DNN Lab

Objectives

- · Understand basic DNN model building process using Keras
- · Analyze model performance and capacity vs generalization tradeoff
- · Modify models to reduce overfitting and improve performance

Exercises

- · Build a DNN model for slump Test Problem
- Start with a model consisting of one hidden layer with 7 neurons
- · Analyze results and explore improvements to model in terms of capacity, regularization

Step 1: Import Libraries

```
In [1]: | %tensorflow_version 2.x
        from numpy.random import seed
        seed(2)
        import tensorflow as tf
        from tensorflow import keras
        from IPython import display
        from matplotlib import cm
        from matplotlib import gridspec
        from matplotlib import pyplot as plt
        import numpy as np
        import pandas as pd
        import os
        import datetime
        from tensorflow.python.data import Dataset
        from sklearn import preprocessing
        from sklearn.preprocessing import StandardScaler, StandardScaler, Normalizer
        from sklearn.model selection import train test split
        from sklearn.metrics import confusion matrix, accuracy score
        from sklearn import metrics
        from sklearn.dummy import DummyRegressor
        print(tf.__version__)
```

2.6.0

Step 2: Import Data

Step 3: Preprocess

```
In [3]: #missing data values is -98 or -97
        clinic data[clinic data.eq(-98).any(1)]
        clinic_data[clinic_data.eq(-97).any(1)]
        #deleted records with missing Online Appointment use
        delete records = clinic data[clinic data.OnlineAppointmentUse <-96].index</pre>
        clinic data.drop(delete records, inplace = True)
In [4]: | #replacing the missing data value of -98 and -97 with np.nan
        #can run a regression to predict the value instead of ultimately using the mea
        clinic_data = clinic_data.replace({-98 : np.NaN, -97 : np.NaN})
        #checking if NaN values replacement worked
        #checking which columns have NaN values
        clinic data[clinic data.isnull().any(axis=1)]
        #checking to see the # of NaN values present
        len(clinic_data[clinic_data.isnull().any(axis=1)])
        #replace the nan values with the mean
        #change to np.NaN
        clinic data.fillna(clinic data.mean(), inplace=True)
In [5]: #remove columns vendor and numpats
        clinic data = clinic data.drop(['vendor', 'numpats'], axis=1)
        #clinic data.shape
In [6]: | #baseline accuracy measure
        clinic data.iloc[:,1:2].mean()
Out[6]: OnlineAppointmentUse
                              0.1371
```

Train/Validation Split

```
In [7]: #Creating a training and validation dataset with a 80/20 split
    X_train,X_test, y_train, y_test = train_test_split(clinic_data.iloc[:,2:],clin
    ic_data.iloc[:,1:2], test_size=0.2, random_state=1)
```

dtype: float64

```
In [8]: X_train.head()
```

Out[8]:

	malepct	unemp	age16to24	age25to34	age35to44	age45to54	age55to64	age65to74	age
5129	0.4665	0.0137	0.0774	0.1087	0.1005	0.1838	0.2341	0.1994	(
4375	0.5677	0.0272	0.0935	0.2117	0.2163	0.1839	0.1059	0.0947	(
571	0.4646	0.0321	0.1099	0.1373	0.0707	0.2095	0.2085	0.1269	(
3926	0.4517	0.0280	0.0366	0.1619	0.1416	0.2058	0.2210	0.1210	(
3921	0.4278	0.0103	0.0952	0.1379	0.0643	0.1776	0.2155	0.1528	(
4									•

Step 4: Build Model

https://www.tensorflow.org/api_docs/python/tf/keras/Model (https://www.tensorflow.org/api_docs/python/tf/keras/Model)

https://www.tensorflow.org/api_docs/python/tf/keras/layers/Dense (https://www.tensorflow.org/api_docs/python/tf/keras/layers/Dense)

https://keras.io/optimizers/ (https://keras.io/optimizers/)

