Introduction to Machine Learning: Linear and Logistic Regression and Neural Networks using Python

Chapter 7 Case Studies

Case Studies

So far in this course:

- We have discussed underlying mathematics and algorithms for Linear Regression, Logistic Regression and Neural Network approaches for Supervised Learning
- We have developed a machine learning framework for Supervised Learning that can apply these approaches
- We have discussed approaches for improving optimization for the training algorithm, measuring performance, regularization, and addressing Underfitting and Overfitting
- In this chapter we apply these ideas to address 3 case studies

Case Studies

Section	Case Study	Type	Description
7.1	House Price Prediction	Regression	This case study uses Linear Regression to predict house prices. It also shows how to use “exploratory data analysis” and “feature preprocessing” to prepare the data.
7.2	Spam Classification	Binary Classification	This case study uses a Neural Network to create a spam filter. It shows an approach for converting text into a feature matrix.
7.3	MNIST Digits Classification	Multiclass Classification	This case study uses a Neural Network to identify digits from images. It shows how to convert an image into a feature matrix.

7.1 Case Study: House Price Prediction

Case Study: House Price Prediction

Goal of this Section:

- Show how to use Linear Regression for House Price Prediction
- Introduce Exploratory Data Analysis and Feature Preprocessing to set up the machine learning problem

House Price Dataset - Citation

- House Price Dataset compiled from data in Sindian Dist., New Taipei City, Taiwan
- Source: (University of California, Irvine, Machine Learning Repository)

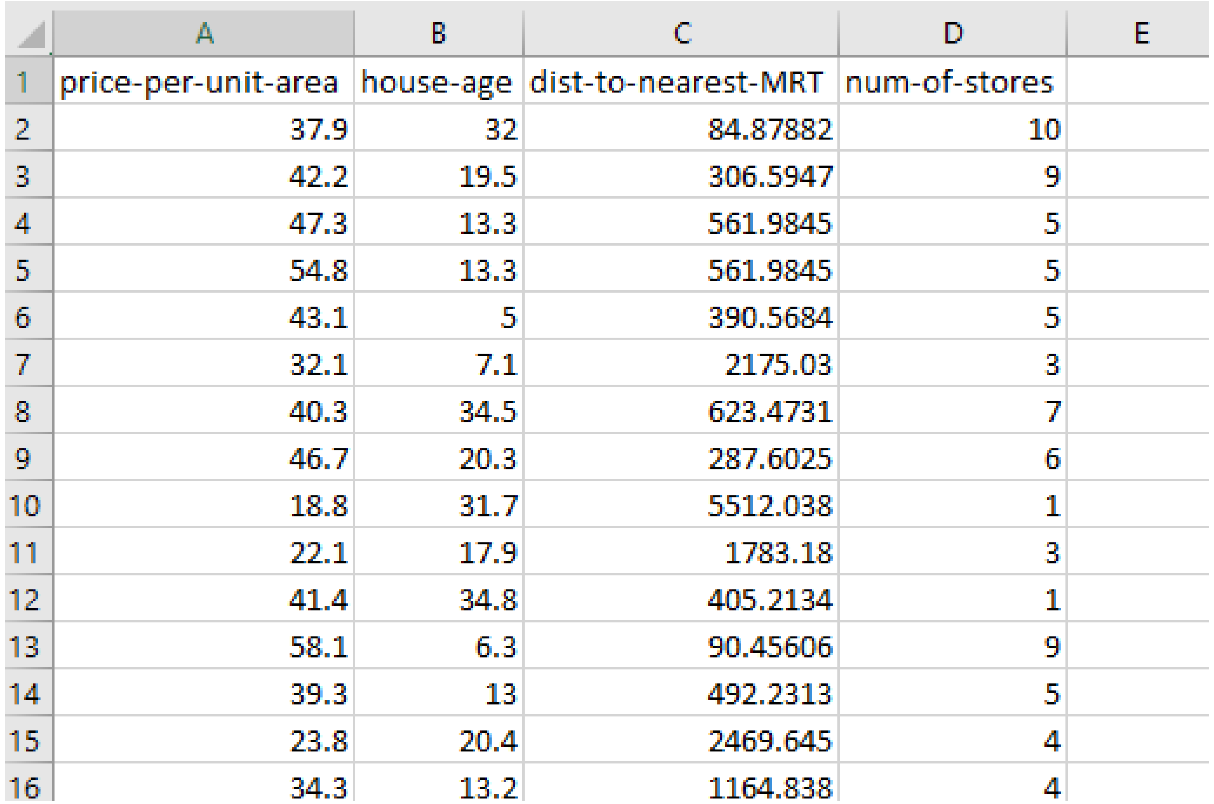
https://archive.ics.uci.edu/ml/datasets/Real+estate+valuation+data+set

- Paper describing work:

Yeh, I. C., & Hsu, T. K. (2018). Building real estate valuation models with comparative approach through case-based reasoning. Applied Soft Computing, 65, 260-271.

House Price Dataset

- Data located in folder IntroML/Code/Data_House:
  - File: house.csv
  - 414 data samples
  - 1 Value (price-per-unit-area),
  - 3 features (house-age (years), dist-to-nearest-MRT (meters), num-of-stores)
  - Original dataset has 3 additional features not used here (transaction date & house coordinates)



	A	B	C	D	E
1	price-per-unit-area	house-age	dist-to-nearest-MRT	num-of-stores	
2	37.9	32	84.87882	10	
3	42.2	19.5	306.5947	9	
4	47.3	13.3	561.9845	5	
5	54.8	13.3	561.9845	5	
6	43.1	5	390.5684	5	
7	32.1	7.1	2175.03	3	
8	40.3	34.5	623.4731	7	
9	46.7	20.3	287.6025	6	
10	18.8	31.7	5512.038	1	
11	22.1	17.9	1783.18	3	
12	41.4	34.8	405.2134	1	
13	58.1	6.3	90.45606	9	
14	39.3	13	492.2313	5	
15	23.8	20.4	2469.645	4	
16	34.3	13.2	1164.838	4	

Exploratory Data Analysis & Feature Preprocessing

Exploratory Data Analysis

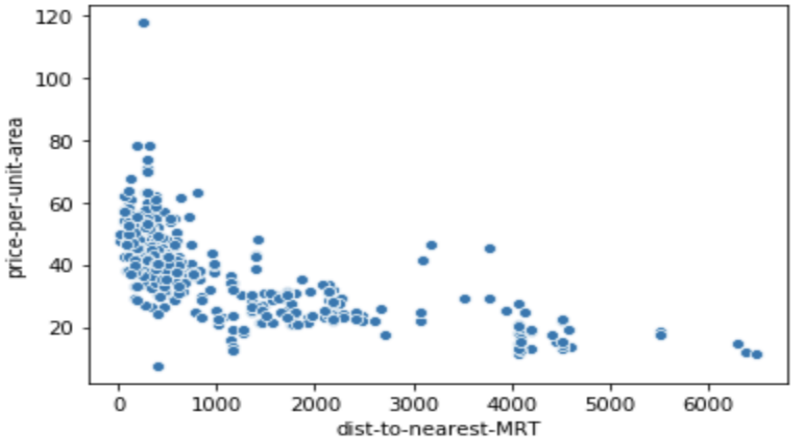
- Approach for analyzing data sets to understand relationships between variables often using visual tools
- For House Price Prediction, do not expect house prices to be linearly dependent on features
- Use Exploratory Data Analysis to determine relationship between prices and features to determine transformations to be made

