

n-gram Model:

* To estimate the probability of a sentence, decompose sentence probability into a product of conditional probabilities using chain rule:

$$P(s) = P(w_1, w_2, w_3 \dots w_n)$$

$$= P(w_1) P(w_2|w_1) P(w_3|w_1 w_2) P(w_4|w_1 w_2 w_3) \dots$$

$$\dots (P(w_n|w_1 w_2 \dots w_{n-1}))$$

$$= \prod_{i=1}^n P(w_i | h_i)$$

($h_i \rightarrow$ history of word w_i
 $\hookrightarrow w_1 w_2 \dots w_{i-1}$)

* To get sentence probability, we need to calculate the word probability which is preceding it in a sentence.

* The ~~time~~ history (hi) to the previous one word only.

↳ bi-gram ($n=1$)

* previous 2 words \rightarrow lei-gram ($n=2$)

* $P(s) \approx \prod_{i=1}^n P(w_i/w_{i-1}) \rightarrow \text{Bi-gram}$

$$P(s) \approx \prod_{i=1}^n P(w_i | w_{i-2}, w_{i-1}) \quad \text{Tri-gram.}$$

* Ex: P (east / The Arabian Knights are fairy tales of the)

↳ $p(\text{east} | \text{the})$ — Bi-gram

↳ $P(\text{east of the}) - \text{tri gram}$

* $\text{pseudoword}(\langle s \rangle)$ is introduced to mark the beginning of the sentence
 2 bi-gram $\langle s_1 \rangle$ - trigram $\rightarrow \langle s_1 \rangle \& \langle s_2 \rangle$.

Advantage

λ -Gram.

①

- * Easy to understand, implement
- * Can be easily convert to any gram

Disadv:

- * Underflow due to multiplication of probabilities

Sol: Use log. Add probabilities

- * Zero probability problem.

Sol: Use Laplace Smoothing

Given Corpus:

$$\sum_{i=1}^n \left[\frac{\text{value} + 1}{\text{value} + (\text{unique words})} \right] \text{ except } \langle S \rangle$$

$\langle S \rangle$ I am Henry $\langle /S \rangle$

$\langle S \rangle$ I like College $\langle /S \rangle$

$\langle S \rangle$ Do Henry like College $\langle /S \rangle$

$\langle S \rangle$ Henry I am $\langle /S \rangle$

$\langle S \rangle$ Do I like Henry $\langle /S \rangle$

$\langle S \rangle$ Do I like College $\langle /S \rangle$

$\langle S \rangle$ I do like Henry $\langle /S \rangle$

~~Do I like College~~ $\langle /S \rangle$

$$= P(I | \langle S \rangle) \times P(\text{like} | I) \times P(\text{College} | \text{like}) \times P(\langle /S \rangle | \text{College})$$
$$= \frac{3}{7} \times \frac{3}{6} \times \frac{3}{5} \times \frac{3}{3} = \frac{9}{70} = 0.13$$
$$= \log_e \left(\frac{3}{7} \right) + \log_e \left(\frac{3}{6} \right) + \log_e \left(\frac{3}{5} \right) + \log_e \left(\frac{3}{3} \right) = -2.0513$$

Perplexity

It is the inverse probability of the test data which is normalized by the number of words.

$$PP(w) = P(w_1, w_2, w_3 \dots w_n)^{-1/N}$$

$$PP(w) = \left(\prod_{i=1}^n \frac{1}{P(w_i | w_{i-1})} \right)^{1/N}$$

Ex: $\langle s \rangle$ I like college $\langle /s \rangle$

$$\begin{aligned} \left[\begin{array}{l} \text{Perplexity} \\ \text{for} \\ \text{Bigram} \end{array} \right] &= P(1 | \langle s \rangle) \times P(\text{like} | 1) \times P(\text{college} | \text{like}) \times P(\langle /s \rangle | \text{college}) \\ &= 3/7 \times 3/6 \times 3/5 \times 3/3 \\ &= 9/70 \\ &= 0.13 \end{aligned}$$

$$PP(w) = (1/0.13)^{1/4} = \underline{\underline{1.67}}$$

Perplexity
for
Trigram

$$\begin{aligned} P(w) &= P(\text{like} | \langle s \rangle) \times P(\text{college} | \text{like}) \times P(\langle /s \rangle | \text{like college}) \\ P(w) &= 1/3 \times 2/3 \times 3/3 = \\ &= 2/9 \end{aligned}$$

$$\begin{aligned} &= 0.22 \\ PP(w) &= \left(\frac{1}{0.22} \right)^{1/3} \end{aligned}$$

$$= \underline{\underline{1.66}}$$

less probability
so ~~more~~ best
Predicting model.

