Problem 1: Laplace Smoothing

Let |V| = 5 where V is the vocabulary and $N = \sum_{i=1}^{|V|} freq(w_i) = 1,200$ where N is the number of words in the corpus. Without smoothing, the probabilities of each noun in the corpus are:

$$\begin{split} P(maple) &= \frac{freq(maple)}{N} = \frac{600}{1,200} = 0.5 \\ P(oak) &= \frac{freq(oak)}{N} = \frac{400}{1,200} = 0.333 \\ P(pine) &= \frac{freq(pine)}{N} = \frac{180}{1,200} = 0.15 \\ P(spruce) &= \frac{freq(spruce)}{N} = \frac{20}{1,200} = 0.167 \\ P(aspen) &= \frac{freq(aspen)}{N} = \frac{0}{1,200} = 0 \end{split}$$

Using Laplace smoothing (aka: Add-One Smoothing), the new frequencies for each noun:

$$\begin{split} new_freq(maple) &= (freq(maple) + 1) * \frac{N}{N+V} = (600 + 1) * \frac{1,200}{1,200+5} = \frac{721,200}{1,205} = 598.506 \\ new_freq(oak) &= (freq(oak) + 1) * \frac{N}{N+V} = (400 + 1) * \frac{1,200}{1,200+5} = \frac{481,200}{1,205} = 399.336 \\ new_freq(pine) &= (freq(pine) + 1) * \frac{N}{N+V} = (180 + 1) * \frac{1,200}{1,200+5} = \frac{217,200}{1,205} = 180.249 \\ new_freq(spruce) &= (freq(spruce) + 1) * \frac{N}{N+V} = (20 + 1) * \frac{1,200}{1,200+5} = \frac{25,200}{1,205} = 20.913 \\ new_freq(aspen) &= (freq(aspen) + 1) * \frac{N}{N+V} = (0 + 1) * \frac{1,200}{1,200+5} = \frac{1,200}{1,205} = 0.966 \end{split}$$

Given these new frequencies, the new probabilities are calculated:

$$new_P(maple) = \frac{new_freq(maple)}{N} = \frac{598.506}{1,200} = 0.499$$

$$new_P(oak) = \frac{new_freq(oak)}{N} = \frac{399.336}{1,200} = 0.333$$

$$new_P(pine) = \frac{new_freq(pine)}{N} = \frac{180.249}{1,200} = 0.15$$

$$new_P(spruce) = \frac{new_freq(spruce)}{N} = \frac{20.913}{1,200} = 0.017$$

$$new_P(aspen) = \frac{new_freq(aspen)}{N} = \frac{0.996}{1,200} = 0.001$$

Completing the table:

| Noun | Freq. | Unsmoothed Prob. | Smoothed Freq. | Smoothed Prob. |
|--------|-------|------------------|----------------|----------------|
| maple | 600 | 0.5 | 598.506 | 0.499 |
| oak | 400 | 0.333 | 399.336 | 0.333 |
| pine | 180 | 0.15 | 180.249 | 0.15 |
| spruce | 20 | 0.017 | 20.913 | 0.017 |
| aspen | 0 | 0 | 0.996 | 0.001 |

Table 1: Unsmoothed and smoothed probabilities and frequencies.

2: Grammars and Recursive Transition Networks

(a) Grammar A and Grammar B - **DIFFERENT**

Grammar A requires the NP to begin with an article but Grammar B does not.

An example POS tag sequence accepted by Grammar B and not by Grammar A is: noun.

(b) Grammar A and Grammar C - DIFFERENT

Grammar C requires one or more adjectives after the article but Grammar A requires zero or more adjectives after the article.

An example POS tag sequence accepted by Grammar A and not by Grammar C is: art noun.

(c) Grammar A and RTN-2 - DIFFERENT

Grammar A requires the NP to begin with an article but RTN-2 does not.

An example POS tag sequence accepted by RTN-2 and not by Grammar A is: noun.

(d) Grammar A and RTN-3 - **DIFFERENT**

RTN-3 requires one or more adjectives after the article but Grammar A requires zero or more adjectives after the article.

An example POS tag sequence accepted by Grammar A and not by RTN-3 is: art noun.

(e) Grammar B and RTN-2 - SAME

(f) Grammar C and RTN-1 - **DIFFERENT**

Grammar C requires the NP to end with one or more nouns but RTN-1 does not.

An example POS tag sequence accepted by RTN-1 and not by Grammar C is: art adj.

(g) Grammar C and RTN-3 - SAME

(h) RTN-1 and RTN-3 - **DIFFERENT**

RTN-3 requires the NP to end with one or more nouns but RTN-1 does not.

An example POS tag sequence accepted by RTN-1 and not by Grammar C is: art adj.

3: N-Gram Probabilities

Let k denote the number of distinct lexical unigrams in the text corpus.

(a)
$$P(the) = \frac{freq(the)}{\sum\limits_{i}^{k} freq(w_i)} = \boxed{\frac{5}{34}}$$

Let k denote the number of distinct POS unigrams in the text corpus.