Build Model

```
In [9]:
        #model is continuous, so which is best
        model1 = keras.Sequential()
        model1.add(keras.layers.Dense(18, activation=tf.nn.leaky relu,
                                input shape=(X train.shape[1],)))
        keras.layers.Dropout(0.75),
        model1.add(keras.layers.Dense(9, activation=tf.nn.relu
        keras.layers.Dropout(0.75),
        model1.add(keras.layers.Dense(5, activation=tf.nn.leaky relu
        keras.layers.Dropout(0.75),
        #model1.add(keras.layers.Dense(3, activation=tf.nn.relu
        #keras.Layers.Dropout(0.75),
        model1.add(keras.layers.Dense(1, activation=tf.nn.sigmoid))
        #optimizer = tf.keras.optimizers.RMSprop(0.001)
        #optimizer = tf.keras.optimizers.Adam()
        model1.compile(loss='mse',
                         optimizer='sgd',
                         metrics=['mae'])
        model1.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 18)	342
dense_1 (Dense)	(None, 9)	171
dense_2 (Dense)	(None, 5)	50
dense_3 (Dense)	(None, 1)	6
Total params: 569		

Trainable params: 569
Non-trainable params: 0

Fit Model

```
Epoch 1/200
0.2074 - val_loss: 0.0147 - val_mae: 0.1040
0.0846 - val_loss: 0.0087 - val_mae: 0.0752
Epoch 3/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0085 - mae:
0.0741 - val_loss: 0.0080 - val_mae: 0.0701
Epoch 4/200
0.0720 - val_loss: 0.0078 - val_mae: 0.0687
Epoch 5/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0081 - mae:
0.0713 - val_loss: 0.0077 - val_mae: 0.0681
Epoch 6/200
0.0709 - val loss: 0.0076 - val mae: 0.0677
Epoch 7/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0080 - mae:
0.0706 - val_loss: 0.0076 - val_mae: 0.0675
Epoch 8/200
0.0705 - val_loss: 0.0075 - val_mae: 0.0673
Epoch 9/200
0.0702 - val loss: 0.0075 - val mae: 0.0671
Epoch 10/200
0.0701 - val_loss: 0.0075 - val_mae: 0.0670
Epoch 11/200
0.0699 - val_loss: 0.0074 - val_mae: 0.0669
Epoch 12/200
0.0698 - val loss: 0.0074 - val mae: 0.0667
Epoch 13/200
0.0696 - val loss: 0.0074 - val mae: 0.0666
Epoch 14/200
0.0695 - val loss: 0.0073 - val mae: 0.0664
Epoch 15/200
0.0694 - val loss: 0.0073 - val mae: 0.0662
Epoch 16/200
0.0691 - val loss: 0.0073 - val mae: 0.0662
Epoch 17/200
0.0691 - val loss: 0.0072 - val mae: 0.0659
Epoch 18/200
0.0689 - val_loss: 0.0072 - val_mae: 0.0658
Epoch 19/200
0.0687 - val loss: 0.0072 - val mae: 0.0657
```

```
Epoch 20/200
0.0686 - val_loss: 0.0072 - val_mae: 0.0656
Epoch 21/200
0.0685 - val_loss: 0.0071 - val_mae: 0.0654
Epoch 22/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0075 - mae:
0.0683 - val_loss: 0.0071 - val_mae: 0.0653
Epoch 23/200
0.0681 - val_loss: 0.0071 - val_mae: 0.0652
Epoch 24/200
0.0680 - val loss: 0.0070 - val mae: 0.0652
0.0679 - val_loss: 0.0070 - val_mae: 0.0650
Epoch 26/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0074 - mae:
0.0678 - val_loss: 0.0070 - val_mae: 0.0648
Epoch 27/200
0.0676 - val loss: 0.0070 - val mae: 0.0647
Epoch 28/200
0.0675 - val loss: 0.0069 - val mae: 0.0645
Epoch 29/200
0.0673 - val loss: 0.0069 - val mae: 0.0644
Epoch 30/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0073 - mae:
0.0672 - val_loss: 0.0069 - val_mae: 0.0642
Epoch 31/200
0.0670 - val_loss: 0.0068 - val_mae: 0.0641
Epoch 32/200
0.0669 - val loss: 0.0068 - val mae: 0.0640
Epoch 33/200
0.0667 - val loss: 0.0068 - val mae: 0.0639
Epoch 34/200
0.0666 - val_loss: 0.0068 - val_mae: 0.0638
Epoch 35/200
0.0664 - val loss: 0.0067 - val mae: 0.0637
Epoch 36/200
0.0663 - val loss: 0.0067 - val mae: 0.0635
Epoch 37/200
0.0661 - val loss: 0.0067 - val mae: 0.0634
Epoch 38/200
0.0660 - val loss: 0.0066 - val mae: 0.0632
```

