

### Polynomial regression with regularization

Membrane pressure drop When purifying drinking water, you can use a so-called membrane filtration. In an experiment one wishes to examine the relationship between the pressure drop across a membrane and the flux (flow per area) through the membrane. We observe the following 10 related values of pressure (x) and flux (y):

Use polynomial regression with regularization (gradient descent algorithm) to fit the following data to the hypothesis.

$$h_{\theta}(x) = \theta_0 + \theta_1 * x^1 + \theta_2 * x^2 + \theta_3 * x^3 + \theta_4 * x^4 + \theta_5 * x^5 + \theta_6 * x^6$$

<b>Pressure (x)</b>	1.02	2.08	2.89	4.01	5.32	5.83	7.26	7.96	9.11	9.99
<b>Flux (y)</b>	1.15	0.85	1.56	1.72	4.32	5.07	5.00	5.31	6.17	7.04

let initial  $\theta_0 = \theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = 0$  , learning rate  $\alpha = 0.005$ ,  
regularization parameter  $\lambda = 0.5$

calculate two epochs

#### solution:

- 1- Normalize features x

$$X\_scaled = \frac{x - \text{mean}}{\text{std}}$$

- 2- You are free to regularize  $\theta_0$  or not

in this example  $\theta_0$  is regularized for simplicity of calculations.

- 3- Cost function:  $J(\theta) = \frac{1}{2m} \sum err^2 + \frac{\lambda}{2m} \sum \theta^2$

- 4- Weight update:  $\theta_j = \theta_j * \left(1 - \frac{\alpha \lambda}{m}\right) - \frac{\alpha}{m} \sum err * x^j$

1<sup>st</sup> epoch:

#	x	y	$h = \sum \theta_i * x^i$	$err = h - y$	$err * x$	$err * x^2$	$err * x^3$	$err * x^4$	$err * x^5$	$err * x^6$	$err^2$
1	-1.4884	1.1500	0	-1.1500	1.7117	-2.5476	3.7919	-5.6439	8.4003	-12.5030	1.3225
2	-1.1399	0.8500	0	-0.8500	0.9689	-1.1045	1.2590	-1.4351	1.6359	-1.8647	0.7225
3	-0.8736	1.5600	0	-1.5600	1.3628	-1.1906	1.0401	-0.9086	0.7938	-0.6934	2.4336
4	-0.5053	1.7200	0	-1.7200	0.8691	-0.4392	0.2219	-0.1121	0.0567	-0.0286	2.9584
5	-0.0746	4.3200	0	-4.3200	0.3223	-0.0240	0.0018	-0.0001	0.0000	0.0000	18.6624
6	0.0930	5.0700	0	-5.0700	-0.4715	-0.0439	-0.0041	-0.0004	0.0000	0.0000	25.7049
7	0.5632	5.0000	0	-5.0000	-2.8160	-1.5860	-0.8932	-0.5031	-0.2833	-0.1596	25.0000
8	0.7933	5.3100	0	-5.3100	-4.2124	-3.3417	-2.6510	-2.1030	-1.6683	-1.3235	28.1961
9	1.1714	6.1700	0	-6.1700	-7.2275	-8.4663	-9.9175	-11.6173	-13.6085	-15.9410	38.0689
10	1.4608	7.0400	0	-7.0400	-10.2840	-15.0229	-21.9455	-32.0579	-46.8302	-68.4096	49.5616
$\Sigma$				-38.1900	-19.7767	-33.7667	-29.0966	-54.3816	-51.5038	-100.9236	192.6309

	$\theta_0$	$\theta_1$	$\theta_2$	$\theta_3$	$\theta_4$	$\theta_5$	$\theta_6$	$\Sigma$		cost	9.6317
	0.0191	0.0099	0.0169	0.0145	0.0272	0.0258	0.0505				
$\theta^2$	0.0004	0.0001	0.0003	0.0002	0.0007	0.0007	0.0025	0.0049			

