| 24 11 2 | 3 | | Deep Learning | |
|---------|------------------------------|---|--|---|
| o Re | cap GAN | | | |
| o ha | rwings in Alms | course | | |
| | | | stimal or equilibrium state | |
| | - V(G,P) = | E [hg | D(x)) + E [lig (1- | D(G(Z))) |
| | = | Example [log | D(n)] + E [ly [1- | D(a))] |
| | - Gisaw | ndul with paral | me ba | |
| | | ndl with par = arg [min'! to Larn of | | |
| 6 | - Alter Dupolati - Fix Fix | nati between up 6 and update D and update | dating of E Og. Of for k iterations - Og - S'G descent - San | Sample ZNP2, IN Polata Shochastic Gradient ascent able 2NP2 |
| 0 | D*(z) = | Parta (2) | | |
| 0 | C(6) = | Plak (2) + 2 (2) - by 4 + 2. | JS (Pall Pg) | |
| | | | and this is achieved w | hum g = parter (dist) |
| D | - GANS 0 | gen models. are difficult to | train | |
| | - Neverth - exav | who GANI are Afile Conditional y: \$ (x 2) | CAN in alditions to | one Several variants 2, he give a conditioning |
| | - The state | ility of GAN to | nining has been signific easier to train than GA | authrupured - e.g. WGAH |
| | - VAES Co - Report th | intime to be a current literal | popular but nut as un | uh os GANS or D.M. |
| | | | | |