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4.562255382537842, 4.559885501861572, 4.5727362632751465, 4.567147731781006, 4.570751667022705, 4.569549560546875, 4.561507225036621, 4.559748649597168, 4.5655837059021, 4.569131851196289]} hist = pd.DataFrame(model_history.history) val loss loss val_mse mse **0** 4119.808594 4118.792969 3451.277832 3450.262207 **1** 3962.562744 3961.547119 3323.419189 3322.404297 **2** 3806.260254 3805.244873 3202.385742 3201.371094 **3** 3700.440674 3699.426270 3075.835205 3074.820801 **4** 3551.013184 3549.998535 2962.407959 2961.394287 5.372094 3.017624 2.214906 582 4.569550 583 3.017066 2.214636 5.363765 4.561507 3.012782 2.210927 585 5.367266 4.565584 3.013782 2.212214 586 5.370528 4.569132 587 rows × 4 columns hist['epoch'] = model history.epoch hist Out[39]: val_mse epoch loss mse val_loss **0** 4119.808594 4118.792969 3451.277832 3450.262207 0 **1** 3962.562744 3961.547119 3323.419189 3322.404297 **2** 3806.260254 3805.244873 3202.385742 3201.371094 2 **3** 3700.440674 3699.426270 3075.835205 3074.820801 3 **4** 3551.013184 3549.998535 2962.407959 2961.394287 4 3.017624 582 2.214906 5.372094 4.569550 582 583 3.017066 2.214636 5.363765 4.561507 583 584 3.014844 2.212701 4.559749 584 5.361718 585 3.012782 2.210927 4.565584 585 5.367266 586 3.013782 2.212214 5.370528 4.569132 586 587 rows × 5 columns In [40]: 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() Model Training Training Loss 4000 Validation Loss **Training and Validation Loss** 3000 2000 1000 0 0 100 200 300 400 500 600 **Epoch Number** In [41]: 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 Training - MSE MSE 4000 VAL_MSE 3000 ₩ 2000 1000 0 0 100 200 300 400 500 600 **Epoch Number Model Evaluation** In [42]: model.get weights() Out[42]: [array([[-0.06692149, -0.11918116, 0.00647938, ..., -0.0463139, 0.09368964, -0.16854094],[0.03880645, 0.09782134, 0.18210599, ..., 0.08798633,-0.16941778, 0.01249855], [0.11023546, -0.04211644, 0.15408164, ..., 0.09474277,-0.03555257, 0.06336047], [-0.15282373, 0.1216042, -0.16169126, ..., 0.11059742, 0.09820643, -0.07787107]], dtype=float32), array([-0.0050367 , 0.0057361 , -0.00192996, -0.00214218, 0.00374088, 0.00388337, 0.00567919, -0.00170535, 0.00070381, -0.00689378, 0.00543956, 0.01581135, 0.00616075, 0.00193988, 0.00419267, $-0.00331371, \ -0.00450264, \ \ 0.00560008, \ \ 0.01336006, \ \ 0.00784956,$ 0.00106189, -0.00596037, -0.00286763, 0.00723396, -0.00376203, -0.00509891, 0.00192765, 0.00097815, -0.00273825, 0.00096033, -0.00672221, 0.00471769, -0.00527557, 0.00520677, 0.00436814, 0.00595919, 0.00222888, -0.00438795, 0.00618835, 0.00293152, 0.01369347, 0.0046662, 0.00661061, -0.00856426, 0.0061499, -0.00386507, 0.00210933, -0.00474657, 0.00559242, 0.00547927, 0.00214138, 0.00835476, -0.00514303, 0.00364806, -0.00436244, -0.00408117, -0.0085962 , 0.00107222, -0.00552727, 0.00461269, -0.00247697, -0.0025538, 0.00693881, -0.00249612, 0.00466043, -0.0011562, 0.00081194, 0.00321999, -0.00126281, 0.00648455, -0.00468673, -0.00189219, -0.01038424, -0.00002253, 0.00148641, -0.00501963, 0.00123138, -0.00151466, -0.00387145, -0.00612714, -0.00231125, 0.00597441, -0.00240223, 0.00116373, 0.00454374, 0.00384843, 0.00329027, -0.00355941, 0.00417888, -0.00176681, -0.00739277, 0.00763472, -0.00560932, 0.00584368, -0.00542123], dtype=float32), 0.16907662, 0.08465107], [0.11305827, 0.03156068, 0.14243452, ..., 0.00535111,-0.03415229, 