

Epoch	194/3000	195/3000	196/3000	197/3000	198/3000	199/3000	200/3000	201/3000	202/3000	203/3000	204/3000	205/3000	206/3000	207/3000	208/3000	209/3000	210/3000	211/3000	212/3000	213/3000	214/3000	215/3000	216/3000	217/3000	218/3000	219/3000	220/3000	221/3000	222/3000	223/3000	224/3000	225/3000	226/3000	227/3000	228/3000	229/3000	230/3000	231/3000	232/3000	233/3000	234/3000	235/3000	236/3000	237/3000	238/3000	239/3000	240/3000	241/3000	242/3000	243/3000	244/3000	245/3000	246/3000	247/3000	248/3000	249/3000	250/3000	251/3000	252/3000	253/3000	254/3000	255/3000	256/3000	257/3000	258/3000	259/3000	260/3000	261/3000	262/3000	263/3000	264/3000	265/3000	266/3000	267/3000	268/3000	269/3000	270/3000	271/3000	272/3000	273/3000	274/3000	275/3000	276/3000	277/3000	278/3000	279/3000	280/3000	281/3000	282/3000	283/3000	284/3000	285/3000	286/3000	287/3000	288/3000	289/3000	290/3000	291/3000	292/3000	293/3000	294/3000	295/3000	296/3000	297/3000	298/3000	299/3000	300/3000	301/3000	302/3000	303/3000	304/3000	305/3000	306/3000	307/3000	308/3000	309/3000	310/3000	311/3000	312/3000	313/3000	314/3000	315/3000	316/3000	317/3000	318/3000	319/3000	320/3000	321/3000	322/3000	323/3000	324/3000	325/3000	326/3000	327/3000	328/3000	329/3000	330/3000	331/3000	332/3000	333/3000	334/3000	335/3000	336/3000	337/3000	338/3000	339/3000	340/3000	341/3000	342/3000	343/3000	344/3000	345/3000	346/3000	347/3000	348/3000	349/3000	350/3000	351/3000	352/3000	353/3000	354/3000	355/3000	356/3000	357/3000	358/3000	359/3000	360/3000	361/3000	362/3000	363/3000	364/3000	365/3000	366/3000	367/3000	368/3000	369/3000	370/3000	371/3000	372/3000	373/3000	374/3000	375/3000	376/3000	377/3000	378/3000	379/3000	380/3000	381/3000	382/3000	383/3000	384/3000	385/3000	386/3000	387/3000	388/3000	389/3000	390/3000	391/3000	392/3000	393/3000	394/3000	395/3000	396/3000	397/3000	398/3000	399/3000	400/3000	401/3000	402/3000	403/3000	404/3000	405/3000	406/3000	407/3000	408/3000	409/3000	410/3000	411/3000	412/3000	413/3000	414/3000	415/3000	416/3000	417/3000	418/3000	419/3000	420/3000	421/3000	422/3000	423/3000	424/3000	425/3000	426/3000	427/3000	428/3000	429/3000	430/3000	431/3000	432/3000	433/3000	434/3000	435/3000	436/3000	437/3000	438/3000	439/3000	440/3000	441/3000	442/3000	443/3000	444/3000	445/3000	446/3000	447/3000	448/3000	449/3000	450/3000	451/3000	452/3000	453/3000	454/3000	455/3000	456/3000	457/3000	458/3000	459/3000	460/3000	461/3000	462/3000	463/3000	464/3000	465/3000	466/3000	467/3000	468/3000	469/3000	470/3000	471/3000	472/3000	473/3000	474/3000	475/3000	476/3000	477/3000	478/3000	479/3000	480/3000	481/3000	482/3000	483/3000	484/3000	485/3000	486/3000	487/3000	488/3000	489/3000	490/3000	491/3000	492/3000	493/3000	494/3000	495/3000	496/3000	497/3000	498/3000	499/3000	500/3000	501/3000	502/3000	503/3000	504/3000	505/3000	506/3000	507/3000	508/3000	509/3000	510/3000	511/3000	512/3000	513/3000	514/3000	515/3000	516/3000	517/3000	518/3000	519/3000	520/3000	521/3000	522/3000	523/3000	524/3000	525/3000	526/3000	527/3000	528/3000	529/3000	530/3000	531/3000	532/3000	533/3000	534/3000	535/3000	536/3000	537/3000	538/3000	539/3000	540/3000	541/3000	542/3000	543/3000	544/3000	545/3000	546/3000	547/3000	548/3000	549/3000	550/3000	551/3000	552/3000	553/3000	554/3000	555/3000	556/3000	557/3000	558/3000	559/3000	560/3000	561/3000	562/3000	563/3000	564/3000	565/3000	566/3000	567/3000	568/3000	569/3000	570/3000	571/3000	572/3000	573/3000	574/3000	575/3000	576/3000	577/3000	578/3000	579/3000	580/3000	581/3000	582/3000	583/3000	584/3000	585/3000	586/3000	587/3000	588/3000	589/3000	590/3000	591/3000	592/3000	593/3000	594/3000	595/3000	596/3000	597/3000	598/3000	599/3000	600/3000																																																																																																																																																																																																																																										