```
Epoch 39/200
0.0658 - val_loss: 0.0066 - val_mae: 0.0631
Epoch 40/200
0.0657 - val_loss: 0.0066 - val_mae: 0.0629
Epoch 41/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0069 - mae:
0.0656 - val_loss: 0.0065 - val_mae: 0.0627
Epoch 42/200
0.0653 - val_loss: 0.0065 - val_mae: 0.0626
Epoch 43/200
0.0653 - val loss: 0.0065 - val mae: 0.0623
Epoch 44/200
0.0649 - val_loss: 0.0064 - val_mae: 0.0623
Epoch 45/200
0.0648 - val_loss: 0.0064 - val_mae: 0.0622
Epoch 46/200
0.0647 - val loss: 0.0064 - val mae: 0.0619
Epoch 47/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0066 - mae:
0.0644 - val loss: 0.0063 - val mae: 0.0618
Epoch 48/200
0.0643 - val loss: 0.0063 - val mae: 0.0615
Epoch 49/200
0.0639 - val_loss: 0.0062 - val_mae: 0.0614
Epoch 50/200
0.0637 - val_loss: 0.0062 - val_mae: 0.0612
Epoch 51/200
0.0635 - val loss: 0.0061 - val mae: 0.0608
Epoch 52/200
0.0631 - val loss: 0.0060 - val mae: 0.0606
Epoch 53/200
0.0628 - val_loss: 0.0060 - val_mae: 0.0604
Epoch 54/200
0.0624 - val loss: 0.0059 - val mae: 0.0600
Epoch 55/200
0.0621 - val loss: 0.0058 - val mae: 0.0596
Epoch 56/200
0.0616 - val loss: 0.0058 - val mae: 0.0593
Epoch 57/200
0.0613 - val_loss: 0.0057 - val_mae: 0.0590
```