0.0641544], [0.16799307, -0.05228799, -0.07698134, ..., 0.07654466,0.09417668, 0.10768475], [0.06958847, 0.04072955, 0.14748767, ..., 0.12383068, -0.01577906, -0.08006766], [0.10588089, 0.00865349, -0.02511424, ..., 0.01933053, -0.01661848, 0.01357626]], dtype=float32), array([-0.00290215, 0.00721631, -0.0034876, 0.00522459, -0.00539645, -0.01289506, -0.01346471, -0.00493843, 0.00519098, 0.00493228, $-0.00424107, \quad 0.00530977, \quad 0.00477421, \quad -0.00495508, \quad -0.00495807,$ -0.00058637, -0.01240844, 0.00512769, 0.00505565, 0.00061412, 0.00483486, -0.01076483, -0.00710617, -0.0005836, -0.00500103, -0.00496955, -0.01322378, 0.01148133, -0.00500341, -0.00212564, 0.02416029, 0.00084283, 0.00532361, 0.00168238, 0.00402742, 0.00087139, 0. , 0.00032552, -0.0013239 , 0.00507729, 0.00509705, -0.01137773, 0.00072997, 0.01210183, 0.00555676, -0.00414948, 0.0051337, 0.00628288, 0.0217368, 0.00550904, -0.00222294, 0.00508358, 0.00426696, -0.00335418, 0.00056086, , -0.00339361, -0.00485787, -0.00500436, -0.00504616, 0. -0.00498241, -0.00491671, -0.0054395, -0.01119232, -0.00966717, -0.00281474, 0.00367388, -0.00404825, -0.00385823, -0.00653877, -0.00441082, -0.00372645, -0.00041777, 0.00637347, 0.00165427, 0.01468014, -0.00539759, 0.00620594, 0. , 0.01036723, 0.00219306, 0.00108964, 0.00494218, -0.0049989, -0.00534647, 0.00508055, -0.00469416, 0.01227204, -0.00443336, 0.00219077, -0.00411663, 0.01578879, -0.00762428, 0.0050556, -0.00284704, 0.00183356, 0.00068756, -0.00501034, 0.00510741, 0.00611015], dtype=float32), array([-0.14785807],[0.12231623], [-0.00238066], [0.18846594], [-0.04307169], [-0.2300941],[0.09036354], [-0.06268132], [0.04245079], [0.2003136], [-0.17680526], [0.0248916], [0.09582332], [-0.23809977], [-0.0636276], [0.03374527], [-0.07878704], [0.07637405], [0.24536511], [-0.21648343], [0.19513804], [-0.10586401], [-0.02086056], [0.11685456], [-0.15919109], [-0.12299158], [0.22135863], [0.24863423], [-0.22239625], [-0.00416952], [0.01950584], [0.217599], [0.18481399], [0.07198253], [0.06771594], [0.1665416], [0.14886484], [-0.00192831], [0.10382697], [0.14568514], [0.11989952], [-0.19997025], [-0.15378475], [-0.09417084], [0.2424759], [-0.07797949], [0.06206232], [0.0065717], [0.09534227], [0.07173148], [0.07236681], [0.12001739], [0.19073345], [-0.17270698], [0.02529016], [-0.069327], [-0.01644886], [-0.20528129], [-0.20445007], [-0.09722018], [-0.19289073], [-0.05168707], [-0.22626981], [-0.21994588], [-0.17354701], [-0.14938849], [-0.24563487], [-0.00196588], [-0.14584386], [-0.12944664], [-0.13896921], [0.18674292], [0.09051076], [0.07555529], [0.18189043], [-0.24899463], [-0.15757743], [0.00918794], [-0.22455129], [-0.1635428], [0.22179256], [0.08625703], [0.2445817], [-0.19281271], [-0.193432], [0.14260483], [-0.09445037], [0.15463966], [-0.05927893], [-0.15517698], [-0.07415263], [0.0115212], [0.02725275], [0.23516424], [0.09976053], [0.02591992], [-0.18524128], [-0.21759205], [0.10536728], [-0.11459419]], dtype=float32), array([0.00503275], dtype=float32)] In [43]: test_loss, test_mse = model.evaluate(X_test,y_test) print("Test MSE: {}".format(test_mse)) In [44]: Test MSE: 2.3028433322906494 **Model Prediction** In [45]: y_pred = model.predict(X_test) y_pred[0:5] In [46]: Out[46]: array([[0.7172812], [0.06949318], [0.1189203], [-0.02114202], [0.09577706]], dtype=float32) In [47]: y_pred.round()[0:5] Out[47]: array([[1.], [0.], [0.], [-0.], [0.]], dtype=float32) In [48]: y_test[0:5] Out[48]: array([4., 0., 