(b)
$$P(the) = \frac{freq(VERB)}{\sum\limits_{i}^{k} freq(T_i)} = \boxed{\frac{6}{34}}$$

Let $freq(W_{n-m},...,W_{n-1},W_n)$ denote the frequency of the phrase $W_{n-m},...,W_{n-1},W_n$ appearing in the text corpus.

(c)
$$P(young \mid girl) = \frac{freq(W_{n-1}, W_n)}{freq(W_{n-1})} = \frac{freq(girl \ young)}{freq(girl)} = \boxed{\frac{0}{3}}$$

(d)
$$P(girl \mid young) = \frac{freq(W_{n-1}, W_n)}{freq(W_{n-1})} = \frac{freq(young \ girl)}{freq(young)} = \boxed{\frac{2}{3}}$$

(e)
$$P(and \mid women) = \frac{freq(W_{n-1}, W_n)}{freq(W_{n-1})} = \frac{freq(women \ and)}{freq(women)} = \boxed{\frac{1}{3}}$$

(f)
$$P(thanked \mid young \ girl) = \frac{freq(W_{n-2}, W_{n-1}, W_n)}{freq(W_{n-2}, W_{n-1})} = \frac{freq(young \ girl \ thanked)}{freq(young \ girl)} = \boxed{\frac{0}{2}}$$

(g)
$$P(five \mid gave \ her) = \frac{freq(W_{n-2}, W_{n-1}, W_n)}{freq(W_{n-2}, W_{n-1})} = \frac{freq(gave \ her \ five)}{freq(gave \ her)} = \boxed{\frac{1}{2}}$$

Let C(event) denote the count of the given event occurring in the text corpus.

(h)
$$P(the \mid ART) = \frac{C(w_i \text{ with } tag \ T_i)}{C(any \text{ word } with \text{ } tag \ T_i)} = \frac{C(the \text{ with } tag \ ART)}{C(any \text{ word } with \text{ } tag \ ART)} = \boxed{\frac{5}{8}}$$

(i)
$$P(cross \mid NOUN) = \frac{C(w_i \text{ with tag } T_i)}{C(any \text{ word with tag } T_i)} = \frac{C(cross \text{ with tag } NOUN)}{C(any \text{ word with tag } NOUN)} = \boxed{\frac{0}{9}}$$

(j)
$$P(thanked \mid NOUN) = \frac{C(thanked \ with \ tag \ NOUN)}{C(any \ word \ with \ tag \ T_i)} = \frac{C(thanked \ with \ tag \ NOUN)}{C(any \ word \ with \ tag \ NOUN)} = \boxed{\frac{0}{9}}$$

(k)
$$P(NUM \mid PRO) = \frac{C(T_i \text{ immediately follows } T_{i-1})}{C(\text{any tag immediately follows } T_{i-1})} = \frac{C(NUM \text{ immediately follows } PRO)}{C(\text{any tag immediately follows } PRO)} = \boxed{\frac{1}{2}}$$

(1)
$$P(ART \mid VERB) = \frac{C(T_i \text{ immediately follows } T_{i-1})}{C(\text{any tag immediately follows } T_{i-1})} = \frac{C(ART \text{ immediately follows } VERB)}{C(\text{any tag immediately follows } VERB)} = \boxed{\frac{4}{6}}$$

4: Viterbi Algorithm

(a)
$$P(light = VERB) = P(VERB \mid \phi) * P(light \mid VERB) = 0.25 * 0.5 = 0.125$$

(b)
$$P(light = NOUN) = P(NOUN \mid \phi) * P(light \mid NOUN) = 0.7 * 0.6 = \boxed{0.42}$$

(c)
$$P(light = ADJ) = P(ADJ \mid \phi) * P(light \mid ADJ) = 0.15 * 0.2 = \boxed{0.03}$$

(d)
$$P(shows = VERB) = P(shows \mid V) * MAX[(P(light = V) * P(V \mid V)), (P(light = N) * P(V \mid N)), (P(light = A) * P(V \mid A))]$$

$$P(shows = VERB) = 0.3 * MAX[(0.125 * 0.4), (0.42 * 0.5), (0.03, 0.1)] = \boxed{0.063}$$

(e)
$$P(shows = NOUN) = P(shows \mid N) * MAX[(P(light = V) * P(V \mid V)), (P(light = N) * P(V \mid N)), (P(light = A) * P(VE \mid A))]$$

$$P(shows = NOUN) = 0.4 * MAX[(0.125 * 0.3), (0.42 * 0.8), (0.03, 0.6)] = \underbrace{\quad 0.1344}_{\quad \ \ }$$

(f)
$$P(shows = ADJ) = P(shows \mid A) * MAX[(P(light = V) * P(V \mid V)), (P(light = N) * P(V \mid N)), (P(light = A) * P(V \mid A))]$$

$$P(shows = ADJ) = 0.1 * MAX[(0.125 * 0.7), (0.42 * 0.2), (0.03, 0.9)] = \boxed{0.00875}$$

The most likely sequence of POS tags for the sentence " $Light\ shows$ " is Light=NOUN and shows=NOUN.