```
Epoch 58/200
0.0610 - val_loss: 0.0057 - val_mae: 0.0586
Epoch 59/200
0.0606 - val_loss: 0.0056 - val_mae: 0.0584
Epoch 60/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0058 - mae:
0.0603 - val_loss: 0.0056 - val_mae: 0.0582
Epoch 61/200
0.0601 - val_loss: 0.0055 - val_mae: 0.0578
Epoch 62/200
0.0598 - val loss: 0.0055 - val mae: 0.0574
0.0595 - val_loss: 0.0054 - val_mae: 0.0572
Epoch 64/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0056 - mae:
0.0592 - val_loss: 0.0054 - val_mae: 0.0570
Epoch 65/200
0.0589 - val loss: 0.0053 - val mae: 0.0569
Epoch 66/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0055 - mae:
0.0587 - val loss: 0.0053 - val mae: 0.0566
Epoch 67/200
0.0584 - val loss: 0.0052 - val mae: 0.0563
Epoch 68/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0054 - mae:
0.0581 - val_loss: 0.0052 - val_mae: 0.0562
Epoch 69/200
0.0578 - val_loss: 0.0051 - val_mae: 0.0559
Epoch 70/200
171/171 [=============== ] - Os 2ms/step - loss: 0.0053 - mae:
0.0575 - val loss: 0.0051 - val mae: 0.0559
Epoch 71/200
0.0574 - val loss: 0.0051 - val mae: 0.0555
Epoch 72/200
0.0571 - val_loss: 0.0050 - val_mae: 0.0552
Epoch 73/200
0.0568 - val loss: 0.0050 - val mae: 0.0550
Epoch 74/200
0.0565 - val loss: 0.0049 - val mae: 0.0547
Epoch 75/200
0.0563 - val loss: 0.0049 - val mae: 0.0544
Epoch 76/200
0.0560 - val_loss: 0.0048 - val_mae: 0.0542
```

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Epoch 77/200
0.0557 - val_loss: 0.0048 - val_mae: 0.0540
Epoch 78/200
0.0555 - val_loss: 0.0047 - val_mae: 0.0537
Epoch 79/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0049 - mae:
0.0551 - val_loss: 0.0047 - val_mae: 0.0535
Epoch 80/200
0.0549 - val_loss: 0.0047 - val_mae: 0.0534
Epoch 81/200
0.0547 - val loss: 0.0046 - val mae: 0.0531
Epoch 82/200
0.0544 - val_loss: 0.0046 - val_mae: 0.0528
Epoch 83/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0047 - mae:
0.0541 - val_loss: 0.0045 - val_mae: 0.0526
Epoch 84/200
0.0538 - val loss: 0.0045 - val mae: 0.0523
Epoch 85/200
0.0535 - val loss: 0.0044 - val mae: 0.0520
Epoch 86/200
0.0532 - val loss: 0.0044 - val mae: 0.0521
Epoch 87/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0045 - mae:
0.0530 - val_loss: 0.0044 - val_mae: 0.0517
Epoch 88/200
0.0528 - val_loss: 0.0043 - val_mae: 0.0513
Epoch 89/200
0.0524 - val loss: 0.0043 - val mae: 0.0510
Epoch 90/200
0.0522 - val loss: 0.0042 - val mae: 0.0507
Epoch 91/200
0.0519 - val_loss: 0.0042 - val_mae: 0.0504
Epoch 92/200
0.0516 - val loss: 0.0042 - val mae: 0.0503
Epoch 93/200
0.0513 - val loss: 0.0041 - val mae: 0.0501
Epoch 94/200
0.0511 - val loss: 0.0041 - val mae: 0.0499
Epoch 95/200
0.0509 - val loss: 0.0040 - val mae: 0.0496
```

```
Epoch 96/200
0.0506 - val_loss: 0.0040 - val_mae: 0.0494
Epoch 97/200
0.0503 - val_loss: 0.0040 - val_mae: 0.0490
Epoch 98/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0040 - mae:
0.0500 - val_loss: 0.0039 - val_mae: 0.0488
Epoch 99/200
0.0498 - val_loss: 0.0039 - val_mae: 0.0488
Epoch 100/200
0.0495 - val loss: 0.0039 - val mae: 0.0486
Epoch 101/200
0.0493 - val_loss: 0.0038 - val_mae: 0.0485
Epoch 102/200
0.0491 - val_loss: 0.0038 - val_mae: 0.0480
Epoch 103/200
0.0488 - val loss: 0.0038 - val mae: 0.0479
Epoch 104/200
0.0486 - val_loss: 0.0037 - val_mae: 0.0475
Epoch 105/200
0.0483 - val loss: 0.0037 - val mae: 0.0474
Epoch 106/200
0.0481 - val_loss: 0.0037 - val_mae: 0.0471
Epoch 107/200
0.0478 - val_loss: 0.0036 - val_mae: 0.0470
Epoch 108/200
0.0477 - val loss: 0.0036 - val mae: 0.0467
Epoch 109/200
0.0474 - val loss: 0.0036 - val mae: 0.0464
Epoch 110/200
0.0471 - val_loss: 0.0035 - val_mae: 0.0464
Epoch 111/200
0.0470 - val loss: 0.0035 - val mae: 0.0462