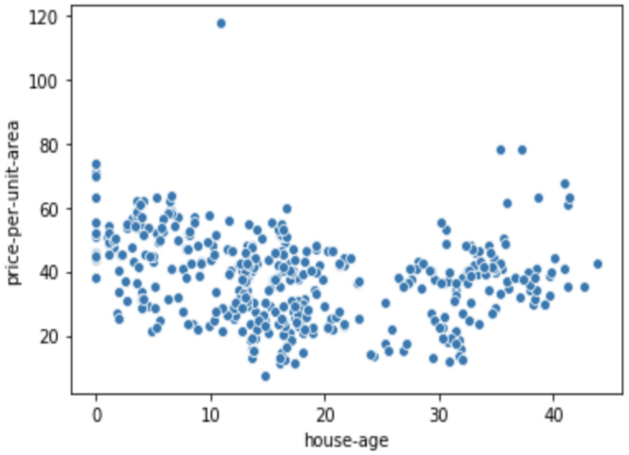
Feature Preprocessing

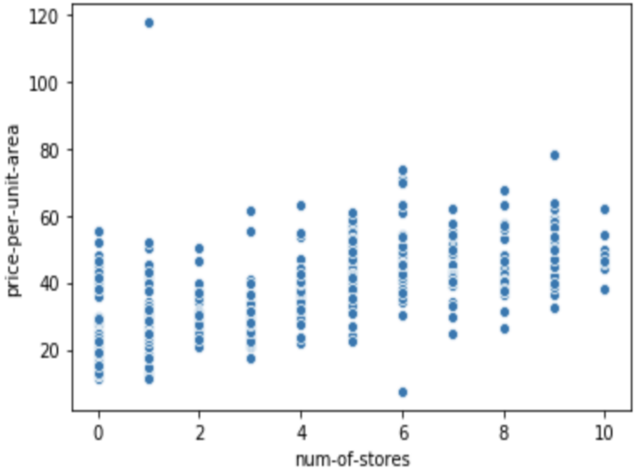
- Apply transformations to feature variables suggested by exploratory data analysis
- “Standardize” or “normalize” variables so they are all of roughly the same size
- Remove outliers

Exploratory Data Analysis

- Scatter plots show relationships between price-per-unit area and each of the features
- Scatter plots suggest non-linear relationships between price-per-unit-area and distance to nearest MRT and house age

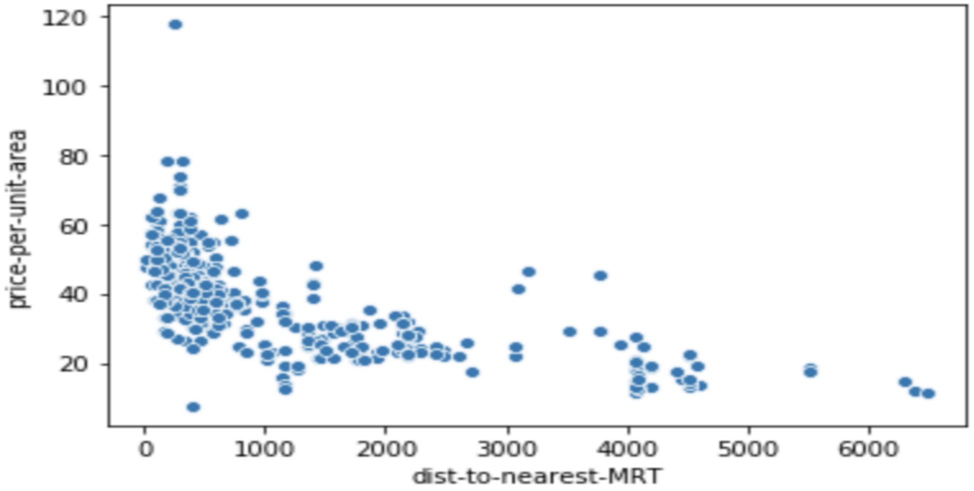


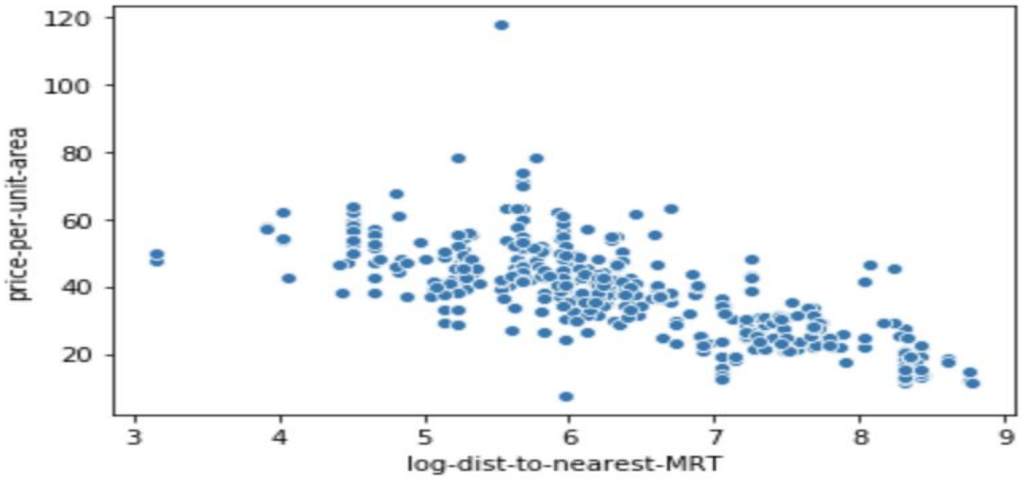




Variable Transformations

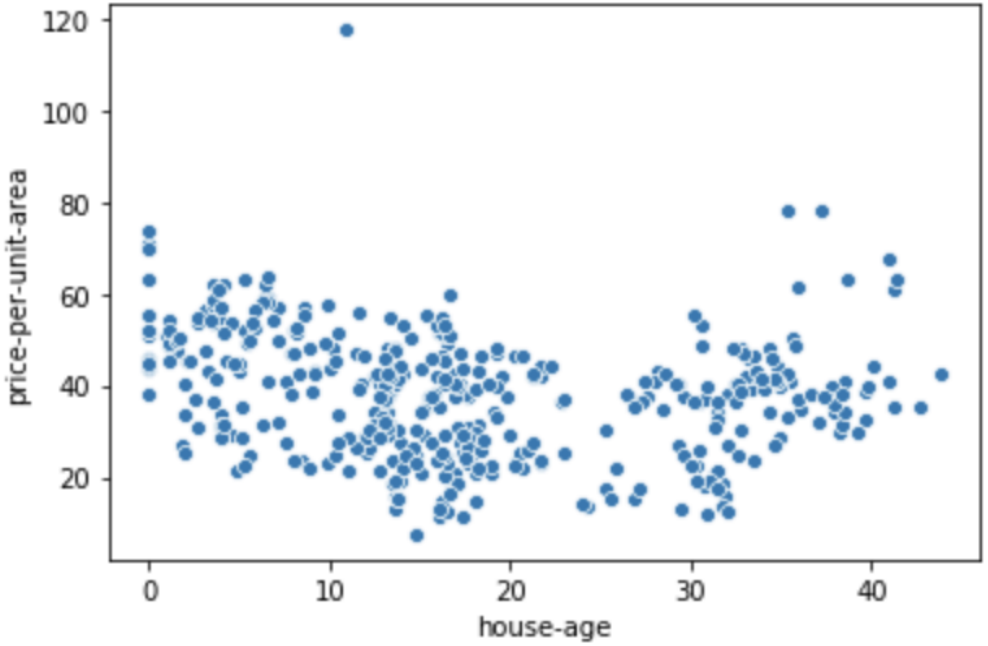
- A log transformation is applied to the variable **dist-to-nearest-MRT**
  - Improves linearity between the feature and price

