

Markov Models

PA154 Jazykové modelování (5.1)

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Source: Introduction to Natural Language Processing (600.465)
Jan Hajič, CS Dept., Johns Hopkins Univ.
www.cs.jhu.edu/~hajic

Review: Markov Process

- Bayes formula (chain rule):

$$P(W) = P(w_1, w_2, \dots, w_T) = \prod_{i=1..T} p(w_i \mid w_1, w_2, \dots, w_{i-n+1}, \dots, w_{i-1})$$

- n-gram language models:

- ▶ Markov process (chain) of the order n-1:

$$P(W) = P(w_1, w_2, \dots, w_T) = \prod_{i=1..T} p(w_i \mid w_{i-n+1}, w_{i-n+2}, \dots, w_{i-1})$$

Using just one distribution (Ex.: trigram model: $p(w_i \mid w_{i-2}, w_{i-1})$):

Positions: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Words: My car broke down , and within hours Bob 's can broke down , too .

$$p(, \mid \text{broke down}) = p(w_5 \mid w_3, w_4) = p(w_{14} \mid w_{12}, w_{13})$$

approximation

Markov Properties

- Generalize to any process (not just words/LM):

- ▶ Sequence of random variables: $X = (X_1, X_2, \dots, X_T)$
- ▶ Sample space S (states), size N : $S = (S_0, S_1, S_2, \dots, S_N)$

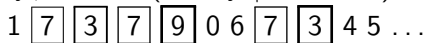
1. Limited History (Context, Horizon):

$$\forall i \in 1..T; P(X_i | X_1, \dots, X_{i-1}) = (X_i | X_{i-1})$$



2. Time invariance (M.C. is stationary, homogenous)

$$\forall i \in 1..T, \forall y, x \in S; P(X_i = y | X_{i-1} = x) = p(y | x)$$



ok... same **distribution**

Long History Possible

- What if we want trigrams:

1 7 3 7 9 0 6 7 3 4 5...

- Formally, use transformation:

Define new variables Q_i , such that $X_i = Q_{i-1}, Q_i$:

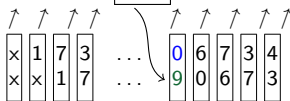
Then

$$P(X_i | X_{i-1}) = P(Q_{i-1}, Q_i | Q_{i-2}, Q_{i-1})$$

Predicting (X_i)

1 7 3 7 9 0 6 7 3 4 5...

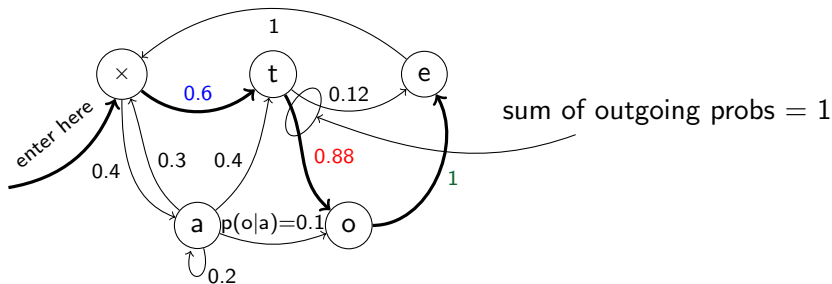
History ($X_i = \{Q_{i-2}, Q_{i-1}\}$):



Graph Representation: State Diagram

- $S = \{s_0, s_1, s_2, \dots, s_n\}$: states
- Distribution $P(X_i | X_{i-1})$:
 - ▶ transitions (as arcs) with probabilities attached to them:

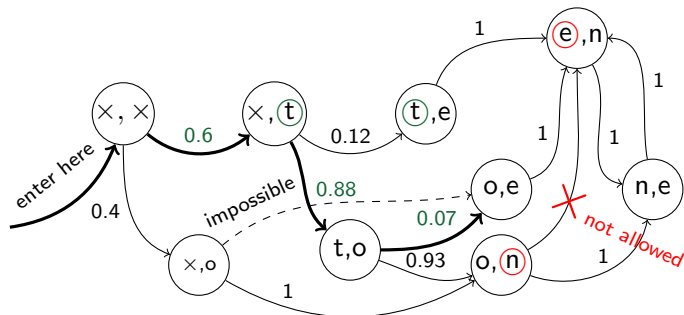
Bigram case:



$$p(\text{toe}) = .6 \times .88 \times 1 = .528$$

The Trigram Case

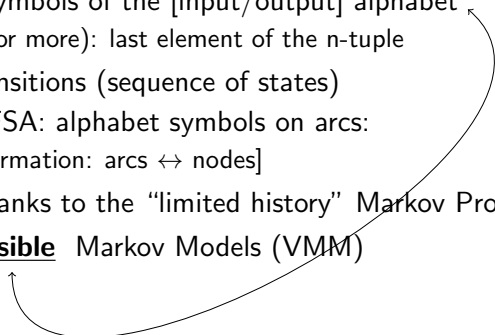
- $S = \{s_0, s_1, s_2, \dots, s_n\}$: states: pairs $s_i = (x,y)$
- Distribution $P(X_i | X_{i-1})$: (r.v. X : generates pairs s_i)



$$p(\text{toe}) = .6 \times .88 \times .07 \cong .037$$

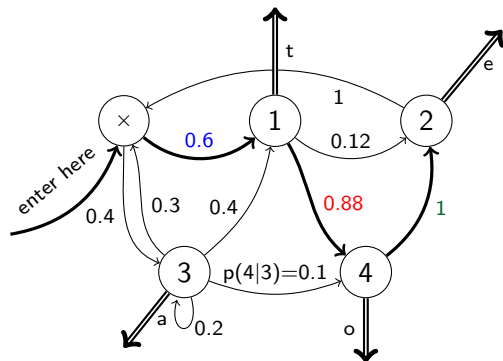
$$p(\text{one}) = ?$$

Finite State Automaton

- States \sim symbols of the [input/output] alphabet
 - ▶ pairs (or more): last element of the n-tuple
 - Arcs \sim transitions (sequence of states)
 - [Classical FSA: alphabet symbols on arcs:
 - ▶ transformation: arcs \leftrightarrow nodes]
 - Possible thanks to the “limited history” Markov Property
 - So far: **Visible** Markov Models (VMM)
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Hidden Markov Models

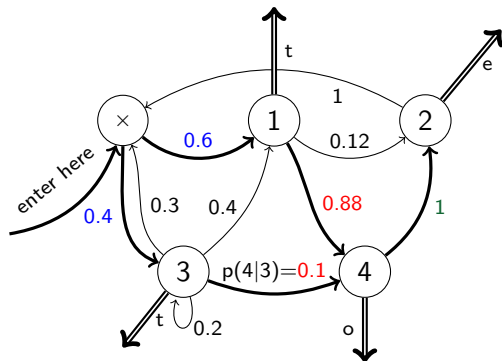
- The simplest HMM: states generate [observable] output (using the “data” alphabet) but remain “invisible”:



$$p(\text{toe}) = .6 \times .88 \times 1 = .528$$

Added Flexibility...

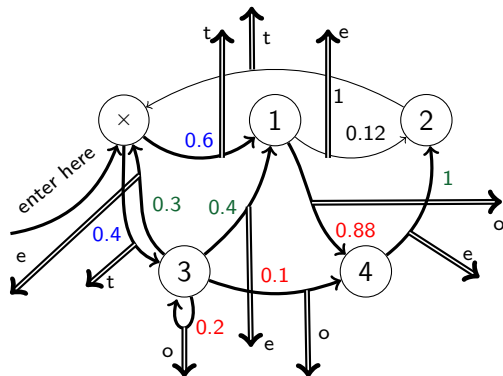
- So far, no change; but different states may generate the same output (why not?):



$$p(\text{toe}) = .6 \times .88 \times 1 + .4 \times .1 \times 1 = .568$$

Output from Arcs...

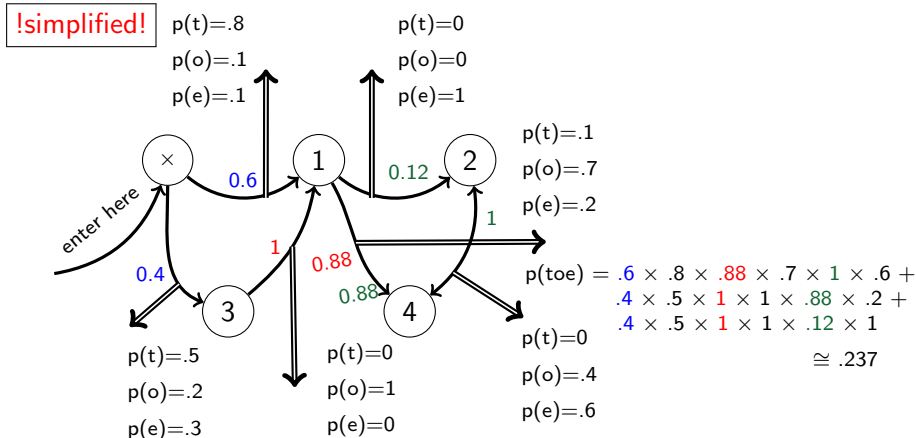
- Added flexibility: Generate output from arcs, not states:



$$\begin{aligned} p(\text{toe}) &= .6 \times .88 \times 1 + \\ &\quad .4 \times .1 \times 1 + \\ &\quad .4 \times .2 \times .3 + \\ &\quad .4 \times .2 \times .4 = .624 \end{aligned}$$

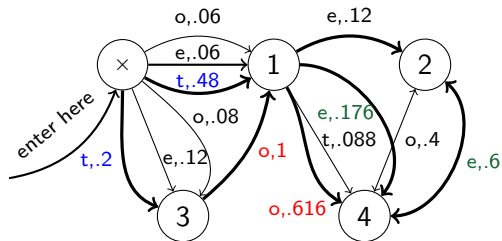
... and Finally, Add Output Probabilities

- Maximum flexibility: [Unigram] distribution (sample space: output alphabet) at each output arc:



Slightly Different View

- Allow for multiple arcs from $s_i \rightarrow s_j$, mark them by output symbol s , get rid of output distributions:



$$\begin{aligned} p(\text{toe}) &= .48 \times .616 \times .6 + \\ &\quad .2 \times 1 \times .176 + \\ &\quad .2 \times 1 \times .12 \cong .237 \end{aligned}$$

In the future, we will use the view more convenient for the problem at hand.

HMM (the most general case):

- five-tuple (S, s_0, Y, P_S, P_Y) , where:
 - ▶ $S = \{s_0, s_1, s_2, \dots, s_T\}$ is the set of states, s_0 is the initial state,
 - ▶ $Y = \{y_1, y_2, \dots, y_V\}$ is the output alphabet,
 - ▶ $P_S(s_j | s_i)$ is the set of prob. distributions of transitions,
 - ▶ size of $P_S : |S|^2$.
 - ▶ $P_Y(y_k | s_i, s_j)$ is the set of output (emission) probability distributions.
 - ▶ size of $P_Y : |S|^2 \times |Y|$

Example:

- $S = x, 1, 2, 3, 4, s_0 = x$
- $Y = \{t, o, e\}$

Formalization - Example

■ Example (for graph, see foils 11,12):

▶ $S = \{x, 1, 2, 3, 4\}, s_0 = x$

▶ $Y = \{e, o, t\}$

▶ $P_S :$

| | x | 1 | 2 | 3 | 4 |
|---|---|----|-----|----|-----|
| x | 0 | .6 | 0 | .4 | 0 |
| 1 | 0 | 0 | .12 | 0 | .88 |
| 2 | 0 | 0 | 0 | 0 | 1 |
| 3 | 0 | 1 | 0 | 0 | 0 |
| 4 | 0 | 0 | 1 | 0 | 0 |

→ $\Sigma = 1$

$P_Y :$

| | | e | x | 1 | 2 | 3 | 4 |
|---|---|----|---|----|----|----|----|
| t | o | | | | | | |
| t | x | | | | | | .2 |
| x | | .8 | | .5 | | .7 | |
| 1 | | | 0 | | .1 | | |
| 2 | | | | | 0 | | |
| 3 | | 0 | | | | | |
| 4 | | | 0 | | | | |

→ $\Sigma = 1$

- The generation algorithm (of limited value :-)):
 - 1 Start in $s = s_0$.
 - 2 Move from s to s' with probability $P_S(s' | s)$.
 - 3 Output (emit) symbol y_k with probability $P_S(y_k | s, s')$.
 - 4 Repeat from step 2 (until somebody says enough).
- More interesting usage:
 - ▶ Given an output sequence $Y = \{y_1, y_2, \dots, y_k\}$ compute its probability.
 - ▶ Given an output sequence $Y = \{y_1, y_2, \dots, y_k\}$ compute the most likely sequence of states which has generated it.
 - ▶ ... plus variations: e.g., n best state sequences