loss	4.9737	4.9681	4.9621	4.9565	4.9506	4.9446	4.9386	4.9326	4.9267	4.9207	4.9147	4.9087	4.9027	4.8967	4.8907	4.8847	4.8787	4.8727	4.8667	4.8607	4.8547	4.8487	4.8427	4.8367	4.8307	4.8247	4.8187	4.8127	4.8067	4.8007	4.7947	4.7887	4.7827	4.7767	4.7707	4.7647	4.7587	4.7527	4.7467	4.7407	4.7347	4.7287	4.7227	4.7167	4.7107	4.7047	4.6987	4.6927	4.6867	4.6807	4.6747	4.6687	4.6627	4.6567	4.6507	4.6447	4.6387	4.6327	4.6267	4.6207	4.6147	4.6087	4.6027	4.5967	4.5907	4.5847	4.5787	4.5727	4.5667	4.5607	4.5547	4.5487	4.5427	4.5367	4.5307	4.5247	4.5187	4.5127	4.5067	4.5007	4.4947	4.4887	4.4827	4.4767	4.4707	4.4647	4.4587	4.4527	4.4467	4.4407	4.4347	4.4287	4.4227	4.4167	4.4107	4.4047	4.3987	4.3927	4.3867	4.3807	4.3747	4.3687	4.3627	4.3567	4.3507	4.3447	4.3387	4.3327	4.3267	4.3207	4.3147	4.3087	4.3027	4.2967	4.2907	4.2847	4.2787	4.2727	4.2667	4.2607	4.2547	4.2487	4.2427	4.2367	4.2307	4.2247	4.2187	4.2127	4.2067	4.2007	4.1947	4.1887	4.1827	4.1767	4.1707	4.1647	4.1587	4.1527	4.1467	4.1407	4.1347	4.1287	4.1227	4.1167	4.1107	4.1047	4.0987	4.0927	4.0867	4.0807	4.0747	4.0687	4.0627	4.0567	4.0507	4.0447	4.0387	4.0327	4.0267	4.0207	4.0147	4.0087	4.0027	3.9967	3.9907	3.9847	3.9787	3.9727	3.9667	3.9607	3.9547	3.9487	3.9427	3.9367	3.9307	3.9247	3.9187	3.9127	3.9067	3.9007	3.8947	3.8887	3.8827	3.8767	3.8707	3.8647	3.8587	3.8527	3.8467	3.8407	3.8347	3.8287	3.8227	3.8167	3.8107	3.8047	3.7987	3.7927	3.7867	3.7807	3.7747	3.7687	3.7627	3.7567	3.7507	3.7447	3.7387	3.7327	3.7267	3.7207	3.7147	3.7087	3.7027	3.6967	3.6907	3.6847	3.6787	3.6727	3.6667	3.6607	3.6547	3.6487	3.6427	3.6367	3.6307	3.6247	3.6187	3.6127	3.6067	3.6007	3.5947	3.5887	3.5827	3.5767	3.5707	3.5647	3.5587	3.5527	3.5467	3.5407	3.5347	3.5287	3.5227	3.5167	3.5107	3.5047	3.4987	3.4927	3.4867	3.4807	3.4747	3.4687	3.4627	3.4567	3.4507	3.4447	3.4387	3.4327	3.4267	3.4207	3.4147	3.4087	3.4027	3.3967	3.3907	3.3847	3.3787	3.3727	3.3667	3.3607	3.3547	3.3487	3.3427	3.3367	3.3307	3.3247	3.3187	3.3127	3.3067	3.3007	3.2947	3.2887	3.2827	3.2767	3.2707	3.2647	3.2587	3.2527	3.2467	3.2407	3.2347	3.2287	3.2227	3.2167	3.2107	3.2047	3.1987	3.1927	3.1867	3.1807	3.1747	3.1687	3.1627	3.1567	3.1507	3.1447	3.1387	3.1327	3.1267	3.1207	3.1147	3.1087	3.1027	3.0967	3.0907	3.0847	3.0787	3.0727	3.0667	3.0607	3.0547	3.0487	3.0427	3.0367	3.0307	3.0247	3.0187	3.0127	3.0067	3.0007	2.9947	2.9887	2.9827	2.9767	2.9707	2.9647	2.9587	2.9527	2.9467	2.9407	2.9347	2.9287	2.9227	2.9167	2.9107	2.9047	2.8987	2.8927	2.8867	2.8807	2.8747	2.8687	2.8627	2.8567	2.8507	2.8447	2.8387	2.8327	2.8267	2.8207	2.8147	2.8087	2.8027	2.7967	2.7907	2.7847	2.7787	2.7727	2.7667	2.7607	2.7547	2.7487	2.7427	2.7367	2.7307	2.7247	2.7187	2.7127	2.7067	2.7007	2.6947	2.6887	2.6827	2.6767	2.6707	2.6647	2.6587	2.6527	2.6467	2.6407	2.6347	2.6287	2.6227	2.6167	2.6107	2.6047	2.5987	2.5927	2.5867	2.5807	2.5747	2.5687	2.5627	2.5567	2.5507	2.5447	2.5387	2.5327	2.5267	2.5207	2.5147	2.5087	2.5027	2.4967	2.4907	2.4847	2.4787	2.4727	2.4667	2.4607	2.4547	2.4487	2.4427	2.4367	2.4307	2.4247	2.4187	2.4127	2.4067	2.4007	2.3947	2.3887	2.3827	2.3767	2.3707	2.3647	2.3587	2.3527	2.3467	2.3407	2.3347	2.3287	2.3227	2.3167	2.3107	2.3047	2.2987	2.2927	2.2867	2.2807	2.2747	2.2687	2.2627	2.2567	2.2507	2.2447	2.2387	2.2327	2.2267	2.2207	2.2147	2.2087	2.2027	2.1967	2.1907	2.1847	2.1787	2.1727	2.1667	2.1607	2.1547	2.1487	2.1427	2.1367	2.1307	2.1247	2.1187	2.1127	2.1067	2.1007	2.0947	2.0887	2.0827	2.0767	2.0707	2.0647	2.0587	2.0527	2.0467	2.0407	2.0347	2.0287	2.0227	2.0167	2.0107	2.0047	1.9987	1.9927	1.9867	1.9807	1.9747	1.9687	1.9627	1.9567	1.9507	1.9447	1.9387	1.9327	1.9267	1.9207	1.9147	1.9087	1.9027	1.8967	1.8907	1.8847	1.8787	1.8727	1.8667	1.8607	1.8547	1.8487	1.8427	1.8367	1.8307	1.8247	1.8187	1.8127	1.8067	1.8007	1.7947	1.7887	1.7827	1.7767	1.7707	1.7647	1.7587	1.7527	1.7467	1.7407	1.7347	1.7287	1.7227	1.7167	1.7107	1.7047	1.6987	1.6927	1.6867	1.6807	1.6747	1.6687	1.6627	1.6567	1.6507	1.6447	1.6387	1.6327	1.6267	1.6207	1.6147	1.6087	1.6027	1.5967	1.5907	1.5847	1.5787	1.5727	1.5667	1.5607	1.5547	1.5487	1.5427	1.5367	1.5307	1.5247	1.5187	1.5127	1.5067	1.5007	1.4947	1.4887	1.4827	1.4767	1.4707	1.4647	1.4587	1.4527	1.4467	1.4407	1.4347	1.4287	1.4227	1.4167	1.4107	1.4047	1.3987	1.3927	1.3867	1.3807	1.3747	1.3687	1.3627	1.3567	1.3507	1.3447	1.3387	1.3327	1.3267	1.3207	1.3147	1.3087	1.3027	1.2967	1.2907	1.2847	1.2787	1.2727	1.2667	1.2607	1.2547	1.2487	1.2427	1.2367	1.2307	1.2247	1.2187	1.2127	1.2067	1.2007	1.1947	1.1887	1.1827	1.1767	1.1707	1.1647	1.1587	1.1527	1.1467	1.1407	1.1347</

