpointer[s,t] \leftarrow \operatorname{argmax}_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$
$bestpathprob \leftarrow \max_{s=1}^{N} viterbi[s,T]$ ; termination step
$bestpathpointer \leftarrow \operatorname{argmax}_{s=1}^{N} viterbi[s,T]$ ; termination step
*bestpath* ← the path starting at state *bestpathpointer*, that follows backpointer[] to states back in time
**return** *bestpath*, *bestpathprob*


Thank You