Epoch 112/200
0.0468 - val loss: 0.0035 - val mae: 0.0459
Epoch 113/200
0.0466 - val loss: 0.0035 - val mae: 0.0457
Epoch 114/200
0.0463 - val_loss: 0.0034 - val_mae: 0.0456
```

```
Epoch 115/200
0.0461 - val_loss: 0.0034 - val_mae: 0.0455
Epoch 116/200
0.0460 - val_loss: 0.0034 - val_mae: 0.0452
Epoch 117/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0034 - mae:
0.0458 - val_loss: 0.0033 - val_mae: 0.0448
Epoch 118/200
0.0455 - val_loss: 0.0033 - val_mae: 0.0449
Epoch 119/200
0.0454 - val loss: 0.0033 - val mae: 0.0447
Epoch 120/200
0.0452 - val_loss: 0.0033 - val_mae: 0.0445
Epoch 121/200
0.0450 - val_loss: 0.0033 - val_mae: 0.0444
Epoch 122/200
0.0449 - val loss: 0.0033 - val mae: 0.0442
Epoch 123/200
0.0447 - val loss: 0.0032 - val mae: 0.0440
Epoch 124/200
0.0445 - val loss: 0.0032 - val mae: 0.0438
Epoch 125/200
0.0444 - val_loss: 0.0032 - val_mae: 0.0436
Epoch 126/200
0.0442 - val_loss: 0.0032 - val_mae: 0.0437
Epoch 127/200
0.0441 - val loss: 0.0032 - val mae: 0.0435
Epoch 128/200
0.0439 - val loss: 0.0031 - val mae: 0.0433
Epoch 129/200
0.0438 - val_loss: 0.0031 - val_mae: 0.0434
Epoch 130/200
0.0437 - val loss: 0.0031 - val mae: 0.0431
Epoch 131/200
0.0435 - val loss: 0.0031 - val mae: 0.0431
Epoch 132/200
0.0434 - val loss: 0.0031 - val mae: 0.0431
Epoch 133/200
0.0433 - val loss: 0.0031 - val mae: 0.0429
```

```
Epoch 134/200
0.0432 - val_loss: 0.0031 - val_mae: 0.0427
Epoch 135/200
0.0431 - val_loss: 0.0030 - val_mae: 0.0425
Epoch 136/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0030 - mae:
0.0429 - val_loss: 0.0030 - val_mae: 0.0424
Epoch 137/200
0.0428 - val_loss: 0.0030 - val_mae: 0.0424
Epoch 138/200
0.0427 - val loss: 0.0030 - val mae: 0.0422
Epoch 139/200
0.0426 - val_loss: 0.0030 - val_mae: 0.0422
Epoch 140/200
0.0425 - val_loss: 0.0030 - val_mae: 0.0421
Epoch 141/200
0.0424 - val loss: 0.0030 - val mae: 0.0421
Epoch 142/200
0.0423 - val loss: 0.0030 - val mae: 0.0420
Epoch 143/200
0.0423 - val loss: 0.0030 - val mae: 0.0417
Epoch 144/200
0.0422 - val_loss: 0.0030 - val_mae: 0.0417
Epoch 145/200
0.0421 - val_loss: 0.0029 - val_mae: 0.0415
Epoch 146/200
0.0420 - val loss: 0.0029 - val mae: 0.0417
Epoch 147/200
0.0420 - val loss: 0.0029 - val mae: 0.0415
Epoch 148/200
0.0419 - val_loss: 0.0029 - val_mae: 0.0416
Epoch 149/200
0.0418 - val loss: 0.0029 - val mae: 0.0416
Epoch 150/200
0.0418 - val loss: 0.0029 - val mae: 0.0413
Epoch 151/200
0.0417 - val loss: 0.0029 - val mae: 0.0411
Epoch 152/200
0.0416 - val_loss: 0.0029 - val_mae: 0.0412
```

```
Epoch 153/200
0.0415 - val_loss: 0.0029 - val_mae: 0.0412
Epoch 154/200
0.0415 - val_loss: 0.0029 - val_mae: 0.0412
Epoch 155/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0029 - mae:
0.0414 - val_loss: 0.0029 - val_mae: 0.0411
Epoch 156/200
0.0414 - val_loss: 0.0029 - val_mae: 0.0410
Epoch 157/200
0.0413 - val loss: 0.0029 - val mae: 0.0409
Epoch 158/200
0.0413 - val_loss: 0.0029 - val_mae: 0.0409
Epoch 159/200
0.0412 - val_loss: 0.0029 - val_mae: 0.0409
Epoch 160/200
0.0411 - val loss: 0.0029 - val mae: 0.0409
Epoch 161/200
0.0411 - val loss: 0.0029 - val mae: 0.0408
Epoch 162/200
0.0411 - val loss: 0.0029 - val mae: 0.0408
Epoch 163/200
0.0410 - val_loss: 0.0029 - val_mae: 0.0408
Epoch 164/200
0.0410 - val loss: 0.0028 - val mae: 0.0405
Epoch 165/200
0.0409 - val loss: 0.0028 - val mae: 0.0405
Epoch 166/200
0.0409 - val loss: 0.0028 - val mae: 0.0406
Epoch 167/200
0.0409 - val_loss: 0.0028 - val_mae: 0.0406
Epoch 168/200
0.0408 - val loss: 0.0028 - val mae: 0.0406
Epoch 169/200
0.0408 - val loss: 0.0028 - val mae: 0.0403
Epoch 170/200
0.0407 - val loss: 0.0028 - val mae: 0.0404
Epoch 171/200
0.0407 - val_loss: 0.0028 - val_mae: 0.0404
```