Which language model will have less perplexity is the best model for your data

Parts of speech Tagging (HMM)

①

POS Tagging

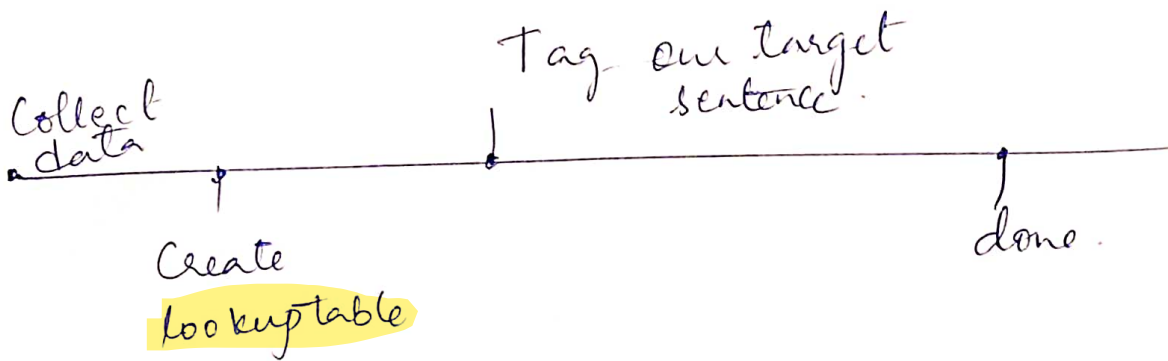
Noun: John, Car, India...

Verb: Run, swim...

Modal Verbs must, will, would, Can, may.

Mary Jane will

Jane saw will



Lookup table

Ex1: Jane saw will
Mary saw Jane

	N	V
Mary	1	-
saw	-	2
Jane	2	-
will	1	-

Ex2:

Mary will see Jane
will will see Mary
Jane will see will

Mary Jane will

Mary will see will

lookup table

	N	V	M
Mary	2	0	0
see	0	3	0
Jane	2	0	0
will	2	0	3

* So should consider "context" into consideration (2)
using Bigram.

	M-N	N-M	N-N
Mary-will	1	-	-
will-see	-	3	-
see-jane	-	-	1
will-will	1	-	-
will-see	0	0	4
see-mary	0	0	1
Jane-will	1	0	0
see-will	0	0	1

Mary will see will
? ? ? ?
Noun M. V (N) ✓

Ex: 3 Mary Jane will Spot

Lookup table

Mary Jane Can See will
Spot will See Mary
will Jane spot Mary?
Mary will ~~spot~~ pat spot.

	M-N	N-M	N-N
Mary-Jane			
Jane-can			
Can-see			
⋮			

Ques stem is Jane will spot will

If the occurrence is not there in data? → HMM

2 types of Probabilities

- ① Transition Probability → How likely ~~to~~ tags probability after another tag
- ② Emission Probability → How likely ~~to~~ tag will allocate for a word.

^NMary ^NJane ^MCan ^VSee ^NWill
^NSpot ^MWill ^VSee ^MMary
^MWill ^NJane ^VSpot ^NMary
^NMary ^MWill ^VSpot ^NSpot

lookup table

	N	M	V
Mary	2/9	0	0
Jane	1/9	0	0
Will	1/9	3/4	0
Spot	2/9	0	1/4
Can	0	1/4	0
See	0	0	2/4
Pat	0	0	1/4

