Assignment 02

Temporal Subsampling of a Discrete Time Markov Process

(a)

$$egin{split} p(x_n,x_{n-1},\ldots,x_2) &= \sum_{x_1} p(x_n,x_{n-1},\ldots,x_1) \ &= \sum_{x_1} p(x_1) p(x_2|x_1) \ldots p(x_n|x_{n-1}) \ &= \prod_{i=3}^n p(x_i|x_{i-1}) imes \sum_{x_1} p(x_2|x_1) p(x_1) \ &= \prod_{i=3}^n p(x_i|x_{i-1}) imes p(x_2) \end{split}$$

Repeat the above process n-k-1 times and we have

$$p(x_n,x_{n-1},\dots,x_{n-k}) = p(x_{n-k}) \prod_{i=n-k+1}^n p(x_i|x_{i-1})$$

(b)

$$egin{aligned} p(x_1,x_3,x_4) &= \sum_{x_2} p(x_1,x_2,x_3,x_4) \ &= \sum_{x_2} p(x_1) p(x_2|x_1) p(x_3|x_2) p(x_4|x_3) \ &= p(x_1) p(x_4|x_3) \sum_{x_2} p(x_3|x_2) p(x_2|x_1) \ &= p(x_1) p(x_3|x_1) p(x_4|x_3) \end{aligned}$$

(c)

From

$$\left\{egin{aligned} p(x_1,x_3,x_4) &= p(x_1,x_3)p(x_4|x_1,x_3) \ p(x_1,x_3,x_4) &= p(x_1)p(x_3|x_1)p(x_4|x_3) \ p(x_1,x_3) &= p(x_1)p(x_3|x_1) \end{aligned}
ight.$$

we can conclude that

$$p(x_4|x_3,x_1) = p(x_4|x_3)$$

(d)

$$egin{aligned} p(x_1,x_2,x_4) &= \sum_{x_3} p(x_1,x_2,x_3,x_4) \ &= \sum_{x_3} p(x_1) p(x_2|x_1) p(x_3|x_2) p(x_4|x_3) \ &= p(x_1) p(x_2|x_1) \sum_{x_3} p(x_4|x_3) p(x_3|x_2) \ &= p(x_1) p(x_2|x_1) p(x_4|x_2) \end{aligned}$$

(e)

From

$$\left\{egin{aligned} p(x_1,x_2,x_4) &= p(x_1)p(x_2|x_1)p(x_4|x_2) \ p(x_1,x_2,x_4) &= p(x_1,x_2)p(x_4|x_1,x_2) \ p(x_1,x_2) &= p(x_1)p(x_2|x_1) \end{aligned}
ight.$$

we can conclude that

$$p(x_4|x_2,x_1) = p(x_4|x_2)$$

(f)

For any subset of random variables from a Markov process, the joint probability can be factored as a product of conditional probabilities, where each conditional probability depends only on the immediate predecessor in the selected subset.

Markov Models for Text: Seuss and Saki

(a)

```
lmhg ixub xrgq whlf ovxd jlgs qaol qqbb lccl ggjk
mrdz qwta uovx liei rjdu rwqu gnuk emzg axyl spgg
tgja senk nkke qxas lgtx uxxi jots tbjb iinn gesh
ielg htzx umhx nlfc ippm cvba jirm juer xslb yfsz
zmtb tcze vhvb ibbv erqb fbyr qrpk pzxp inry tjeq
pguh keov atkm dqyz hbvl twui ognq gcbc dtsa tmkk
kzay jsjb ipwr bjqc xjey bfoc ryzd mhrj pxzo xdej
spgi unwx kaah mety lhym gypn jwty mflo pteb jadr
jnvz owmr ekce tggc twfy smgh mccf jmus laru uqel
paut mdeu lawo fspo oqdu ghao zedh infu bemt oyap
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(b)

```
sidc iokn nrte tman lypl ylnr nnmd bare uyns ulko
teua uwlr otlr udot tnon moim sspo nyye olku ppdi
isww uuwy mdoe fnit uioi leoh anir sple eaep okiw
dpho dlen reyt nhri okeo yrtu nmya lloe wmur cohk
scna tmny acwu suer flyt tnye esds oeei rtnt iitr
prmo nmrl lili tnoo maiv eymr aneo myyl dceo pkyr
eade ieas nowe rnoh leai lyoo leho eoeh ocio laoh
oooc ilsa oeta wnnt loey ekbs cera etai itnl mdrt
hiee mhad iwum etrl aniw oert womi aoit nnel etii
aytt moie odee fiti iita btoy tmsw roki edit hddy
```

(c)

```
yrer omem udou coma noun doth tere ouyo dest noul nomy heem llik rewi youl heer othe atou thev ther keth meee aith like sche ithe reen wifr itom erke thea woul erew rote ther thit nota ouyw noul iker idld evea ceve vill linu sthe inde ithe enth dere leth them idor oule otsp roto rere ouro otam yoth omer eath ncot myoo erke rote erea eend eeno eren thea ilyo inor ikee math itre thet ithe keme ular nyot thin mami oure ulik mare dero here lith oull aman oull youn rere urot youd rere arke ilit hend
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```
ourr notr uldq ldum ther eere otch otzw like eall ayhs like spam midd ldse ther deth ndzg ould uldv lddl itsd ould lewd ould spam read onch otiu erea even hath reat notg deat otan ould dolk ewdh toqq then dopb thin amid myua here cene ikeg even ikek otya beej enec like tany tsfr enee ould from youl ourq rude sche like that uldo ikew ould ould itsu nche will ywhe otlf ther ulde spam then notg your ould here ikev thin hene topa omet eepn ould amid here otxd eate urlc like uldp love meth amid thin
```

(e)

(f)

1. Equiprobable Letters (Part a):

- Generated words are completely random
- No linguistic patterns or structure
- Expected to have very few valid English words
- 2. Letter Probabilities (Part b):
 - Words reflect the frequency distribution of letters in the source text
 - More realistic letter combinations than random
 - o Still lacks sequential dependencies between letters
- 3. First Order Markov Chain (Part c):
 - Considers the probability of the next letter given the current letter
 - Captures basic sequential patterns in the language
 - Should produce more realistic letter sequences
- 4. Second Order Markov Chain (Part d):
 - Considers the probability of the next letter given the previous two letters
 - Captures more complex linguistic patterns
 - Should produce the most realistic letter sequences
- 5. Comparison between Spamiam and Saki Story:
 - Spamiam: Short, repetitive text with limited vocabulary
 - Saki Story: Longer, more diverse text with richer vocabulary
 - Saki Story should produce more varied and realistic word patterns, but with the current amount of data, Spamiam produces more legal English words due to its repetitive nature
- 6. Expected Improvements with Higher Order Models:
 - Higher order models capture more complex dependencies
 - Should produce more valid English words
 - Better approximation of natural language patterns

(g)

Applying the entropy formula for Markov chains we easily get

Spamiam.txt Entropy Rates:

- Zero-order (letter probabilities): 4.0927 bits/letter
- First-order (Markov chain): 1.9503 bits/letter
- Second-order (Markov chain): 1.3253 bits/letter

Saki Story.txt Entropy Rates:

- Zero-order (letter probabilities): 4.1533 bits/letter
- First-order (Markov chain): 3.0546 bits/letter
- Second-order (Markov chain): 1.9179 bits/letter

Analysis:

- 1. Entropy rates generally decrease with higher order models
- 2. Saki Story has higher entropy than Spamiam due to more diverse vocabulary
- 3. Higher order models capture more structure, reducing uncertainty
- 4. The entropy rate approaches the true language entropy as order increases