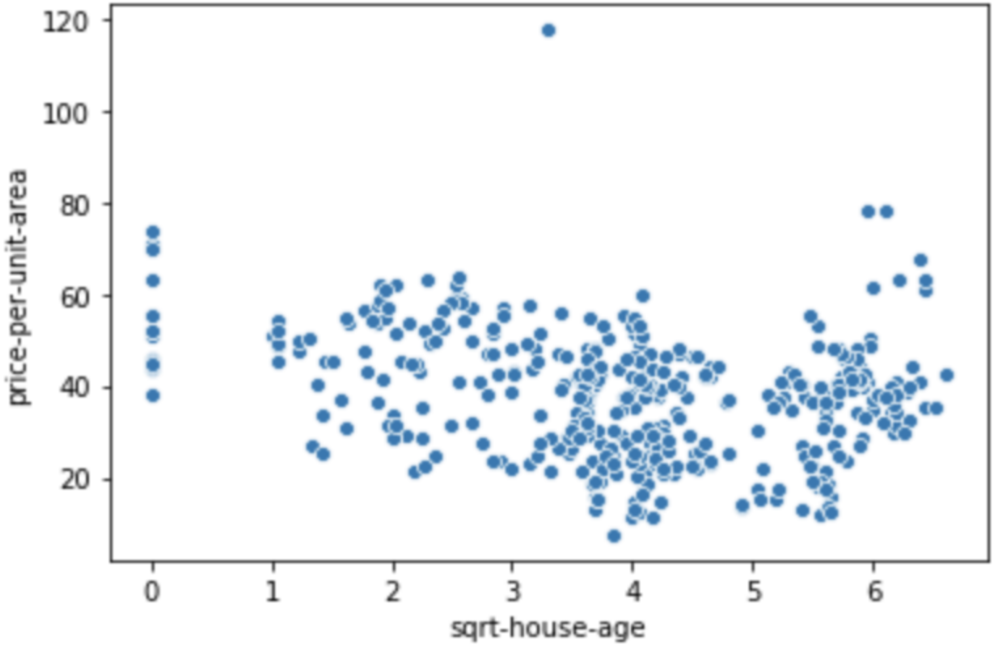




Variable Transformations

- A square root transformation is applied to the variable **house-age**
  - Marginally improves linearity of relationship between price and feature





Feature Standardization

- Feature values are of different magnitudes:
  - Age: roughly 0 – 50
  - Distance to MRT: roughly 0 – 7000
  - Number of stores: 0 - 10
- Standardize Features:
  - Subtract mean and scale by standard deviation of training data for each feature independently
  - Apply same scaling to validation data
  - Results in feature data having mean 0 and standard deviation 1 so that feature values are the same magnitude
- This can improve convergence of optimizer

Value Standardization

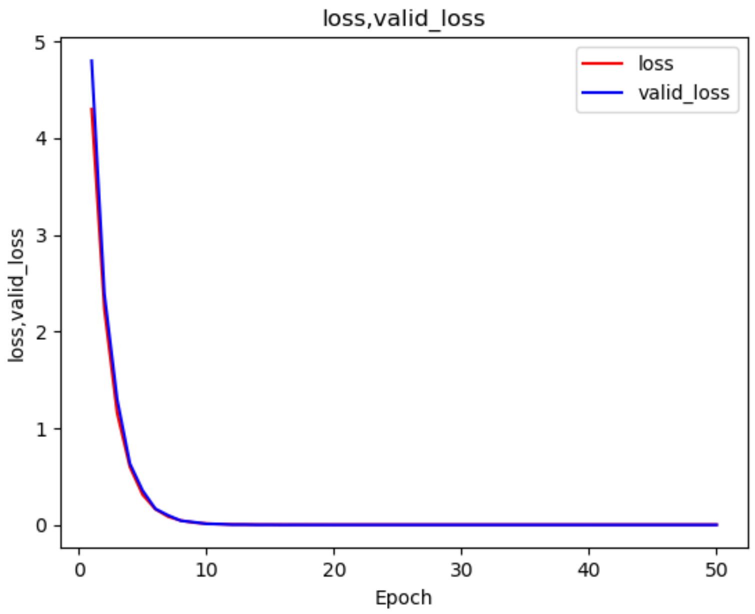
- To improve convergence of optimization, can apply same technique as previous page to standardize price-per-unit-area data
- For simplicity, will simply divide price-per-unit-area data by maximum value in training data set
- Apply exact same scaling factor to validation data set
- Note that predictions of the model will need to be multiplied by this factor to get correct price-per-unit-area

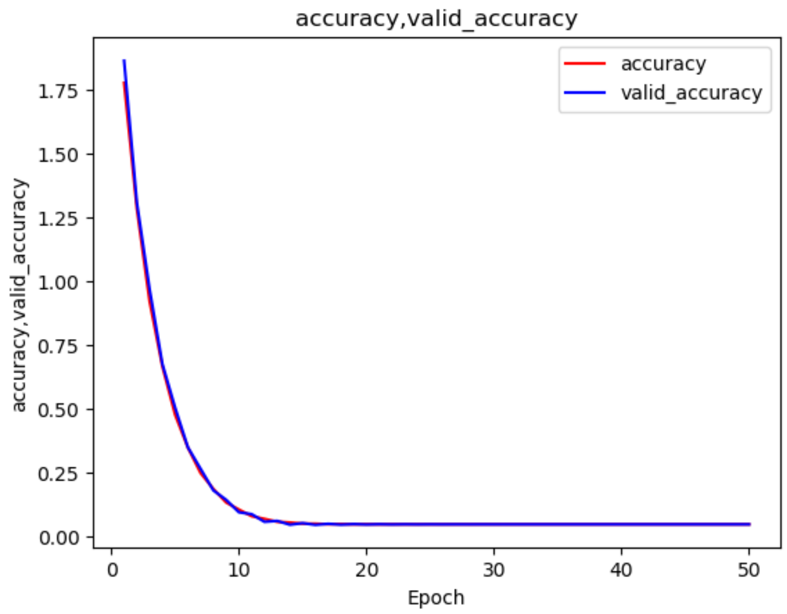
House Price Prediction using Linear Regression

- Example: Dataset
  - 331 samples in training dataset (roughly 80% of samples)
  - 83 samples in validation dataset (roughly 20% of samples)
  - Feature matrix for training (3 x 331)
  - Feature matrix for validation (3 x 83)
- Linear Regression
  - W is 1x3 and b is 1x1
  - $\lambda = 0.0001$ (regularization)
- Optimization:
  - Gradient Descent ($\alpha = 0.5$)
  - 50 epochs
  - Batch optimization
  - Mean squared error loss
- Accuracy Function
  - Mean absolute error

House Price Prediction – Summary of Results

- Run with Transformation, Standardization for X and Y = True
  - Training Loss: 0.0059, Training Accuracy: 0.050 (mean absolute error)
  - Validation Loss: 0.0041, Validation Accuracy: 0.050 (mean absolute error)
  - Loss and Accuracy plots indicate no concerning signs of overfitting





Summary of Results

Run	Transformations/Standardization	Results after 50 epochs
1	Transformation: True Standardization X: True Standardization Y: True	Training Accuracy: 0.050 Validation Accuracy: 0.050
2	Transformation: False Standardization X: True Standardization Y: True	Training Accuracy: 0.056 Validation Accuracy: 0.052
3	Transformation: True Standardization X: False Standardization Y: True	Training Accuracy: Blow up – does not converge Validation Accuracy: Blow up - does not converge