0., 0., 0.]) In [49]: mse = mean squared error(y test,y pred.round()) Out[49]: 2.423076923076923 rmse = np.sqrt(mse) rmse Out[50]: 1.5566235649883124 r2 = r2 score(y test, y pred.round()) Out[51]: 0.1907114624505929 In [52]: n = len(X test)Out[52]: 78 In [53]: p = X_test.shape[1] р Out[53]: 42 In [54]: #Adjusted R2 Score adjr2 = 1 - (1-r2) * (n-1) / (n-p-1)adjr2 Out[54]: -0.7804347826086955 In [55]: 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() Plot to compare actual vs predicted 6 5 4 Predicted 2 1 0 0 2 3 Actual Save the Model model.save("dnnPartA.h5") **Cross Validation** Build a model (regression or classfier) first def build_regressor(): model = Sequential() model.add(Dense(units=100,activation='relu',input_dim=42)) #model.add(BatchNormalization()) #model.add(Dropout(0.2)) model.add(Dense(units=100,activation='relu',kernel_regularizer='12')) #model.add(BatchNormalization()) #model.add(Dropout(0.2)) model.add(Dense(units=1,activation='linear')) optimizer = Adam(learning rate=0.00001) model.compile(optimizer=optimizer, loss='mean squared error', metrics=["mse"]) return model model = KerasRegressor(build_fn=build_regressor, epochs=800) kfold = StratifiedKFold(n splits=5,shuffle=True,random state=0) In [60]: cv = cross_val_score(estimator=model, X=X_train, y=y_train, cv=kfold, n_jobs=-1, verbose=2) [Parallel (n jobs=-1)]: Using backend LokyBackend with 4 concurrent workers. [Parallel(n_jobs=-1)]: Done 5 out of 5 | elapsed: 32.0s finished Out[61]: array([-6.45266533, -2.98656297, -3.08224034, -2.71152568, -4.56542969]) In [62]: cv.mean() Out[62]: -3.9596848011016847 In [63]: cv.std() Out[63]: 1.4040409434972103 In [64]: mse_mean = abs(cv.mean()) mse_mean Out[64]: 3.9596848011016847 In [65]: rmse = np.sqrt(mse_mean) rmse Out[65]: 1.9898956759342146 **Model Hyperparameter Tuning** Create a regressor or classifier function def build_regressor(optimizer): model = Sequential() model.add(Dense(units=100,activation='relu',input_dim=42)) #model.add(BatchNormalization()) #model.add(Dropout(0.2)) model.add(Dense(units=100,activation='relu',kernel_regularizer='12')) #model.add(BatchNormalization()) #model.add(Dropout(0.2)) model.add(Dense(units=1,activation='linear')) optimizer = Adam(learning_rate=0.00001) model.compile(optimizer=optimizer, loss='mean_squared_error', metrics=["mse"]) return model model = KerasRegressor(build_fn=build_regressor) 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, scoring='neg_root_mean_squared_error',n_jobs=-1,cv=5,random_state=0) randomsearchcv = randomsearch.fit(X_train, y_train) randomsearchcv.best_params_ randomsearchcv.best_score_ **Final Model** In []: | model2 = Sequential() model2.add(Dense(units=100,activation='relu',input_dim=42)) #model2.add(BatchNormalization()) #model2.add(Dropout(0.2)) model2.add(Dense(units=100,activation='relu',kernel regularizer='12')) #model2.add(BatchNormalization()) #model2.add(Dropout(0.2)) model2.add(Dense(units=1,activation='linear')) model2.summary() checkpointcb = keras.callbacks.ModelCheckpoint("BestModelPartA.h5", save best only=True) earlystoppingcb = keras.callbacks.EarlyStopping(patience=10, verbose=1) optimizer = SGD(learning rate=0.0001) model2.compile(optimizer=optimizer, loss='mean squared error', metrics=["mse"]) model history 2 = model2.fit(X train, y train,epochs=200,batch size=2, validation split=0.2, verbose=2, callbacks=[checkpointcb,earlystoppingcb]) model_history_2.params Loading [MathJax]/extensions/Safe.js