2<sup>nd</sup> epoch

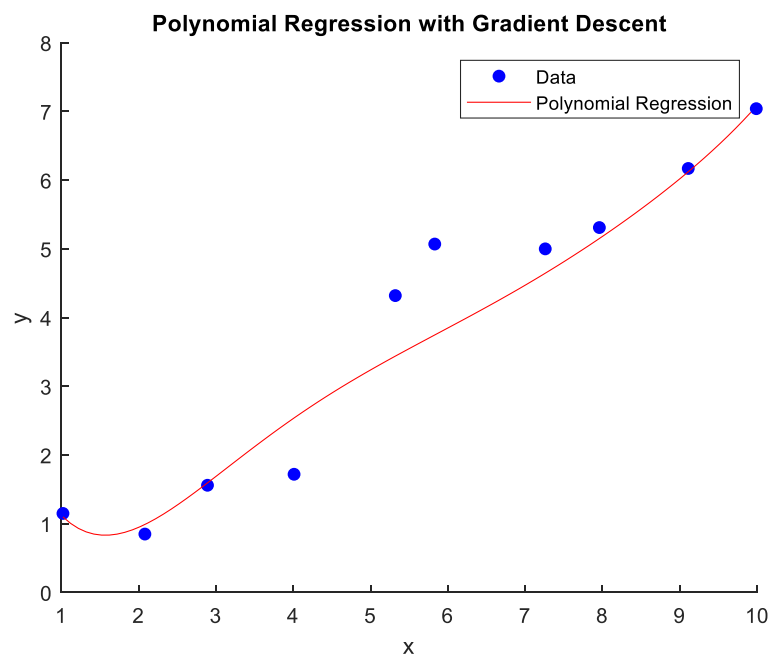
#	x	y	$h = \sum \theta_i x^i$	err = h-y	err*x	err*x <sup>2</sup>	err*x <sup>3</sup>	err*x <sup>4</sup>	err*x <sup>5</sup>	err*x <sup>6</sup>	err <sup>2</sup>
1	1.4884	1.1500	0.4878	-0.6622	0.9857	-1.4670	2.1836	-3.2500	4.8373	-7.1998	0.4385
2	1.1399	0.8500	0.1153	-0.7347	0.8375	-0.9547	1.0883	-1.2405	1.4141	-1.6119	0.5398
3	0.8736	1.5600	0.0388	-1.5212	1.3289	-1.1609	1.0142	-0.8860	0.7740	-0.6762	2.3140
4	0.5053	1.7200	0.0183	-1.7017	0.8599	-0.4345	0.2195	-0.1109	0.0561	-0.0283	2.8958
5	0.0746	4.3200	0.0184	-4.3016	0.3209	-0.0239	0.0018	-0.0001	0.0000	0.0000	18.5034
6	0.0930	5.0700	0.0202	-5.0498	-0.4696	-0.0437	-0.0041	-0.0004	0.0000	0.0000	25.5007
7	0.5632	5.0000	0.0384	-4.9616	-2.7944	-1.5738	-0.8864	-0.4992	-0.2811	-0.1583	24.6172
8	0.7933	5.3100	0.0763	-5.2337	-4.1519	-3.2937	-2.6129	-2.0728	-1.6444	-1.3045	27.3920
9	1.1714	6.1700	0.3156	-5.8544	-6.8578	-8.0333	-9.4102	-11.0231	-12.9124	-15.1256	34.2740
10	1.4608	7.0400	0.9004	-6.1396	-8.9687	-13.1015	-19.1387	-27.9579	-40.8408	-59.6603	37.6948
Σ				-36.1606	18.9096	-30.0871	27.5449	-47.0409	48.5974	-85.7650	174.1703

	θ0	θ1	θ2	θ3	θ4	θ5	θ6	Σ	cost
	0.0181	0.0095	0.0150	0.0138	0.0235	0.0243	0.0429		8.7086
θ <sup>2</sup>	0.0003	0.0001	0.0002	0.0002	0.0006	0.0006	0.0018	0.0038	

Cost 2 < cost 1

After 100000 iterations

θ0	3.5773
θ1	1.8358
θ2	-0.1659
θ3	0.5668
θ4	-0.0559
θ5	-0.2135
θ6	0.1109



At  $\lambda = 0$  (no regularization)