New Code for House Price Prediction

Function/component	Input	Description
load_house	train_pct (float) transform (boolean) standardizeX (boolean) standardizeY (boolean)	Loads house price data and perform feature/value preprocessing. Train_pct ranges from 0.0-1.0 and indicates the proportion of the data to used for training. Input: transform determines if the log and sqrt transformations will be made to features. Inputs standardizeX and standardizeY determine if standardizations will be applied. Return: Xtrain, Ytrain, Xvalid, Yvalid See IntroML/Examples/Chapter2/PandasDemo.ipynb
driver_casestudy_house		Driver for house price prediction

7.1 House Price Prediction DEMO

- Code located at: IntroML/Code/Version4.1
- Data located at: IntroML/Code/Data_House
- How to proceed:
  - Using information from previous videos, see if you can create load_house for loading data and a driver for house price prediction starting with an original Version3.3 of the code
  - Alternatively, watch this video, which walks through the changes and then use as a guide to make changes
  - The examples in the Jupyter notebooks are a useful resource showing how to use pandas and numpy functionality to load and process data

Course Resources at:

- https://github.com/satishchandrareddy/IntroML/

7.2 Case Study: Spam Classification

Case Study: Spam Classification

Goal of this Section:

- Describe approach for using neural networks for spam classification using the SMS dataset

Text Classification

Text Classification is an application of supervised machine learning
Examples include:

- Spam Classification
  - Binary Classification
  - Training Data: messages and labels (spam or not spam)
  - Goal: predict if new message is spam or not (use to filter email, for example)
- Sentiment Classification of Reviews
  - Multiclass classification
  - Training Data: reviews and labels (1, 2, 3, 4 or 5 star, for example)
  - Goal: predict rating for new reviews

SMS Spam Collection Dataset - Citation

- Source: (University of California, Irvine, Machine Learning Repository)

http://archive.ics.uci.edu/ml/datasets/SMS+Spam+Collection

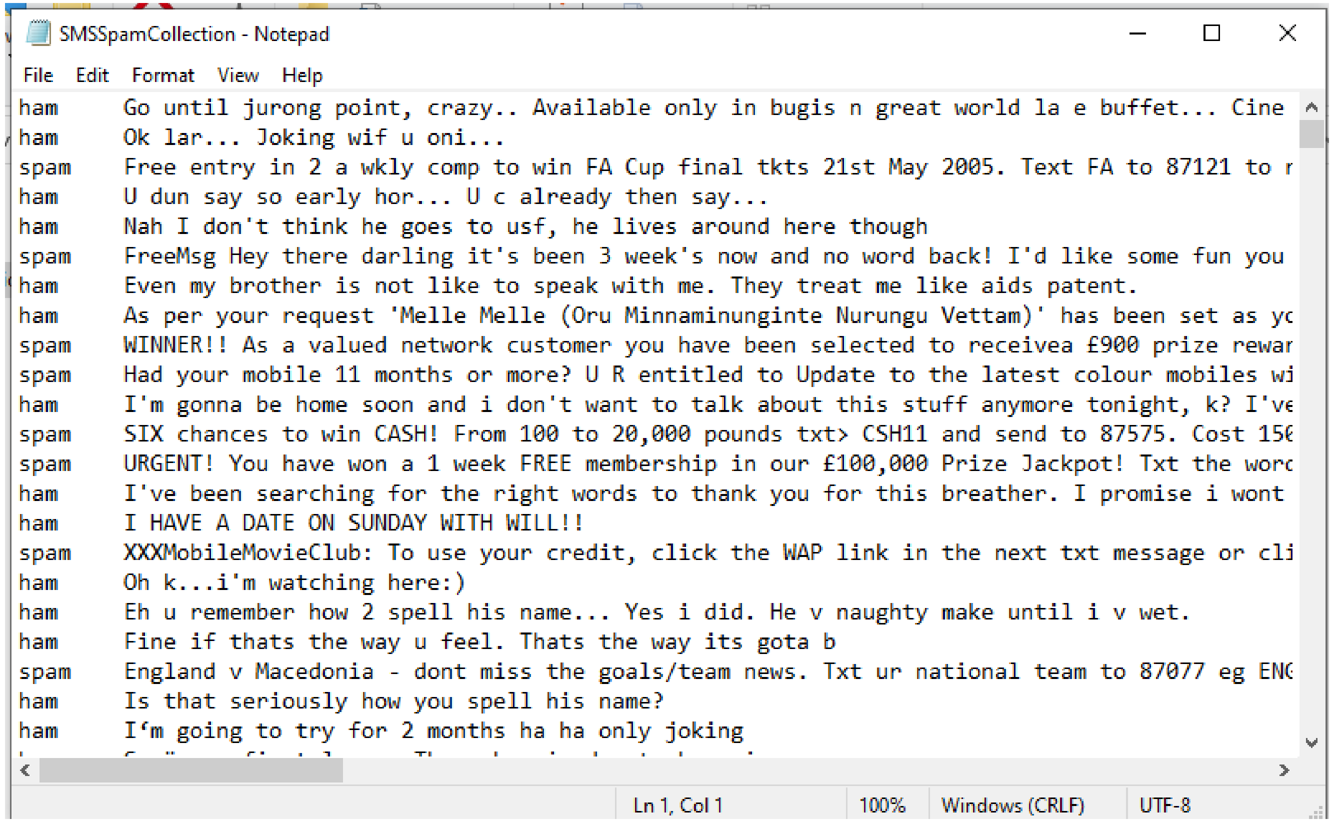
- Paper describing work:

Almeida, T.A., Gómez Hidalgo, J.M., Yamakami, A. Contributions to the study of SMS Spam Filtering: New Collection and Results. Proceedings of the 2011 ACM Symposium on Document Engineering (ACM DOCENG'11), Mountain View, CA, USA, 2011. (Under review)

- See website: http://www.dt.fee.unicamp.br/~tiago/smsspamcollection/

SMS Spam Collection Dataset

- Data located in folder IntroML/Code/Data_Spam
  - readme.txt file provides details about dataset
  - SMSSpamCollection contains the data
- Consist of 5574 text messages: 4827 (not spam) 747 (spam)
- Each line has label (ham or spam) and message



```
ham     Go until jurong point, crazy.. Available only in bugis n great world la e buffet... Cine
ham     Ok lar... Joking wif u oni...
spam    Free entry in 2 a wkly comp to win FA Cup final tkts 21st May 2005. Text FA to 87121 to r
ham     U dun say so early hor... U c already then say...
ham     Nah I don't think he goes to usf, he lives around here though
spam    FreeMsg Hey there darling it's been 3 week's now and no word back! I'd like some fun you
ham     Even my brother is not like to speak with me. They treat me like aids patent.
ham     As per your request 'Melle Melle (Oru Minnaminunginte Nurungu Vettam)' has been set as yo
spam    WINNER!! As a valued network customer you have been selected to receivea £900 prize rewar
spam    Had your mobile 11 months or more? U R entitled to Update to the latest colour mobiles wi
ham     I'm gonna be home soon and i don't want to talk about this stuff anymore tonight, k? I've
spam    SIX chances to win CASH! From 100 to 20,000 pounds txt> CSH11 and send to 87575. Cost 15
spam    URGENT! You have won a 1 week FREE membership in our £100,000 Prize Jackpot! Txt the word
ham     I've been searching for the right words to thank you for this breather. I promise i wont
ham     I HAVE A DATE ON SUNDAY WITH WILL!!
spam    XXXMobileMovieClub: To use your credit, click the WAP link in the next txt message or cli
ham     Oh k...i'm watching here:)
ham     Eh u remember how 2 spell his name... Yes i did. He v naughty make until i v wet.
ham     Fine if thats the way u feel. Thats the way its gota b
spam    England v Macedonia - dont miss the goals/team news. Txt ur national team to 87077 eg ENG
ham     Is that seriously how you spell his name?
ham     I'm going to try for 2 months ha ha only joking
```