Bpoch	671/3000	-	mse	2.6033	-	val_loss	4.9776	-	val_mse	4.1557
Bpoch	672/3000	-	mse	2.6087	-	val_loss	4.9793	-	val_mse	4.1526
Bpoch	673/3000	-	mse	2.6107	-	val_loss	4.9793	-	val_mse	4.1495
Bpoch	674/3000	-	mse	2.6128	-	val_loss	4.9793	-	val_mse	4.1464
Bpoch	675/3000	-	mse	2.6149	-	val_loss	4.9793	-	val_mse	4.1432
Bpoch	676/3000	-	mse	2.6170	-	val_loss	4.9793	-	val_mse	4.1402
Bpoch	677/3000	-	mse	2.6191	-	val_loss	4.9793	-	val_mse	4.1371
Bpoch	678/3000	-	mse	2.6212	-	val_loss	4.9793	-	val_mse	4.1340
Bpoch	679/3000	-	mse	2.6233	-	val_loss	4.9793	-	val_mse	4.1310
Bpoch	680/3000	-	mse	2.6254	-	val_loss	4.9793	-	val_mse	4.1279
Bpoch	681/3000	-	mse	2.6275	-	val_loss	4.9793	-	val_mse	4.1248
Bpoch	682/3000	-	mse	2.6296	-	val_loss	4.9793	-	val_mse	4.1217
Bpoch	683/3000	-	mse	2.6317	-	val_loss	4.9793	-	val_mse	4.1186
Bpoch	684/3000	-	mse	2.6338	-	val_loss	4.9793	-	val_mse	4.1155
Bpoch	685/3000	-	mse	2.6359	-	val_loss	4.9793	-	val_mse	4.1124
Bpoch	686/3000	-	mse	2.6380	-	val_loss	4.9793	-	val_mse	4.1093
Bpoch	687/3000	-	mse	2.6401	-	val_loss	4.9793	-	val_mse	4.1062
Bpoch	688/3000	-	mse	2.6422	-	val_loss	4.9793	-	val_mse	4.1031
Bpoch	689/3000	-	mse	2.6443	-	val_loss	4.9793	-	val_mse	4.1000
Bpoch	690/3000	-	mse	2.6464	-	val_loss	4.9793	-	val_mse	4.0969
Bpoch	691/3000	-	mse	2.6485	-	val_loss	4.9793	-	val_mse	4.0938
Bpoch	692/3000	-	mse	2.6506	-	val_loss	4.9793	-	val_mse	4.0907
Bpoch	693/3000	-	mse	2.6527	-	val_loss	4.9793	-	val_mse	4.0876
Bpoch	694/3000	-	mse	2.6548	-	val_loss	4.9793	-	val_mse	4.0845
Bpoch	695/3000	-	mse	2.6569	-	val_loss	4.9793	-	val_mse	4.0814
Bpoch	696/3000	-	mse	2.6590	-	val_loss	4.9793	-	val_mse	4.0783
Bpoch	697/3000	-	mse	2.6611	-	val_loss	4.9793	-	val_mse	4.0752
Bpoch	698/3000	-	mse	2.6632	-	val_loss	4.9793	-	val_mse	4.0721
Bpoch	699/3000	-	mse	2.6653	-	val_loss	4.9793	-	val_mse	4.0690
Bpoch	700/3000	-	mse	2.6674	-	val_loss	4.9793	-	val_mse	4.0659
Bpoch	701/3000	-	mse	2.6695	-	val_loss	4.9793	-	val_mse	4.0628
Bpoch	702/3000	-	mse	2.6716	-	val_loss	4.9793	-	val_mse	4.0597
Bpoch	703/3000	-	mse	2.6737	-	val_loss	4.9793	-	val_mse	4.0566
Bpoch	704/3000	-	mse	2.6758	-	val_loss	4.9793	-	val_mse	4.0535
Bpoch	705/3000	-	mse	2.6779	-	val_loss	4.9793	-	val_mse	4.0504
Bpoch	706/3000	-	mse	2.6800	-	val_loss	4.9793	-	val_mse	4.0473
Bpoch	707/3000	-	mse	2.6821	-	val_loss	4.9793	-	val_mse	4.0442
Bpoch	708/3000	-	mse	2.6842	-	val_loss	4.9793	-	val_mse	4.0411
Bpoch	709/3000	-	mse	2.6863	-	val_loss	4.9793	-	val_mse	4.0380
Bpoch	710/3000	-	mse	2.6884	-	val_loss	4.9793	-	val_mse	4.0349
Bpoch	711/3000	-	mse	2.6905	-	val_loss	4.9793	-	val_mse	4.0318
Bpoch	712/3000	-	mse	2.6926	-	val_loss	4.9793	-	val_mse	4.0287
Bpoch	713/3000	-	mse	2.6947	-	val_loss	4.9793	-	val_mse	4.0256
Bpoch	714/3000	-	mse	2.6968	-	val_loss	4.9793	-		