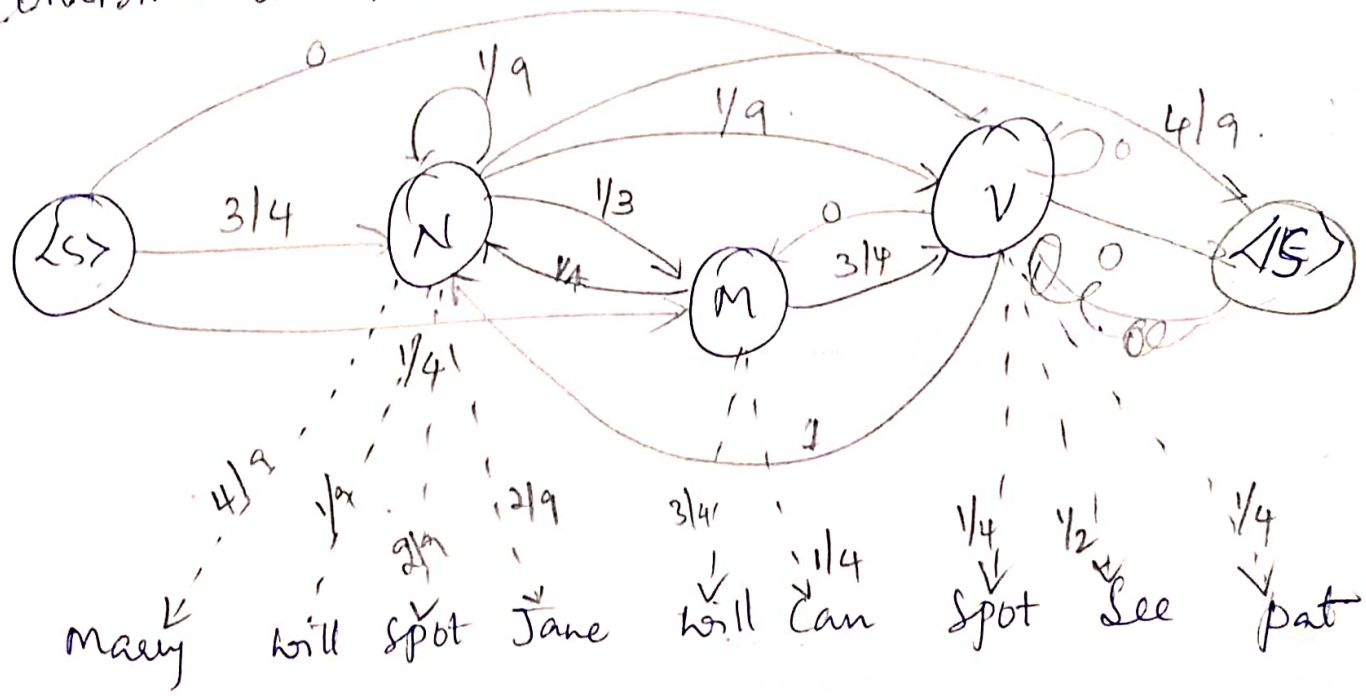
Emission Probability

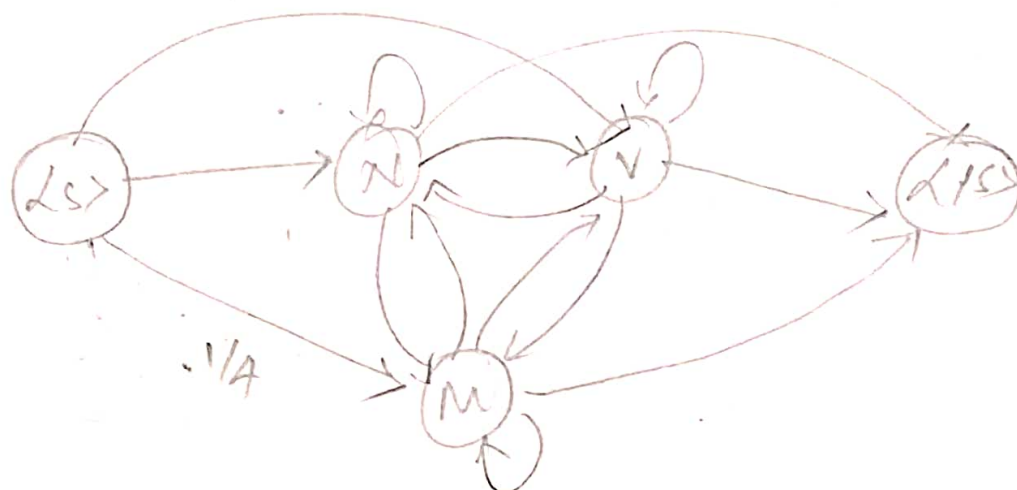
Transition Probability

add <S> & <I>S> to the states.