Converting Messages into a Feature Matrix

- Rudimentary Approach: CountVectorizer (from sklearn package)

1. Build a vocabulary consisting of all words in all messages
   - Default setting is case-insensitive ("my", "My", "MY" are the same)
2. Feature matrix entry X_{ij} is number of times word i appears in message j
3. Feature Matrix has dimensions (# of words x # of messages)

- Can adjust settings to not include some words (called "stop words"), such as "the", "to", "and", …., which probably do not impact classification.
- See https://scikit-learn.org/stable/index.html for details

CountVectorizer - Example

- 3 Messages: “Call me soon”, “CALL to win”, “Pick me up soon”
- CountVectorizer determines unique words (My, my, MY are the same in default setting)
- CountVectorizer creates matrix (# words x # messages) with number of times each word appears in a message

Words

$$\begin{matrix} \boxed{call} \\ \boxed{me} \\ pick \\ \boxed{soon} \\ to \\ up \\ win \end{matrix}$$

Feature Matrix:

$$\begin{bmatrix} \boxed{1} & 1 & 0 \\ \boxed{1} & 0 & 1 \\ 0 & 0 & 1 \\ \boxed{1} & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

Most Common Words

- Sum Feature Matrix in col direction to get count of words for all messages

Words:

$$\begin{matrix} \boxed{call} \\ \boxed{me} \\ \boxed{pick} \\ \boxed{soon} \\ to \\ up \\ win \end{matrix}$$

Feature Matrix:

$$\begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 0 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

Count:

$$\begin{bmatrix} \boxed{2} \\ \boxed{2} \\ \boxed{1} \\ \boxed{2} \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

- Can use numpy argsort function to get indices of most common words:
  - In case of ties, go in order of index
  - Indices of 4 most common words: 0, 1, 3, 2
  - Most common words: call, me, soon, pick

Label Vector

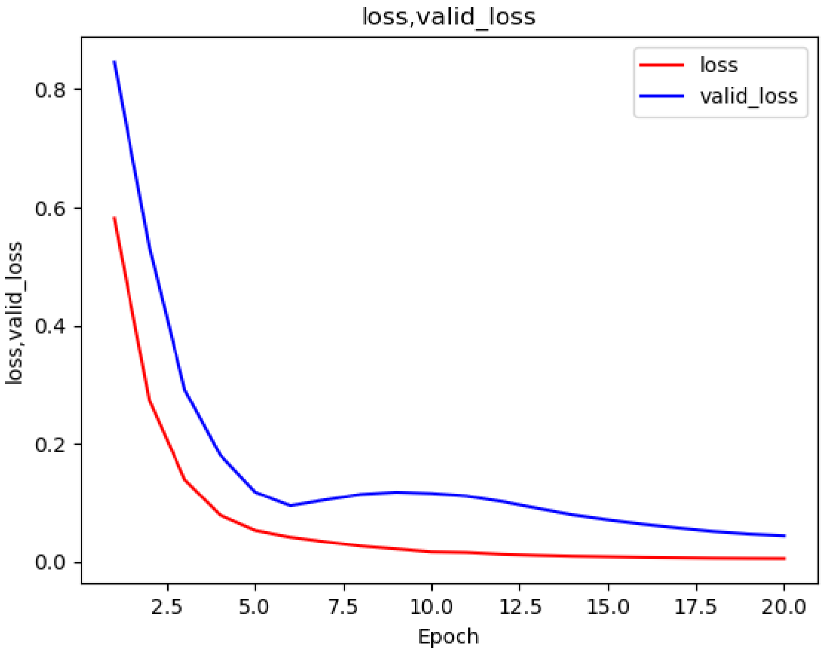
- Label Vector:
    - Convert label ham = 0 and spam = 1

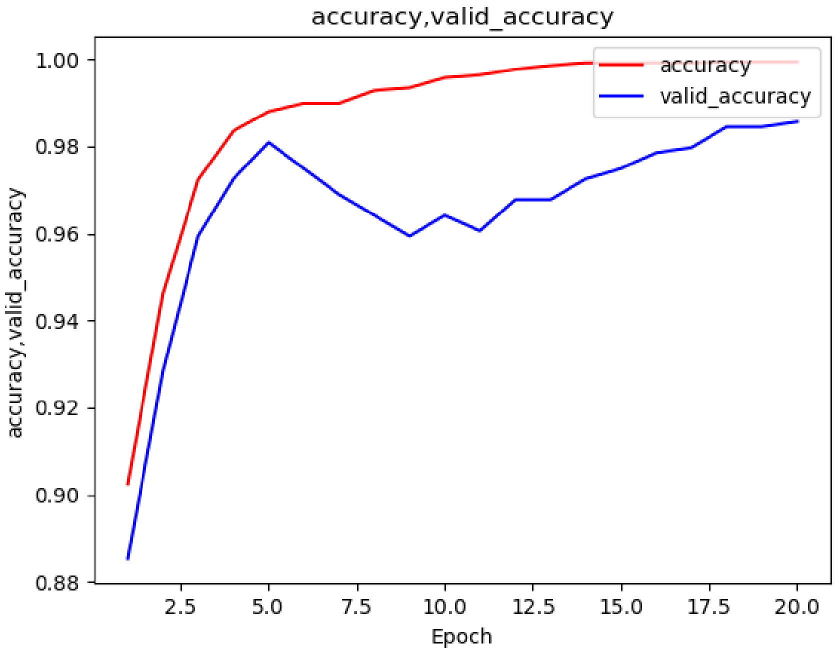
Spam Classification using a Neural Network

- Example: Dataset
  - 4737 (roughly 85%) messages in training dataset
  - 837 (roughly 15%) messages in validation dataset
  - 8572 words in vocabulary
  - Feature matrix for training is (8572 x 4737)
  - Feature matrix for validation is (8572 x 837)
- Neural Network
  - 3 layer neural network
    - Layer 1: 200 units (tanh activation)
    - Layer 2: 50 units (tanh activation)
    - Layer 3: 1 unit (sigmoid activation)
    - Binary Cross Entropy Loss function
    - 1,760,701 total combined entries in $W^{[k]}$ and $b^{[k]}$ in all layers
- Optimization:
  - Adam: α = 0.02, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\varepsilon = 10^{-7}$
  - 20 epochs (batch_size = 4737 - batch gradient descent)
  - Binary cross entropy loss
- Accuracy
  - Proportion of correct predictions