Epoch	6/6	0s	-loss:	2.2663	-mse:	1.5903	-val_loss:	4.1395	-val_mse:	3.4137
Epoch	6/6	0s	-loss:	2.2663	-mse:	1.5903	-val_loss:	4.1395	-val_mse:	3.4137
Epoch	6/6	0s	-loss:	2.3145	-mse:	1.5889	-val_loss:	4.1384	-val_mse:	3.4130
Epoch	1153/3000	0s	-loss:	2.3135	-mse:	1.5892	-val_loss:	4.1380	-val_mse:	3.4128
Epoch	6/6	0s	-loss:	2.3126	-mse:	1.5875	-val_loss:	4.1374	-val_mse:	3.4123
Epoch	6/6	0s	-loss:	2.3117	-mse:	1.5867	-val_loss:	4.1362	-val_mse:	3.4119
Epoch	6/6	0s	-loss:	2.3107	-mse:	1.5859	-val_loss:	4.1362	-val_mse:	3.4115
Epoch	1157/3000	0s	-loss:	2.3089	-mse:	1.5853	-val_loss:	4.1356	-val_mse:	3.4111
Epoch	6/6	0s	-loss:	2.3090	-mse:	1.5846	-val_loss:	4.1349	-val_mse:	3.4106
Epoch	6/6	0s	-loss:	2.3081	-mse:	1.5838	-val_loss:	4.1343	-val_mse:	3.4102
Epoch	1161/3000	0s	-loss:	2.3073	-mse:	1.5833	-val_loss:	4.1337	-val_mse:	3.4098
Epoch	6/6	0s	-loss:	2.3064	-mse:	1.5824	-val_loss:	4.1333	-val_mse:	3.4094
Epoch	1172/3000	0s	-loss:	2.3054	-mse:	1.5818	-val_loss:	4.1326	-val_mse:	3.4091
Epoch	6/6	0s	-loss:	2.3044	-mse:	1.5803	-val_loss:	4.1321	-val_mse:	3.4086
Epoch	6/6	0s	-loss:	2.3035	-mse:	1.5803	-val_loss:	4.1317	-val_mse:	3.4086
Epoch	1176/3000	0s	-loss:	2.3026	-mse:	1.5796	-val_loss:	4.1311	-val_mse:	3.4082
Epoch	6/6	0s	-loss:	2.3018	-mse:	1.5790	-val_loss:	4.1305	-val_mse:	3.4078
Epoch	6/6	0s	-loss:	2.3009	-mse:	1.5783	-val_loss:	4.1300	-val_mse:	3.4076
Epoch	1180/3000	0s	-loss:	2.3001	-mse:	1.5776	-val_loss:	4.1295	-val_mse:	3.4072
Epoch	6/6	0s	-loss:	2.2992	-mse:	1.5768	-val_loss:	4.1289	-val_mse:	3.4067
Epoch	1177/3000	0s	-loss:	2.2982	-mse:	1.5761	-val_loss:	4.1283	-val_mse:	3.4063
Epoch	6/6	0s	-loss:	2.2973	-mse:	1.5754	-val_loss:	4.1278	-val_mse:	3.4061
Epoch	1172/3000	0s	-loss:	2.2964	-mse:	1.5747	-val_loss:	4.1273	-val_mse:	3.4057
Epoch	1173/3000	0s	-loss:	2.2955	-mse:	1.5740	-val_loss:	4.1267	-val_mse:	3.4054
Epoch	6/6	0s	-loss:	2.2947	-mse:	1.5734	-val_loss:	4.1262	-val_mse:	3.4051
Epoch	6/6	0s	-loss:	2.2937	-mse:	1.5726	-val_loss:	4.1255	-val_mse:	3.4046
Epoch	1176/3000	0s	-loss:	2.2928	-mse:	1.5713	-val_loss:	4.1248	-val_mse:	3.4040
Epoch	6/6	0s	-loss:	2.2918	-mse:	1.5711	-val_loss:	4.1244	-val_mse:	3.4038
Epoch	6/6	0s	-loss:	2.2911	-mse:	1.5706	-val_loss:	4.1241	-val_mse:	3.4036
Epoch	6/6	0s	-loss:	2.2902	-mse:	1.5699	-val_loss:	4.1236	-val_mse:	3.4034
Epoch	1180/3000	0s	-loss:	2.2896	-mse:	1.5693	-val_loss:	4.1232	-val_mse:	3.4029
Epoch	6/6	0s	-loss:	2.2884	-mse:	1.5685	-val_loss:	4.1223	-val_mse:	3.4025
Epoch	6/6	0s	-loss:	2.2876	-mse:	1.5678	-val_loss:	4.1216	-val_mse:	3.4021
Epoch	6/6	0s	-loss:	2.2866	-mse:	1.5671	-val_loss:	4.1215	-val_mse:	3.4020
Epoch	1184/3000	0s	-loss:	2.2858	-mse:	1.5665	-val_loss:	4.1208	-val_mse:	3.4016
Epoch	6/6	0s	-loss:	2.2849	-mse:	1.5658	-val_loss:	4.1206	-val_mse:	3.4015
Epoch	6/6	0s	-loss:	2.2840	-mse:	1.5651	-val_loss:	4.1199	-val_mse:	3.4011
Epoch	6/6	0s	-loss:	2.2832	-mse:	1.5645	-val_loss:	4.1196	-val_mse:	3.4010
Epoch	1188/3000	0s	-loss:	2.2826	-mse:	1.5632	-val_loss:	4.1189	-val_mse:	3.4007
Epoch	6/6	0s	-loss:	2.2816	-mse:	1.5630	-val_loss:	4.1182	-val_mse:	3.4002
Epoch	6/6	0s	-loss:	2.2805	-mse:	1.5623	-val_loss:	4.1182	-val_mse:	3.4002
Epoch	6/6	0s	-loss:	2.2796	-mse:	1.5616	-val_loss:	4.1176	-val_mse:	3.3998
Epoch	1192/3000	0s	-loss:	2.2788	-mse:	1.5610	-val_loss:	4.1170	-val_mse:	3.3994
Epoch	6/6	0s	-loss:	2.2778	-mse:	1.5602	-val_loss:	4.1168	-val_mse:	3.3993
Epoch	6/6	0s	-loss:	2.2772	-mse:	1.5598	-val_loss:	4.1164	-val_mse:	3.3993
Epoch	1196/3000	0s	-loss:	2.2765	-mse:	1.5593	-val_loss:	4.1151	-val_mse:	3.3987
Epoch	6/6	0s	-loss:	2.2745	-mse:	1.5587	-val_loss:	4.1146	-val_mse:	3.3983
Epoch	6/6	0s	-loss:	2.2735	-mse:	1.5569	-val_loss:	4.1143	-val_mse:	3.3977
Epoch	6/6	0s	-loss:	2.2727	-mse:	1.5563	-val_loss:	4.1140	-val_mse:	3.3977
Epoch	1200/3000	0s	-loss:	2.2719	-mse:	1.5556	-val_loss:	4.1135	-val_mse:	3.3974
Epoch	6/6	0s	-loss:	2.2710	-mse:	1.5549	-val_loss:	4.1129	-val_mse:	3.3970
Epoch	6/6	0s	-loss:	2.2701	-mse:	1.5543	-val_loss:	4.1125	-val_mse:	3.3968
Epoch	1204/3000	0s	-loss:	2.2693	-mse:	1.5536	-val_loss:	4.1121	-val_mse:	3.3966
Epoch	6/6	0s	-loss:	2.2684	-mse:	1.5529	-val_loss:	4.1114	-val_mse:	3.3960
Epoch	6/6	0s	-loss:	2.2677	-mse:	1.5524	-val_loss:	4.1117	-val_mse:	3.3955
Epoch	6/6	0s	-loss:	2.2667	-mse:	1.5516	-val_loss:	4.1112	-val_mse:	3.3950
Epoch	1208/3000	0s	-loss:	2.2658	-mse:	1.5509	-val_loss:	4.1108	-val_mse:	3.3945
Epoch	6/6	0s	-loss:	2.2650	-mse:	1.5503	-val_loss:	4.1098	-val_mse:	3.3945
Epoch	6/6	0s	-loss:	2.2641	-mse:	1.5495	-val_loss:	4.1087	-val_mse:	3.3943
Epoch	6/6	0s	-loss:	2.2632	-mse:	1.5489	-val_loss:	4.1081	-val_mse:	3.3940
Epoch	1212/3000	0s	-loss:	2.2623	-mse:	1.5482	-val_loss:	4.1077	-val_mse:	3.3936
Epoch	6/6	0s	-loss:	2.2615	-mse:	1.5475	-val_loss:	4.1074	-val_mse:	3.3932
Epoch	6/6	0s	-loss:	2.2605	-mse:	1.5471	-val_loss:	4.1064	-val_mse:	3.3927