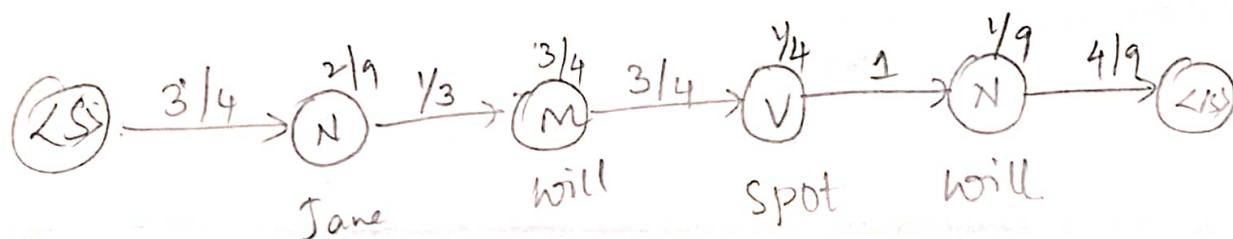
	N	M	V	<I>S>
<S>	3/4	1/4	-	-
N	1/9	2/9	1/9	4/9
M	1/4	0	3/4	-
V	4/9	-	-	-

Combine 2 Probabilities to create HMM.

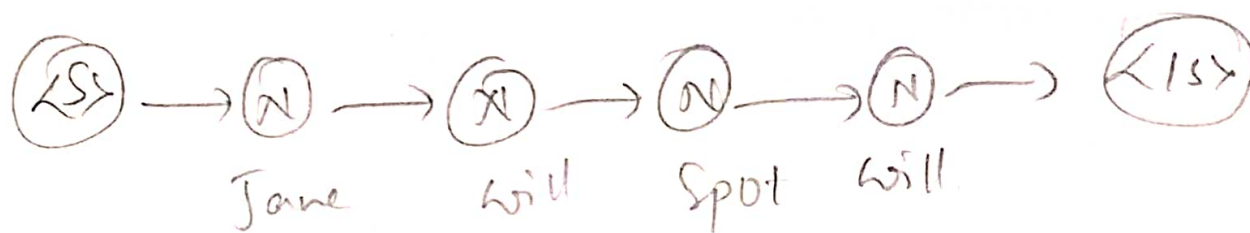




Jane will Spot Kill



= 0.003858 Multiply all the values.



How many combinations to compare: $= 0.0000002788$

$3^4 \Rightarrow 81$ (Hidden states) ^{no. of words in the stmt}

- * Computationally expensive.
- * As data grows the no. of observations & comparing probabilities also grow.

Weather observation

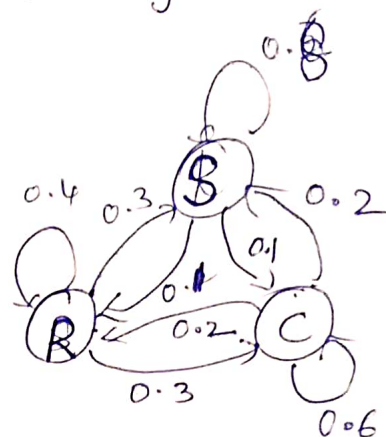
S1: Rainy

S2: Cloudy

S3: Sunny

The state transition probabilities are

$$A = \begin{matrix} & \begin{matrix} R & C & S \end{matrix} \\ \begin{matrix} R \\ C \\ S \end{matrix} & \begin{bmatrix} 0.4 & 0.3 & 0.3 \\ 0.2 & 0.6 & 0.2 \\ 0.1 & 0.1 & 0.8 \end{bmatrix} \end{matrix} \rightarrow \text{sum} = 1$$



Question:

① Given that the weather on day 1 is sunny, what is the probability that the weather for the next 7 day will be "Sun-Sun-rain-rain-sun-Cloudy-sun?"

$$O = \{S_3, S_3, S_3, S_1, S_1, S_3, S_2, S_3\}$$

$$P(O|\text{model}) = P(S_3, S_3, S_3, S_1, S_1, S_3, S_2, S_3 | \text{Model})$$

$$= P(S_3)P(S_3|S_3)P(S_3|S_3)P(S_1|S_3)P(S_1|S_1)$$

$$P(S_3|S_1)P(S_2|S_3)P(S_3|S_2)$$

$$= 1 \times 0.8 \times 0.8 \times 0.1 \times 0.4 \times 0.3 \times 0.1 \times 0.2$$

$$= \underline{\underline{1.536 \times 10^{-4}}}$$

② ~~Today~~ Today is sunny, what is the probability that tomorrow is sunny & next day is Rainy?

$$P(\text{Sunny} | \text{sunny}) \times P(\text{Rainy} | \text{sunny})$$

$$= 0.8 \times 0.1$$

$$= 0.08$$