Spam Classification – Summary of Results

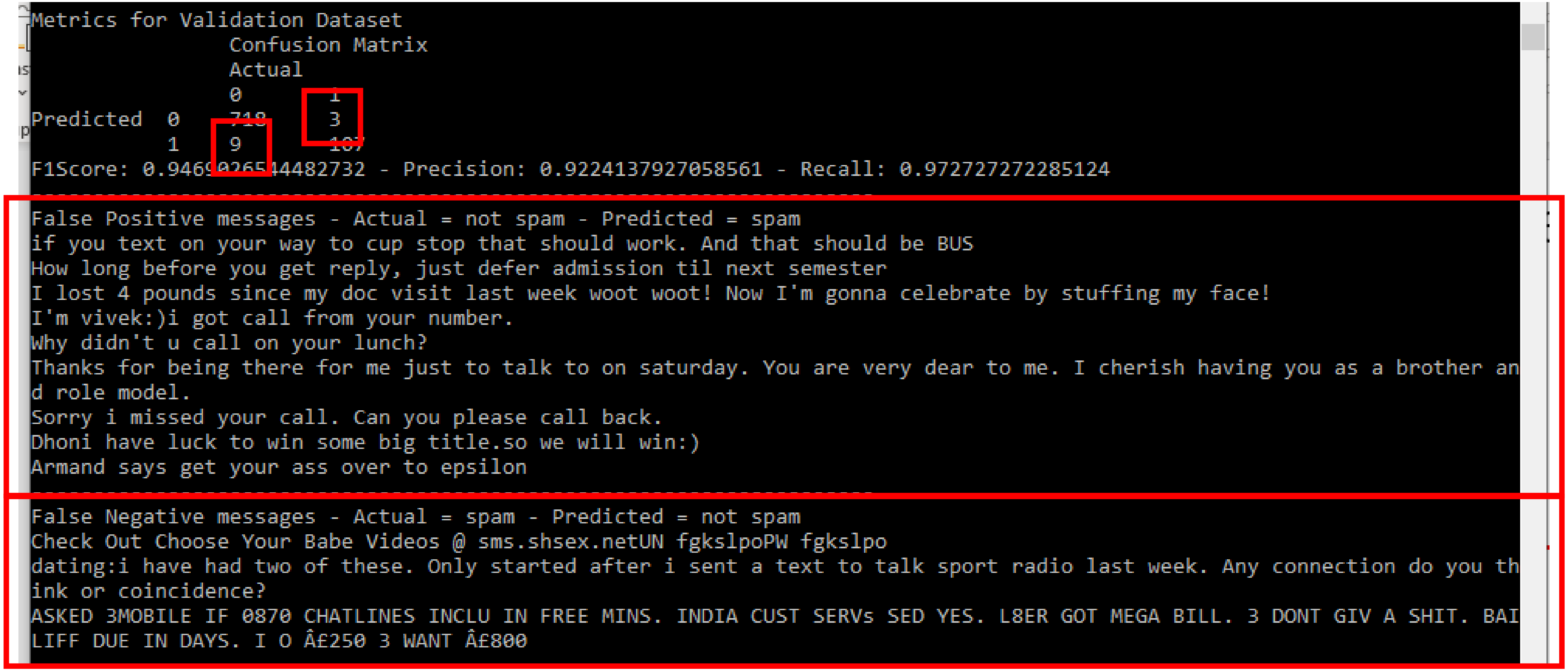
- After 20 epochs:
  - Training Accuracy: 0.9994
  - Validation Accuracy: 0.9857
  - For Validation Set: F1score: 0.9469, Precision: 0.9224, Recall: 0.9727
- Loss and Accuracy plots indicate an overfitting





Spam Classification – Summary of Results

- Confusion matrix for validation dataset:
  - 9 False Positive Messages
  - 3 False Negative Messages



```
Metrics for Validation Dataset
                Confusion Matrix
                Actual
                0       1
Predicted  0    718     3
           1    9       107
F1Score: 0.9469026544482732 - Precision: 0.9224137927058561 - Recall: 0.972727272285124
--------------------------------------------------------------------------------
False Positive messages - Actual = not spam - Predicted = spam
if you text on your way to cup stop that should work. And that should be BUS
How long before you get reply, just defer admission til next semester
I lost 4 pounds since my doc visit last week woot woot! Now I'm gonna celebrate by stuffing my face!
I'm vivek:)i got call from your number.
Why didn't u call on your lunch?
Thanks for being there for me just to talk to on saturday. You are very dear to me. I cherish having you as a brother an
d role model.
Sorry i missed your call. Can you please call back.
Dhoni have luck to win some big title.so we will win:)
Armand says get your ass over to epsilon
--------------------------------------------------------------------------------
False Negative messages - Actual = spam - Predicted = not spam
Check Out Choose Your Babe Videos @ sms.shsex.netUN fgkslpoPW fgkslpo
dating:i have had two of these. Only started after i sent a text to talk sport radio last week. Any connection do you th
ink or coincidence?
ASKED 3MOBILE IF 0870 CHATLINES INCLU IN FREE MINS. INDIA CUST SERVs SED YES. L8ER GOT MEGA BILL. 3 DONT GIV A SHIT. BAI
LIFF DUE IN DAYS. I O Â£250 3 WANT Â£800
```

New Code for Spam Classification

Method	Input	Description
load_spam	train_pct (float)	Loads spam data base and returns train and validation feature matrices (based on CountVectorizer) and label vectors. Also returns original messages in train and validation datasets. Return: Xtrain, Ytrain, Xvalid, Yvalid, Xtrain_raw, Xvalid_raw See IntroML/Examples/Chapter2/PandasDemo.ipynb and IntroML/Examples/Chapter2/sklearnDemo.ipynb
data_analysis	X (numpy array) Y (numpy array) nmostcommon (integer) vectorizer (CountVectorizer instance)	Takes in X feature matrix generated by CountVectorizer and label vector Y and prints nmostcommon words in spam and not spam messages Return: nothing See IntroML/Examples/Chapter2/sklearnDemo.ipynb
text_results	Y (numpy array) Y_pred (numpy array) X_raw (numpy array)	Given actual Y and predicted Y_pred label vectors and raw messages, this function prints the false positive and false negative messages Return: nothing
driver_casestudy_ spam		Driver for spam classification using a neural network

7.2 Spam Classification DEMO

- Code located at: IntroML/Code/Version4.1
- Data located at: IntroML/Code/Data_Spam
- How to proceed:
  - Using information from previous videos, see if you can create functions for loading and processing data and a driver starting with an original Version3.3 of the code
  - Alternatively, watch this video, which walks through the changes and then use as a guide to make changes
  - The examples in the Jupyter notebooks are a useful resource showing how to use pandas, sklearn, and numpy functionality to load and process data

Course Resources at:

- https://github.com/satishchandrareddy/IntroML/

7.3 Case Study: MNIST Digits Classification

MNIST Digits Classification

Goal of this Section:

- Describe approach for using a neural network for image classification using the MNIST Digits dataset

Machine Learning - Image Classification

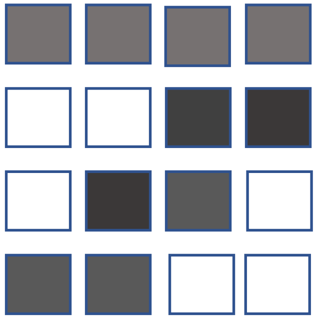
- Image classification (cats and dogs, animals, x-rays, scans, etc) is a principal application of supervised machine learning
- Binary or multi-class
- Training data:
    - Input information = image data
    - Output information = labels
- Goal is to be able to predict label for new images
- Question: how does one convert images into feature matrix to employ neural network approach?