Epoch	6/6	0s	-loss:	2.2598	-mse:	1.5462	-val_loss:	4.1062	-val_mse:	3.3927
Epoch	6/6	0s	-loss:	2.2590	-mse:	1.5456	-val_loss:	4.1056	-val_mse:	3.3923
Epoch	1216/3000	0s	-loss:	2.2581	-mse:	1.5449	-val_loss:	4.1055	-val_mse:	3.3922
Epoch	6/6	0s	-loss:	2.2573	-mse:	1.5443	-val_loss:	4.1050	-val_mse:	3.3921
Epoch	6/6	0s	-loss:	2.2565	-mse:	1.5437	-val_loss:	4.1044	-val_mse:	3.3919
Epoch	1219/3000	0s	-loss:	2.2556	-mse:	1.5430	-val_loss:	4.1042	-val_mse:	3.3918
Epoch	6/6	0s	-loss:	2.2548	-mse:	1.5424	-val_loss:	4.1035	-val_mse:	3.3914
Epoch	6/6	0s	-loss:	2.2540	-mse:	1.5418	-val_loss:	4.1033	-val_mse:	3.3912
Epoch	6/6	0s	-loss:	2.2534	-mse:	1.5413	-val_loss:	4.1025	-val_mse:	3.3906
Epoch	1223/3000	0s	-loss:	2.2523	-mse:	1.5404	-val_loss:	4.1021	-val_mse:	3.3904
Epoch	6/6	0s	-loss:	2.2514	-mse:	1.5398	-val_loss:	4.1017	-val_mse:	3.3902
Epoch	6/6	0s	-loss:	2.2506	-mse:	1.5392	-val_loss:	4.1012	-val_mse:	3.3899
Epoch	6/6	0s	-loss:	2.2497	-mse:	1.5384	-val_loss:	4.1008	-val_mse:	3.3897
Epoch	1227/3000	0s	-loss:	2.2490	-mse:	1.5379	-val_loss:	4.1006	-val_mse:	3.3897
Epoch	6/6	0s	-loss:	2.2480	-mse:	1.5371	-val_loss:	4.1002	-val_mse:	3.3895
Epoch	6/6	0s	-loss:	2.2473	-mse:	1.5366	-val_loss:	4.0994	-val_mse:	3.3893
Epoch	6/6	0s	-loss:	2.2463	-mse:	1.5358	-val_loss:	4.0989	-val_mse:	3.3886
Epoch	1231/3000	0s	-loss:	2.2456	-mse:	1.5352	-val_loss:	4.0986	-val_mse:	3.3884
Epoch	6/6	0s	-loss:	2.2446	-mse:	1.5345	-val_loss:	4.0983	-val_mse:	3.3880
Epoch	6/6	0s	-loss:	2.2438	-mse:	1.5338	-val_loss:	4.0976	-val_mse:	3.3880
Epoch	6/6	0s	-loss:	2.2430	-mse:	1.5332	-val_loss:	4.0971	-val_mse:	3.3874
Epoch	1235/3000	0s	-loss:	2.2420	-mse:	1.5325	-val_loss:	4.0967	-val_mse:	3.3873
Epoch	6/6	0s	-loss:	2.2411	-mse:	1.5317	-val_loss:	4.0961	-val_mse:	3.3869
Epoch	6/6	0s	-loss:	2.2404	-mse:	1.5313	-val_loss:	4.0956	-val_mse:	3.3865
Epoch	6/6	0s	-loss:	2.2396	-mse:	1.5306	-val_loss:	4.0952	-val_mse:	3.3863
Epoch	1239/3000	0s	-loss:	2.2388	-mse:	1.5300	-val_loss:	4.0949	-val_mse:	3.3862
Epoch	6/6	0s	-loss:	2.2379	-mse:	1.5292	-val_loss:	4.0944	-val_mse:	3.3859
Epoch	6/6	0s	-loss:	2.2370	-mse:	1.5285	-val_loss:	4.0940	-val_mse:	3.3857
Epoch	6/6	0s	-loss:	2.2361	-mse:	1.5279	-val_loss:	4.0937	-val_mse:	3.3856
Epoch	1243/3000	0s	-loss:	2.2354	-mse:	1.5273	-val_loss:	4.0931	-val_mse:	3.3852
Epoch	6/6	0s	-loss:	2.2345	-mse:	1.5266	-val_loss:	4.0928	-val_mse:	3.3850
Epoch	6/6	0s	-loss:	2.2337	-mse:	1.5261	-val_loss:	4.0923	-val_mse:	3.3847
Epoch	6/6	0s	-loss:	2.2328	-mse:	1.5253	-val_loss:	4.0920	-val_mse:	3.3846
Epoch	1247/3000	0s	-loss:	2.2320	-mse:	1.5247	-val_loss:	4.0916	-val_mse:	3.3842
Epoch	6/6	0s	-loss:	2.2312	-mse:	1.5241	-val_loss:	4.0913	-val_mse:	3.3844
Epoch	6/6	0s	-loss:	2.2304	-mse:	1.5235	-val_loss:	4.0911	-val_mse:	3.3843
Epoch	6/6	0s	-loss:	2.2297	-mse:	1.5230	-val_loss:	4.0906	-val_mse:	3.3840
Epoch	1251/3000	0s	-loss:	2.2287	-mse:	1.5222	-val_loss:	4.0903	-val_mse:	3.3839
Epoch	6/6	0s	-loss:	2.2281	-mse:	1.5217	-val_loss:	4.0897	-val_mse:	3.3835
Epoch	6/6	0s	-loss:	2.2270	-mse:	1.5209	-val_loss:	4.0894	-val_mse:	3.3833
Epoch	6/6	0s	-loss:	2.2263	-mse:	1.5203	-val_loss:	4.0889	-val_mse:	3.3832
Epoch	1255/3000	0s	-loss:	2.2246	-mse:	1.5190	-val_loss:	4.0882	-val_mse:	3.3829
Epoch	6/6	0s	-loss:	2.2246	-mse:	1.5190	-val_loss:	4.0882	-val_mse:	3.3829
Epoch	6/6	0s	-loss:	2.2238	-mse:	1.5184	-val_loss:	4.0879	-val_mse:	3.3826
Epoch	6/6	0s	-loss:	2.2229	-mse:	1.5178	-val_loss:	4.0876	-val_mse:	3.3825
Epoch	1259/3000	0s	-loss:	2.2222	-mse:	1.5171	-val_loss:	4.0870	-val_mse:	3.3821
Epoch	6/6	0s	-loss:	2.2214	-mse:	1.5165	-val_loss:	4.0865	-val_mse:	3.3817
Epoch	6/6	0s	-loss:	2.2205	-mse:	1.5158	-val_loss:	4.0862	-val_mse:	3.3817
Epoch	1262/3000	0s	-loss:	2.2196	-mse:	1.5151	-val_loss:	4.0859	-val_mse:	3.3816
Epoch	6/6	0s	-loss:	2.2188	-mse:	1.5140	-val_loss:	4.0855	-val_mse:	3.3811
Epoch	6/6	0s	-loss:	2.2181	-mse:	1.5140	-val_loss:	4.0855	-val_mse:	3.3811
Epoch	6/6	0s	-loss:	2.2173	-mse:	1.5133	-val_loss:	4.0849	-val_mse:	3.3810
Epoch	6/6	0s	-loss:	2.2163	-mse:	1.5126	-val_loss:	4.0846	-val_mse:	3.3810
Epoch	1267/3000	0s	-loss:	2.2157	-mse:	1.5121	-val_loss:	4.0841	-val_mse:	3.3807
Epoch	6/6	0s	-loss:	2.2148	-mse:	1.5115	-val_loss:	4.0838	-val_mse:	3.3806
Epoch	6/6	0s	-loss:	2.2140	-mse:	1.5108	-val_loss:	4.0835	-val_mse:	3.3804
Epoch	6/6	0s	-loss:	2.2131	-mse:	1.5102	-val_loss:	4.0832	-val_mse:	3.3803
Epoch	1271/3000	0s	-loss:	2.2126	-mse:	1.5095	-val_loss:	4.0826	-val_mse:	3.3801
Epoch	6/6	0s	-loss:	2.2116	-mse:	1.5090	-val_loss:	4.0820	-val_mse:	3.3803
Epoch	6/6	0s	-loss:	2.2107	-mse:	1.5083	-val_loss:	4.0823	-val_mse:	3.3801
Epoch	6/6	0s	-loss:	2.2099	-mse:	1.5077	-val_loss:	4.0813	-val_mse:	3.3797
Epoch	1275/3000	0s	-loss:	2.2092	-mse:	1.5071	-val_loss:	4.0815	-val_mse:	3.3796
Epoch	6/6	0s	-loss:	2.2085	-mse:	1.5066	-val_loss:	4.0815	-val_mse:	3.3798
Epoch	6/6	0s	-loss:	2.2077	-mse:	1.				

