8. Machine Learning and Real-world Data. special states $3+\frac{1}{2}$ (a) M=(A.B). A: the matrice of the transition probability $\Rightarrow 5\times5$ special states 6+2

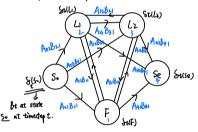
B: the matrice of the emission probability $\Rightarrow 5\times8$ states S= \S So. F, L., L2, Se \S . So. start state. So end state output k= \S to . I. 2. 3. 4. S. 6. to \S ko: start output. the end output Aij = $P(Xt-S_j | Xt-S_i)$, i.jeTo.5)

Bij =P(0t-kj | Xt-k), i.eTo.5), j eTo.8)

(b) A state diagram: Actually, we haven't learnt about this

-> (otherpoind to Ki

For example: the sample term is 1". Here I list all the possible transition pairs.



I label some arcs. with the publicity

malude (F→Sz

Se F

(ii) Count tran $(X_t = 4 \mid X_{t-1} = 1) = 1$. $A_{14} = P(X_{t-2} = 4 \mid X_{t-1} = 1) = 1$ This can be modelled by HMM. The hidden path with Fon the last roll is likely to yield higher probability.

(ountennism (Ot | Xt=3) They may both become small

(iii). Training data counts: Counttime $(Xt=3 \mid Xt+1=m)$ (m can be any state aside from 3) will be small. Hence $P(Xt=3 \mid Xt+1=m)$ will be small too. This behaviour reflects in HMM producing result sequences with fewer L2. It may not be exactly less than 2 in a row, So to some extent, it can be modelled.

civ) It's hard to tell the effect on probabilities and counts, since we're not sure which output dice the Croupier switches to and we only count the associations between V and the dice at the same timestep. Therefore, it can't be modelled by HMM.