Representation of Images

- Images typically are composed of rectangular arrays of pixels
- For black and white images, intensity of greyscale for each pixel is represented by a number (white = 0 to 255 = black)
- Feature vector for image is vector of intensities for all pixels
- For colour images, each pixel represented by 3 values – intensities of red, blue, and green components for that pixel – feature vector in colour case vector will be 3 times longer than in black and white case

Converting Image to Feature Matrix

Original Image:
Greyscale 4x4 =16 pixels



Intensity Matrix
4x4 (white=0 to 255=black)

$$\rightarrow \begin{bmatrix} 190 & 190 & 190 & 190 \\ 0 & 0 & 220 & 220 \\ 0 & 220 & 200 & 0 \\ 200 & 200 & 0 & 0 \end{bmatrix} \rightarrow$$

Feature Vector 16x1

$$\begin{bmatrix} 190 \\ 190 \\ 190 \\ 190 \\ 0 \\ 0 \\ 220 \\ 220 \\ 0 \\ 220 \\ 200 \\ 0 \\ 200 \\ 200 \\ 0 \\ 0 \end{bmatrix}$$

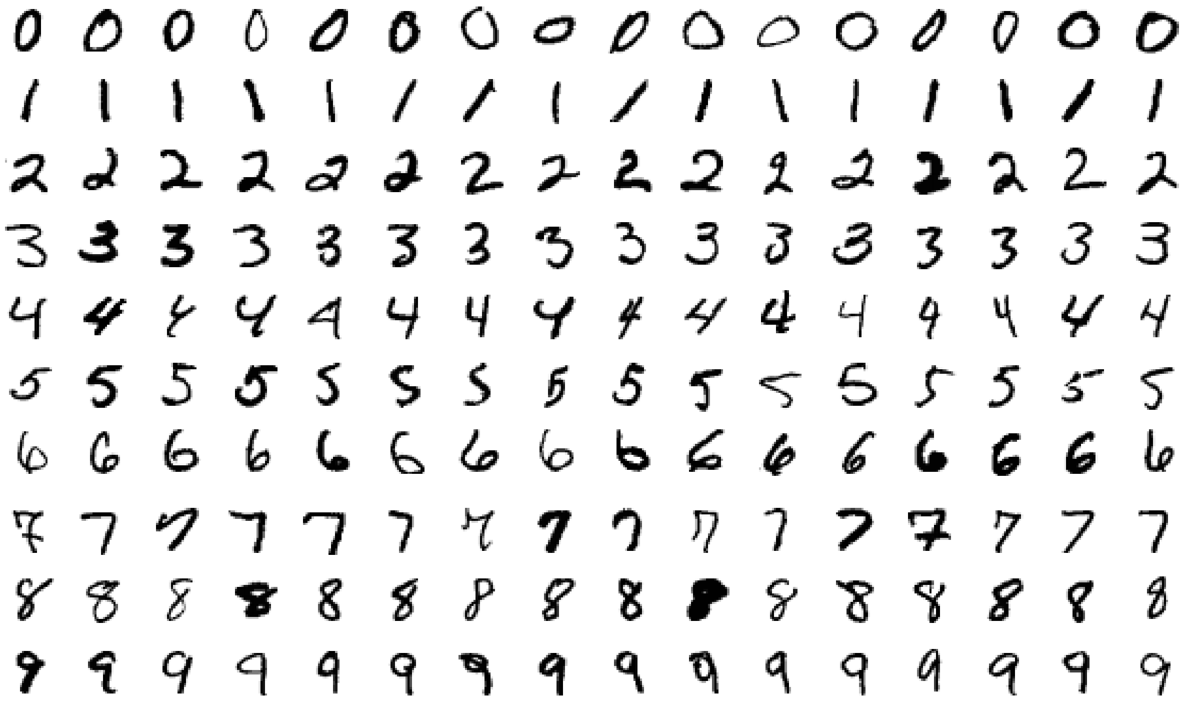
Choice of Labels

- For Binary Classification, arbitrarily assign 0, 1 to the classes
  - Example: for classification of cats and dogs (assign 0 for cat and 1 for dog)
  - Example: X-rays assign (0 normal and 1 for broken)
  - Choice is arbitrary (can use 1 for cat and 0 for dog) – doesn't matter
- For Multiclass Classification (c classes) assign 0,1,…,c-1 to classes
  - For digits classification, 10 classes – obviously assign 0 to 0, 1 to 1, …, 9 to 9
  - For pictures of cats, dogs, rabbits, ferrets, ducks (5 classes), assign 0 to cats, 1 to dogs, 2 to rabbits, 3 to ferrets, and 4 to ducks.

MNIST Digits Database

- NIST is acronym for National Institute of Standards and Technology, which is a physical sciences laboratory and a non-regulatory agency of the United States Department of Commerce
- MNIST (Modified National Institute of Standards and Technology) digits database is a large collection of black and white handwritten digit images used for training and testing of machine learning algorithms
- Digit images are of uniform resolution (28x28 = 784 pixels)
- 60,000 individual digit images (0 – 9 with labels) for training
- 10,000 individual digit images (0 – 9 with labels) for testing
- Data Source: http://yann.lecun.com/exdb/mnist/

Sample of Digit Images

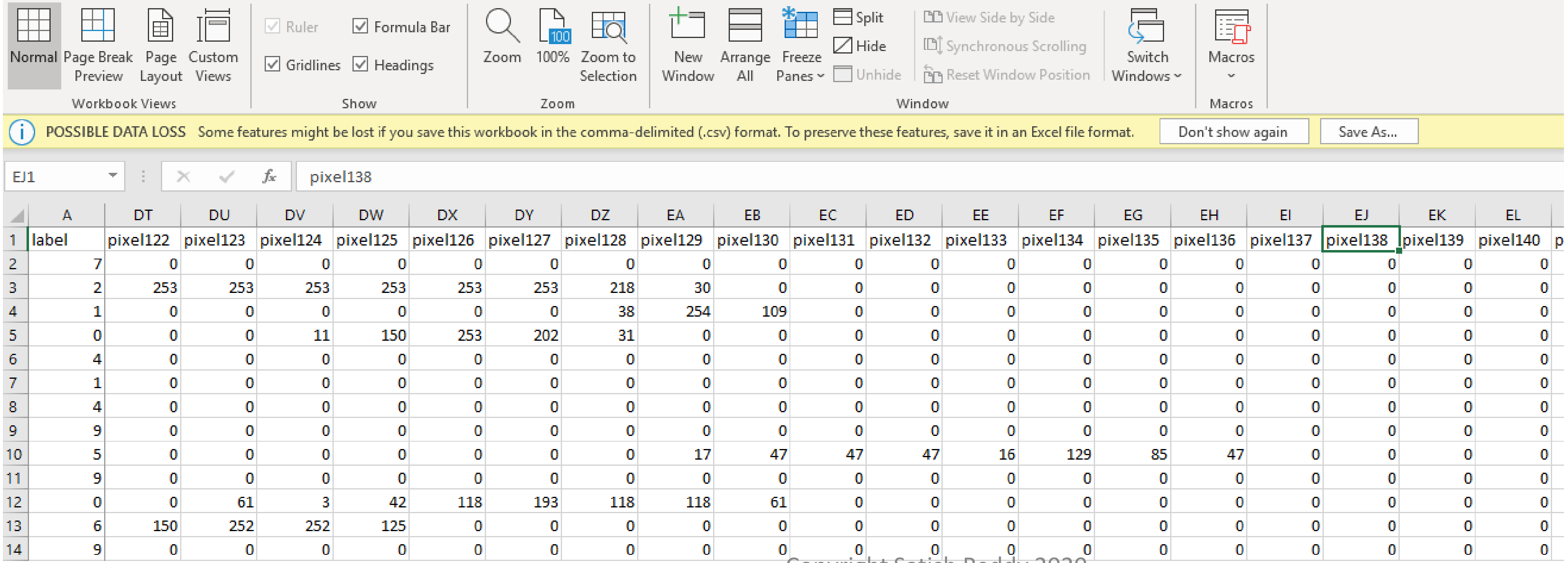


- Collage of 160 individual digit images
- Citation for above image

By Josef Steppan - Own work, CC BY-SA 4.0,
https://commons.wikimedia.org/w/index.php?curid=64810040

MNIST Digits – Format of Data Files

- Each row represents label and intensities for one image
  - First column is the digit label (0,1,…,9)
  - Columns 2 – 785 are the intensities
  - Take transpose to convert feature matrix and value vector to correct format
  - Standard practice is to divide pixel values by 255 so between 0 and 1



POSSIBLE DATA LOSS Some features might be lost if you save this workbook in the comma-delimited (.csv) format. To preserve these features, save it in an Excel file format.