Epoch 1966/3000					
6/6 - Ds - loss: 1.7359	- mse:	1.1354	- val_loss:	3.9936	- val_mse: 3.3931
Epoch 1967/3000					
6/6 - Ds - loss: 1.7353	- mse:	1.1348	- val_loss:	3.9935	- val_mse: 3.3930
Epoch 1968/3000					
6/6 - Ds - loss: 1.7347	- mse:	1.1344	- val_loss:	3.9935	- val_mse: 3.3932
Epoch 1969/3000					
6/6 - Ds - loss: 1.7342	- mse:	1.1340	- val_loss:	3.9935	- val_mse: 3.3933
Epoch 1970/3000					

Epoch	1971/3000								
6/6	0s	loss:	1.7329	mse:	1.1329	val_loss:	3.9936	val_mse:	3.3936
Epoch	1972/3000								
6/6	0s	loss:	1.7324	mse:	1.1325	val_loss:	3.9936	val_mse:	3.3937
Epoch	1973/3000								
6/6	0s	loss:	1.7317	mse:	1.1319	val_loss:	3.9934	val_mse:	3.3937
Epoch	1974/3000								
6/6	0s	loss:	1.7311	mse:	1.1314	val_loss:	3.9934	val_mse:	3.3938
Epoch	1975/3000								
6/6	0s	loss:	1.7307	mse:	1.1311	val_loss:	3.9935	val_mse:	3.3939

```

6/6 - Ds - Loss: 1.7299 - mae: 1.1304 - val_loss: 3.9935 - val_mae: 3.3941
Epoch 1979/3000
6/6 - Ds - Loss: 1.7293 - mae: 1.1300 - val_loss: 3.9932 - val_mae: 3.3942
Epoch 1980/3000
6/6 - Ds - Loss: 1.7287 - mae: 1.1295 - val_loss: 3.9932 - val_mae: 3.3940
Epoch 1979/3000
6/6 - Ds - Loss: 1.7281 - mae: 1.1290 - val_loss: 3.9933 - val_mae: 3.3942
Epoch 1980/3000
6/6 - Ds - Loss: 1.7274 - mae: 1.1284 - val_loss: 3.9934 - val_mae: 3.3944
Epoch 1981/3000
6/6 - Ds - Loss: 1.7268 - mae: 1.1279 - val_loss: 3.9935 - val_mae: 3.3946
Epoch 1982/3000
6/6 - Ds - Loss: 1.7261 - mae: 1.1274 - val_loss: 3.9934 - val_mae: 3.3947
Epoch 1983/3000
6/6 - Ds - Loss: 1.7256 - mae: 1.1269 - val_loss: 3.9933 - val_mae: 3.3946
Epoch 1984/3000
6/6 - Ds - Loss: 1.7250 - mae: 1.1264 - val_loss: 3.9935 - val_mae: 3.3950
Epoch 1985/3000
6/6 - Ds - Loss: 1.7243 - mae: 1.1258 - val_loss: 3.9934 - val_mae: 3.3949
Epoch 1986/3000
6/6 - Ds - Loss: 1.7237 - mae: 1.1253 - val_loss: 3.9932 - val_mae: 3.3949
Epoch 1987/3000
6/6 - Ds - Loss: 1.7231 - mae: 1.1248 - val_loss: 3.9931 - val_mae: 3.3949
Epoch 1988/3000
6/6 - Ds - Loss: 1.7225 - mae: 1.1244 - val_loss: 3.9931 - val_mae: 3.3950
Epoch 1989/3000
6/6 - Ds - Loss: 1.7219 - mae: 1.1239 - val_loss: 3.9930 - val_mae: 3.3950
Epoch 1990/3000
6/6 - Ds - Loss: 1.7213 - mae: 1.1233 - val_loss: 3.9931 - val_mae: 3.3953
Epoch 1991/3000
6/6 - Ds - Loss: 1.7208 - mae: 1.1229 - val_loss: 3.9931 - val_mae: 3.3953
Epoch 1992/3000
6/6 - Ds - Loss: 1.7200 - mae: 1.1223 - val_loss: 3.9933 - val_mae: 3.3956
Epoch 1993/3000
6/6 - Ds - Loss: 1.7195 - mae: 1.1218 - val_loss: 3.9930 - val_mae: 3.3955
Epoch 1994/3000
6/6 - Ds - Loss: 1.7188 - mae: 1.1213 - val_loss: 3.9931 - val_mae: 3.3957
Epoch 1995/3000
6/6 - Ds - Loss: 1.7181 - mae: 1.1207 - val_loss: 3.9931 - val_mae: 3.3958
Epoch 1996/3000
6/6 - Ds - Loss: 1.7175 - mae: 1.1202 - val_loss: 3.9930 - val_mae: 3.3957
Epoch 1997/3000
6/6 - Ds - Loss: 1.7169 - mae: 1.1197 - val_loss: 3.9929 - val_mae: 3.3958
Epoch 1998/3000
6/6 - Ds - Loss: 1.7163 - mae: 1.1193 - val_loss: 3.9929 - val_mae: 3.3958
Epoch 1999/3000
6/6 - Ds - Loss: 1.7157 - mae: 1.1187 - val_loss: 3.9926 - val_mae: 3.3957
Epoch 2000/3000
6/6 - Ds - Loss: 1.7150 - mae: 1.1182 - val_loss: 3.9927 - val_mae: 3.3959
Epoch 2001/3000
6/6 - Ds - Loss: 1.7145 - mae: 1.1177 - val_loss: 3.9927 - val_mae: 3.3960
Epoch 2002/3000
6/6 - Ds - Loss: 1.7139 - mae: 1.1172 - val_loss: 3.9927 - val_mae: 3.3961
Epoch 2003/3000
6/6 - Ds - Loss: 1.7132 - mae: 1.1166 - val_loss: 3.9927 - val_mae: 3.3961
Epoch 2004/3000
6/6 - Ds - Loss: 1.7126 - mae: 1.1161 - val_loss: 3.9929 - val_mae: 3.3961
Epoch 2005/3000
6/6 - Ds - Loss: 1.7121 - mae: 1.1157 - val_loss: 3.9926 - val_mae: 3.3963
Epoch 2006/3000
6/6 - Ds - Loss: 1.7114 - mae: 1.1152 - val_loss: 3.9929 - val_mae: 3.3961
Epoch 2007/3000
6/6 - Ds - Loss: 1.7108 - mae: 1.1146 - val_loss: 3.9923 - val_mae: 3.3962
Epoch 2008/3000
6/6 - Ds - Loss: 1.7102 - mae: 1.1142 - val_loss: 3.9922 - val_mae: 3.3962
Epoch 2009/3000
6/6 - Ds - Loss: 1.7096 - mae: 1.1136 - val_loss: 3.9921 - val_mae: 3.3962
Epoch 2010/3000
6/6 - Ds - Loss: 1.7089 - mae: 1.1131 - val_loss: 3.9921 - val_mae: 3.3964
Epoch 2011/3000
6/6 - Ds - Loss: 1.7083 - mae: 1.1126 - val_loss: 3.9922 - val_mae: 3.3966
Epoch 2012/3000
6/6 - Ds - Loss: 1.7079 - mae: 1.1122 - val_loss: 3.9921 - val_mae: 3.3966
Epoch 2013/3000
6/6 - Ds - Loss: 1.7072 - mae: 1.1117 - val_loss: 3.9924 - val_mae: 3.3969
Epoch 2014/3000
6/6 - Ds - Loss: 1.7065 - mae: 1.1111 - val_loss: 3.9925 - val_mae: 3.3971
Epoch 2015/3000
6/6 - Ds - Loss: 1.7059 - mae: 1.1106 - val_loss: 3.9925 - val_mae: 3.3973
Epoch 2016/3000
6/6 - Ds - Loss: 1.7053 - mae: 1.1101 - val_loss: 3.9926 - val_mae: 3.3975
Epoch 2017/3000
6/6 - Ds - Loss: 1.7047 - mae: 1.1097 - val_loss: 3.9925 - val_mae: 3.3975
Epoch 2018/3000
6/6 - Ds - Loss: 1.7041 - mae: 1.1092 - val_loss: 3.9927 - val_mae: 3.3978
Epoch 2019/3000
6/6 - Ds - Loss: 1.7035 - mae: 1.1086 - val_loss: 3.9928 - val_mae: 3.3980
Epoch 2020/19: early stopping

In [36]: model.history.params

Out[36]: {'verbose': 2, 'epochs': 3000, 'steps': 6}

In [37]: model.history.history

Out[37]: {'loss': [6.228052616119385,
6.211391730162574,
6.210800647735586,
6.203500270845506,
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6.186576366424505,
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6.170066356589355,
6.1620235824985,
6.153896331787159,
6.145241260528545,
6.13754400323959,
6.12999153137207,
6.121374607086182,
6.11355590820128,
6.105292320251465,
6.0976881980896,
6.08951711544631,
6.081489132476807,
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6.058482606201372,
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6.034007341003418,
6.027013007732422,
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6.012867521333559,
6.004425048828125,
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5.98939326841256,
5.981525421142578,
5.974214661181641,
5.966867174530259,
5.95950984954934,
5.9515790393231055,
5.944617748260498,
5.937183180126953,
5.92955884661855,
5.922434329885752,
5.9151748864180721,
5.907642364501953,
5.900479363037109,
5.89304256439209,
5.886322021484375,
5.87874020837402,
5.87143559014748,
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5.856604099273680,
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5.835660934448242,
5.828393943508595,
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5.814719732507119,
5.807278633117676,
5.800406455991652,
5.793094158172607,
5.786536693572998,
5.779261112231336,
5.772721633148193,
5.765589714050295,
5.758778570282515,
5.7512593269348145,
5.744391166687012,
5.738003253936768,
```


