x2 + x 2 , whe It's The science of getting computers to learn without being explicity Applications of Machine learning AGI vartificial general Linear Regression Model Parts ailultinaidai in Surperviser learning Model in The is as to los des à abilition Hade to it is a sein classification Hadel sto it sie a + gives Small number of Possible outputs gives infinitely Many Possible outpute Regression Models all to Lie Notation win X: "in Put" Variable @ "inPut" Feature) y nontfut " resulted in farget in variable feed wis m: number of training examples (X,4): Single training example (x(1)y(1)); (the training example of st, 2nd, 3rd) feature & A Predictional estimated you How to represent f? of wb(x)-wx+6 opens is a see xxx -unction .. squared error Cost function .. J(w,b) = 1 & (flu,b(x(1)) -y(0))2 int wition tree Machine learning lafield of study that gives computers the ability to learn without being explicitly programmed

(3) W=W- X dw J(w) -oIF K is too small Gradient descent may be slow -If a is too large covershoot braver reach winimum Can reach local minimum with Fixed learning rater of ail to converge 1 J(w) diverge Near a local minimum L Derivative becomes smaller le update Steps become smaller + Can reach minimum without decreasing Cearning rate fu, b (x(1)) = wx + b Gradient descent forlinear regression linear regression model Cost Function Fub (x)= wx+b J(W, 6) = 1 & (For, 6) x(1) - y(1) 2 Gradient descent algorithm repeat until convergence & w=w-d, & J(w,b) - = { (Fu,b (x)-y') } b=b-d = J(w,b) = = { (Fu,b (x) - y') } (Fu,b (x) - y') "Botch"; tach Step of gradient descent uses all the training examp