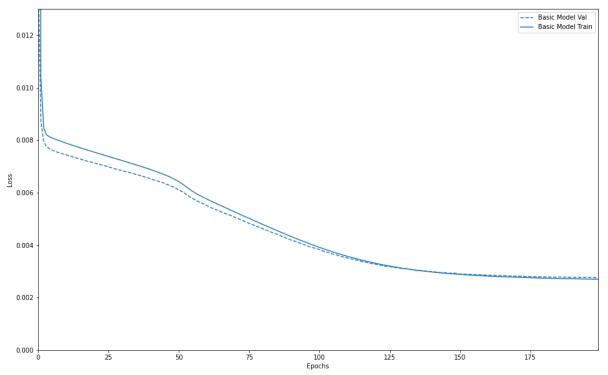
```
Epoch 172/200
0.0407 - val_loss: 0.0028 - val_mae: 0.0403
Epoch 173/200
0.0406 - val_loss: 0.0028 - val_mae: 0.0404
Epoch 174/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0028 - mae:
0.0406 - val_loss: 0.0028 - val_mae: 0.0402
Epoch 175/200
0.0406 - val_loss: 0.0028 - val_mae: 0.0403
Epoch 176/200
0.0405 - val loss: 0.0028 - val mae: 0.0403
Epoch 177/200
0.0405 - val_loss: 0.0028 - val_mae: 0.0402
Epoch 178/200
0.0405 - val_loss: 0.0028 - val_mae: 0.0402
Epoch 179/200
0.0405 - val loss: 0.0028 - val mae: 0.0402
Epoch 180/200
0.0404 - val loss: 0.0028 - val mae: 0.0401
Epoch 181/200
0.0404 - val loss: 0.0028 - val mae: 0.0401
Epoch 182/200
0.0404 - val_loss: 0.0028 - val_mae: 0.0401
Epoch 183/200
0.0404 - val_loss: 0.0028 - val_mae: 0.0400
Epoch 184/200
0.0404 - val loss: 0.0028 - val mae: 0.0400
Epoch 185/200
0.0403 - val loss: 0.0028 - val mae: 0.0400
Epoch 186/200
0.0403 - val_loss: 0.0028 - val_mae: 0.0401
Epoch 187/200
0.0403 - val loss: 0.0028 - val mae: 0.0401
Epoch 188/200
0.0403 - val loss: 0.0028 - val mae: 0.0400
Epoch 189/200
0.0402 - val loss: 0.0028 - val mae: 0.0401
Epoch 190/200
0.0402 - val_loss: 0.0028 - val_mae: 0.0399
```

```
Epoch 191/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0027 - mae:
0.0402 - val_loss: 0.0028 - val_mae: 0.0399
Epoch 192/200
0.0402 - val_loss: 0.0028 - val_mae: 0.0399
Epoch 193/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0027 - mae:
0.0401 - val_loss: 0.0028 - val_mae: 0.0399
Epoch 194/200
0.0402 - val_loss: 0.0028 - val_mae: 0.0399
Epoch 195/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0027 - mae:
0.0401 - val loss: 0.0028 - val mae: 0.0398
Epoch 196/200
0.0401 - val_loss: 0.0028 - val_mae: 0.0399
Epoch 197/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0027 - mae:
0.0401 - val_loss: 0.0028 - val_mae: 0.0398
Epoch 198/200
0.0401 - val_loss: 0.0028 - val_mae: 0.0398
Epoch 199/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0027 - mae:
0.0401 - val loss: 0.0028 - val mae: 0.0397
Epoch 200/200
171/171 [============== ] - 0s 2ms/step - loss: 0.0027 - mae:
0.0400 - val loss: 0.0028 - val mae: 0.0396
```

Lowest Validation Error

Step 5: Plot Results

```
In [11]:
         import matplotlib.pyplot as plt
         def plot_history(histories, key='loss'):
           plt.figure(figsize=(16,10))
           for name, history in histories:
             val = plt.plot(m1_history.epoch, m1_history.history['val_'+key],
                             '--', label=name.title()+' Val')
             plt.plot(m1 history.epoch, m1 history.history[key], color=val[0].get color
         (),
                       label=name.title()+' Train')
           plt.xlabel('Epochs')
           plt.ylabel(key.replace('_',' ').title())
           plt.legend()
           plt.xlim([0,max(m1_history.epoch)])
           plt.ylim([0,0.013])
         plot_history([('Basic Model', m1_history)])
         #Plot Multiple Model Results
         #plot history([('Plain', m1 history),('L1',model1)])
```



Goal: Predict the percentage of patients that will use the Online Appointment System. After researching online it stated to use the mean of the target. The mean of Online Appointment use is 13.71%.

In the model my min Mean Absolute Error for the validation data was .03964 or .40. In the graph the training and validation model converge, so we don't have any overfitting, underfitting or generalization issues.