[illegible]

[illegible]

hist

Out [38]:

	loss	mse	val_loss	val_mse
0	6.228052	5.212002	8.505991	7.490143
1	6.219394	5.203680	8.497508	7.481991
2	6.210801	5.195415	8.489076	7.473888
3	6.203500	5.188440	8.480375	7.465508
4	6.194484	5.179749	8.472036	7.457499
...
2014	1.705927	1.110648	3.992495	3.397284
2015	1.705299	1.110135	3.992620	3.397521
2016	1.704737	1.109681	3.992536	3.397540
2017	1.704114	1.109159	3.992657	3.397762
2018	1.703473	1.108623	3.992794	3.398008
2019	rows x 4 columns			

In [39]:

hist["epoch"] = model_history.epoch

In [40]:

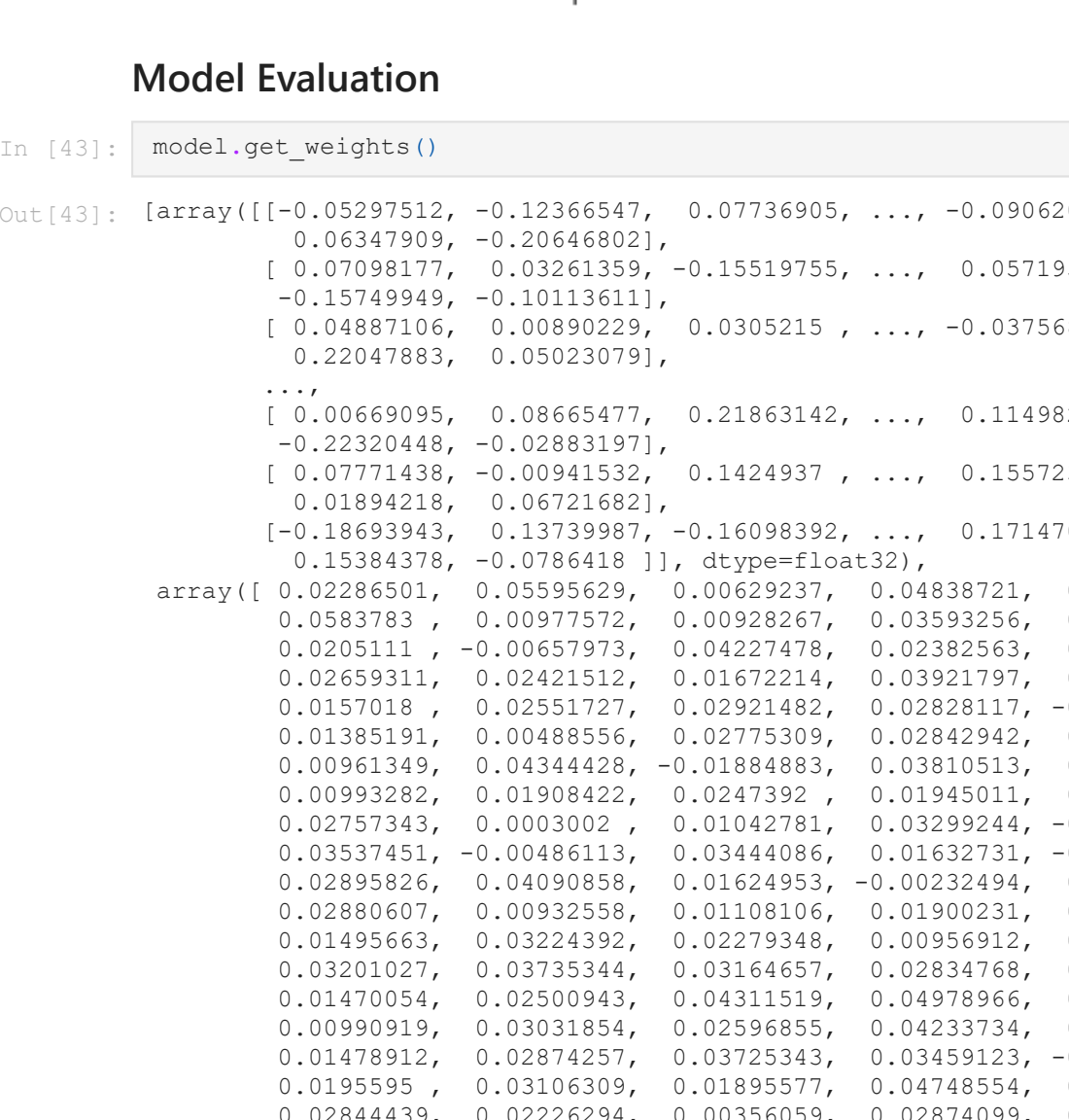
hist

Out [40]:

	loss	mse	val_loss	val_mse	epoch
0	6.228053	5.212002	8.505991	7.490143	0
1	6.219394	5.203680	8.497508	7.481991	1
2	6.210801	5.195415	8.489076	7.473888	2
3	6.203500	5.188440	8.480375	7.465508	3
4	6.194484	5.179749	8.472036	7.457499	4
...
2014	1.705927	1.110648	3.992495	3.397284	2014
2015	1.705299	1.110135	3.992620	3.397521	2015
2016	1.704737	1.109681	3.992536	3.397540	2016
2017	1.704114	1.109159	3.992657	3.397762	2017
2018	1.703473	1.108623	3.992794	3.398008	2018
2019	rows x 5 columns				

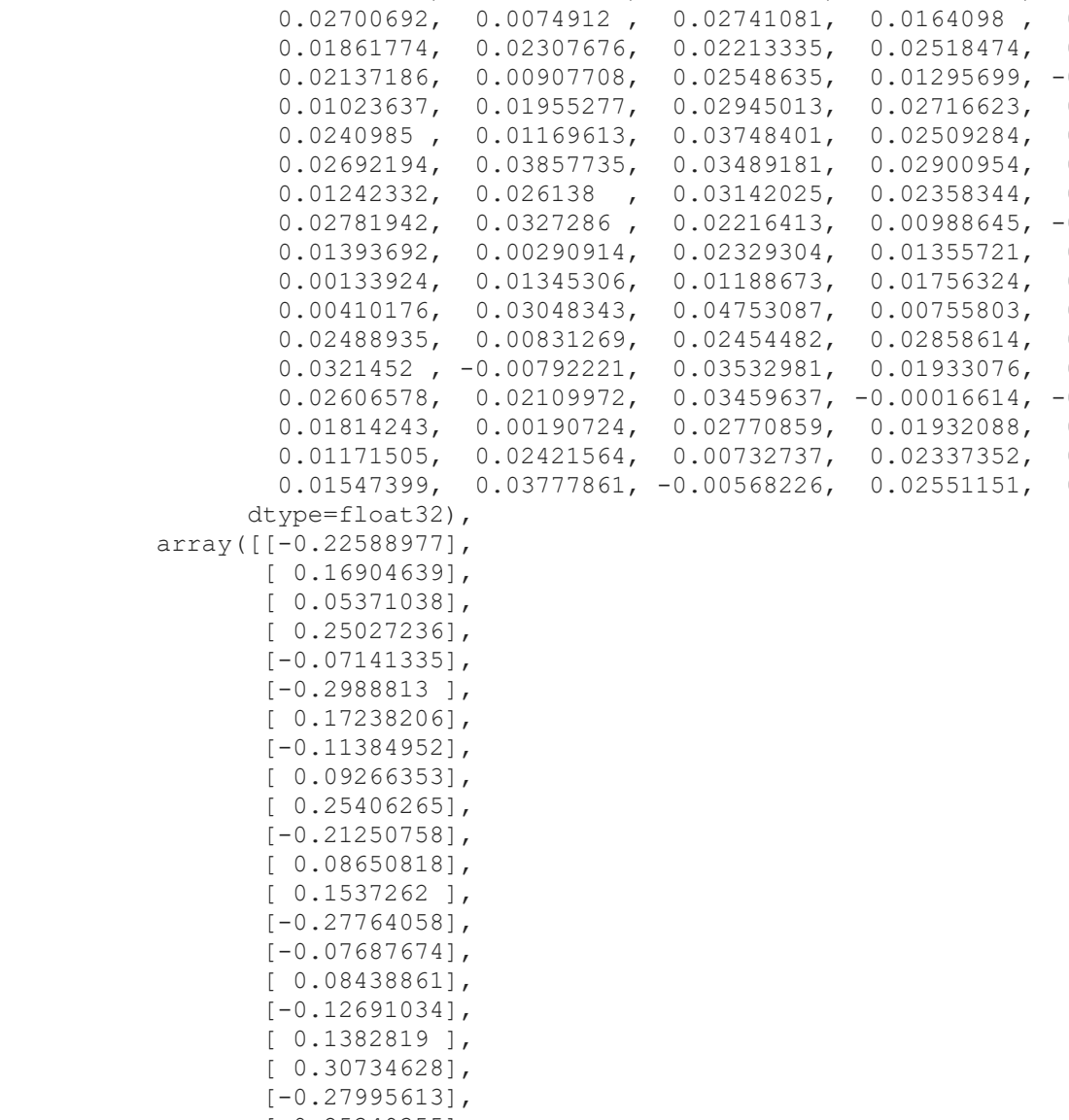
In [41]:

```
plt.figure(figsize=(8,5))
plt.plot(model_history.history['loss'])
plt.plot(model_history.history['val_loss'])
plt.title("Model Training")
plt.ylabel("Training and Validation Loss")
plt.xlabel("Epoch Number")
plt.legend(['Training Loss', 'Validation Loss'])
plt.show()
```



In [42]:

```
plt.figure(figsize=(8,5))
plt.plot(model_history.history['mse'])
plt.plot(model_history.history['val_mse'])
plt.title("Model Training - MSE")
plt.ylabel("MSE")
plt.xlabel("Epoch Number")
plt.legend(['mse', 'VAL_MSE'])
plt.show()
```



Model Evaluation

In [43]:

model.get_weights()

Out [43]:

[array([[-0.05297512, -0.12366547, 0.07736905, ..., -0.09062039,
 0.06347909, -0.20646802],
 [0.07098197, 0.03261359, -0.15519755, ..., 0.05719507,
 -0.15749949, -0.10113611],
 [0.04887106, 0.00890229, 0.0305215 , ..., -0.03756858,
 0.22047863, 0.05020379],
 ...,
 [0.00649095, 0.08083477, 0.21863142, ..., 0.11498241,
 -0.22320449, -0.02883197],
 [0.07771438, -0.00941532, 0.1424937 , ..., 0.15572394,
 0.03984218, 0.06721682],
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 0.15384378, -0.0786418], dtype=float32),
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 0.05837783 , 0.00977572, 0.00982867, 0.03593256, 0.03126949,
 0.0205111 , 0.00657979, 0.04227478, 0.02382563, 0.01991147,
 0.02659311, 0.02451512, 0.01672214, 0.03211797, 0.01866397,
 0.0157018 , 0.02551727, 0.02921482, 0.02828117, -0.0395299,
 0.0193191, 0.00468556, 0.02775309, 0.02849342, 0.01569038,
 0.00961309, 0.04344428, 0.01864853, 0.03810513, 0.04133326,
 0.00993282, 0.01908422, 0.0247392 , 0.01945011, 0.01810755,
 0.02757345, 0.00030002, 0.01042781, 0.03299244, -0.00842451,
 0.03537451, -0.00486113, 0.03444086, 0.01632731, -0.00494784,
 0.02895826, 0.04090858, 0.01624953, -0.00232494, 0.03320777,
 0.02806007, 0.00592538, 0.01108106, 0.01300231, 0.00530762,
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 0.03201027, 0.03735344, 0.03164657, 0.02838769, 0.02409827,
 0.01470054, 0.0250994 , 0.04311519, 0.04978966, 0.04149166,
 0.0099019 , 0.03031854, 0.02596835, 0.04237374, 0.00717267,
 0.04749912, 0.02874257, 0.03725442, 0.03495929, -0.00623979,
 0.0195595 , 0.03106309, 0.01895577, 0.04748554, 0.0296518 ,
 0.02844439, 0.02262694, 0.00356059, 0.02874099, 0.00481089,
 0.02929419, 0.04231519, 0.02573755, 0.03442017, 0.02466399],
dtype=float32),
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 -0.06678991, -0.09619927],
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 0.12347442, 0.0700211],
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 -0.00207024, 0.08678914],
 ...,
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 0.12938897, -0.09798318],
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 0.00426583, 0.02821421, 0.02721922, -0.01164966, -0.01868976,
 0.02708932, 0.0074912 , 0.02741081, 0.0164098 , 0.02065276,
 0.01861774, 0.02307676, 0.02213335, 0.02518474, 0.0012639 ,
 0.02137186, 0.00907708, 0.02548635, 0.01956999, -0.02586252,
 0.02023637, 0.01955277, 0.02945013, 0.02716623, 0.02647329,
 0.02404985 , 0.01169613, 0.03748401, 0.02509284, 0.02338381,
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 [-0.16682777],
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 [-0.098427],
 [-0.28043368],
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 [-0.19419248],
 [-0.3210378],
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 [-0.18817177],
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 [0.28342387],
 [0.14152497],
 [0.3000794],
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 [0.2080392],
 [-0.12197859],
 [0.20669596],
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 [-0.19274994],
 [0.1150918],
 [-0.05561753],
 [-0.02352708],
 [0.2887438],
 [0.1723902],
 [0.07957457],
 [-0.252106],
 [-0.27027738],
 [0.16019855],
 [-0.19936158]], dtype=float32),
array([0.02274321]), dtype=float32))

In [46]:

test_loss, test_mse = model.evaluate(X_test_scaled,y_test)

Out [46]:

3/3 [-----] - 0s 998us/step - loss: 2.4563 - mse: 1.8615

In [45]:

print("Test MSE: {}".format(test_mse))

Test MSE: 1.8615323305138005

Model Prediction

In [46]:

y_pred = model.predict(X_test_scaled)

Out [46]:

y_pred[0:5]

Out [47]:

array([[1.239335],
 [-0.07362135],
 [-0.10825673],
 [0.42340029],
 [0.45786145]], dtype=float32)

In [48]:

y_pred.round()[0:5]

Out [48]:

array([[1.],
 [0.],
 [0.],
 [0.],
 [0.]], dtype=float32)

In [49]:

y_test[0:5]

Out [49]:

array([4., 0., 0., 0., 0.])

In [50]:

mse = mean_squared_error(y_test,y_pred.round())

Out [50]:

2.051282051282051

In [51]:

rmse = np.sqrt(mse)

Out [51]:

1.4322297480788657

In [52]:

r2 = r2_score(y_test,y_pred.round())

Out [52]:

0.31488801054018445

In [53]:

n = len(X_test)

Out [53]:

78

In [54]:

p = X_test.shape[1]

Out [54]:

42

In [55]:

#Adjusted R2 Score

Out [55]:

-0.5072463768115942

In [56]:

fig, ax = plt.subplots(figsize=(10,5))
sns.regplot(x=y_test, y=y_pred.round(), ax=ax)
plt.title("Plot to compare actual vs predicted")
plt.ylabel("Predicted")
plt.xlabel("Actual")
plt.show()



Save the Model

In [57]:

model.save("dmnPartA.h5")

Cross Validation

Build a model (regression or classifier) first

In [58]:

```
def build_regressor():
    model = Sequential()
    model.add(Dense(units=100,activation='relu',input_dim=42))
    #model.add(BatchNormalisation())
    #model.add(Dropout(0.2))
    model.add(Dense(units=100,activation='relu',kernel_regularizer='l2'))
    #model.add(BatchNormalisation())
    #model.add(Dropout(0.2))
    model.add(Dense(units=100,activation='linear'))
    optimizer = Adam(learning_rate=0.0001)
    model.compile(optimizer=optimizer, loss='mean_squared_error', metrics=["mse"])
    return model
```

In [59]:

model = KerasRegressor(build_fn=build_regressor, epochs=3000)

In [60]:

kfold = StratifiedKFold(n_splits=5,shuffle=True,random_state=0)

In [61]:

cv = cross_val_score(estimator=model,X=X_train_scaled, y=y_train, cv=kfold, n_jobs=-1, verbose=2)

Out [61]:

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done 9 out of 5 | elapsed: 1.3min finished

In [62]:

cv

Out [62]:

array([-4.08172989, -3.07706287, -4.10006762, -2.18819921, -3.49925804])

In [63]:

cv.mean()

Out [63]:

-3.5280261039733887

In [64]:

cv.std()

Out [64]:

0.501070195491264

In [65]:

mse_mean = abs(cv.mean())

Out [65]:

3.5280261039733887

In [66]:

rmse = np.sqrt(mse_mean)

Out [66]:

1.8783040499273245

Model Hyperparameter Tuning

Create a regressor or classifier function

In []:

```
def build_regressor(optimizer):
    model = Sequential()
    model.add(Dense(units=100,activation='relu',input_dim=42))
    #model.add(BatchNormalisation())
    #model.add(Dropout(0.2))
    model.add(Dense(units=100,activation='relu',kernel_regularizer='l2'))
    #model.add(BatchNormalisation())
    #model.add(Dropout(0.2))
    model.add(Dense(units=100,activation='linear'))
    optimizer = Adam(learning_rate=0.0001)
    model.compile(optimizer=optimizer, loss='mean_squared_error', metrics=["mse"])
    return model
```

In []:

model = KerasRegressor(build_fn=build_regressor)

In []:

params = {'batch_size': [1,2,5],
 'epochs': [100,200,300],
 'optimizer': ['Adam', 'RMSProp', 'SGD']
}

Use RandomSearch CV

In []:

randomsearch = RandomizedSearchCV(estimator=model, param_distributions=params,n_iter=10,

In []:

randomsearchcv = randomsearch.fit(X_train, y_train)

In []:

randomsearchcv.best_params_

In []:

randomsearchcv.best_score

Final Model

In []:

model2 = Sequential()
model2.add(Dense(units=100,activation='relu',input_dim=42))
#model2.add(BatchNormalisation())
#model2.add(Dropout(0.2))
model2.add(Dense(units=100,activation='relu',kernel_regularizer='l2'))
#model2.add(BatchNormalisation())
#model2.add(Dropout(0.2))
model2.add(Dense(units=1,activation='linear'))

In []:

model2.summary()

In []:

checkpointcb = keras.callbacks.ModelCheckpoint("bestModelPartA.h5",save_best_only=True)

In []:

earlystoppingcb = keras.callbacks.EarlyStopping(patience=10, verbose=1)

In []:

optimizer = SGD(learning_rate=0.0001)

In []:

model2.compile(optimizer=optimizer, loss='mean_squared_error', metrics=["mse"])

In []:

model_history_2 = model2.fit(X_train, y_train,epochs=200,batch_size=2,
 validation_split=0.2, verbose=2, callbacks=[checkpointcb,earlystoppingcb])

In []:

model_history_2.params