EJ1 pixel138

	A	DT	DU	DV	DW	DX	DY	DZ	EA	EB	EC	ED	EE	EF	EG	EH	EI	EJ	EK	EL
1	label	pixel122	pixel123	pixel124	pixel125	pixel126	pixel127	pixel128	pixel129	pixel130	pixel131	pixel132	pixel133	pixel134	pixel135	pixel136	pixel137	pixel138	pixel139	pixel140
2	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	2	253	253	253	253	253	253	218	30	0	0	0	0	0	0	0	0	0	0	0
4	1	0	0	0	0	0	0	38	254	109	0	0	0	0	0	0	0	0	0	0
5	0	0	0	11	150	253	202	31	0	0	0	0	0	0	0	0	0	0	0	0
6	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	5	0	0	0	0	0	0	0	17	47	47	47	16	129	85	47	0	0	0	0
11	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	61	3	42	118	193	118	118	61	0	0	0	0	0	0	0	0	0	0
13	6	150	252	252	125	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Training and Validation Data

- Data located in folder IntroML/Code/Data_MNIST:
  - 60000 training data samples split into 2 files (because of Github limitations)
    - MNIST_train_set1_30K.csv
    - MNIST_train_set2_30K.csv
    - 1 data sample for each row consisting of digit label plus 784=28x28 pixel values
  - 10000 validation data samples in file:
    - MNIST_valid_10K.csv
    - 1 data sample for each row consisting of digit label plus 784=28x28 pixel values

MNIST Distribution of Digits

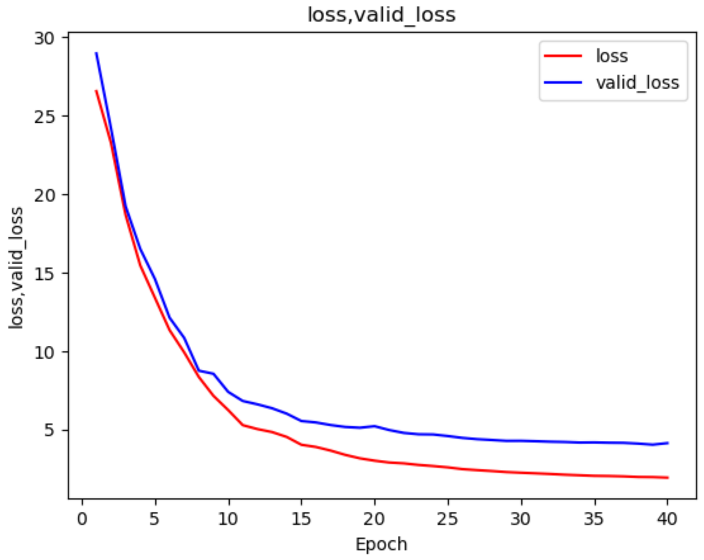
Digit	# Training 60K	# Valid 10K	# Training 6K	# Validation 1K
0	5923	980	592	85
1	6742	1135	671	126
2	5958	1032	581	116
3	6131	1010	608	107
4	5842	982	623	110
5	5421	892	514	87
6	5918	958	608	87
7	6265	1028	651	99
8	5851	974	551	89
9	5949	1009	601	94

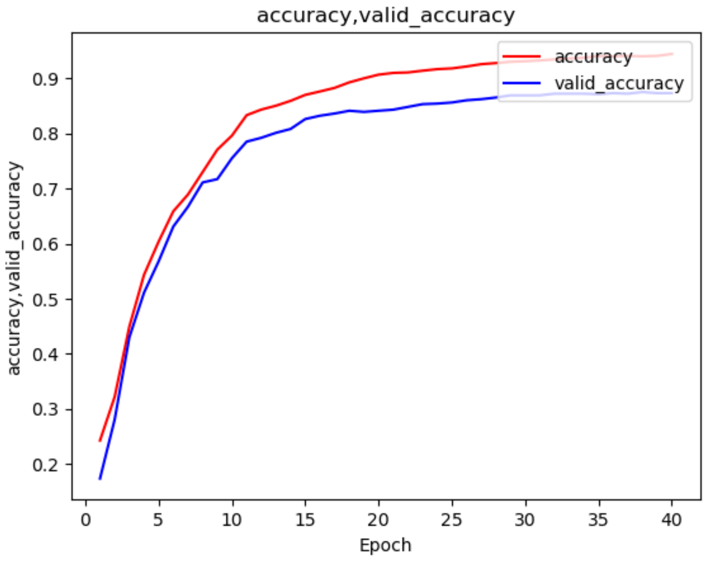
MNIST Digit Classification using a Neural Network

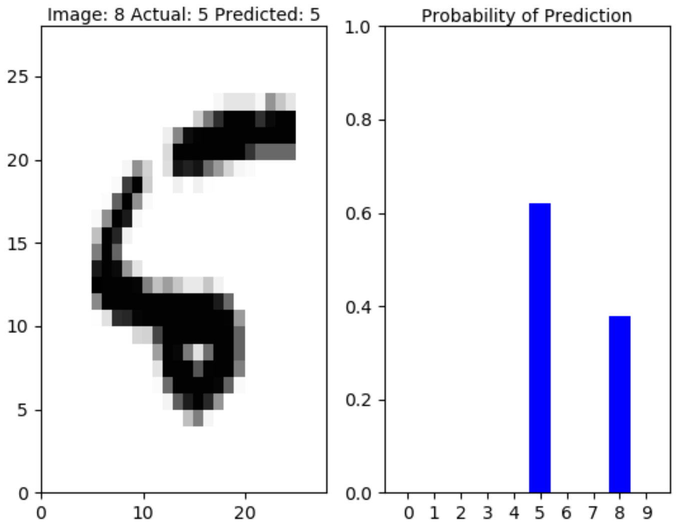
- Example: Dataset
  - 6000 images (28x28 resolution) in training dataset
  - 1000 images in validation dataset
  - Feature matrix for training is (784 x 6000)
  - Feature matrix for validation is (784 x 1000)
- Neural Network
  - 2 layer neural network
    - Layer 1: 128 units (relu activation)
    - Layer 2: 10 unit (softmax activation)
    - 101,770 combined total entries in $W^{[k]}$ and $b^{[k]}$ for all layers
- Optimization:
  - Adam α=0.02, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\varepsilon = 10^{-7}$
  - 40 epochs (batch_size = 6000 batch gradient descent)
  - Cross entropy loss
- Accuracy
  - Proportion of correct prediction

Digit Classification – Summary of Results

- After 40 epochs:
  - Training Accuracy: 0.944
  - Validation Accuracy: 0.873
- Loss and Accuracy plots indicate an underfitting (also an overfitting)
  - Expect training accuracy to be higher – should be closer to 100%
- Plot of Image and Probability:
  - Probability bar chart obtained from final activation for validation image (index 8)
  - Actual image is 5 and predicted is 5
  - Bar chart shows that probability of prediction of 5 is ~63% and prediction of 8 is ~37%

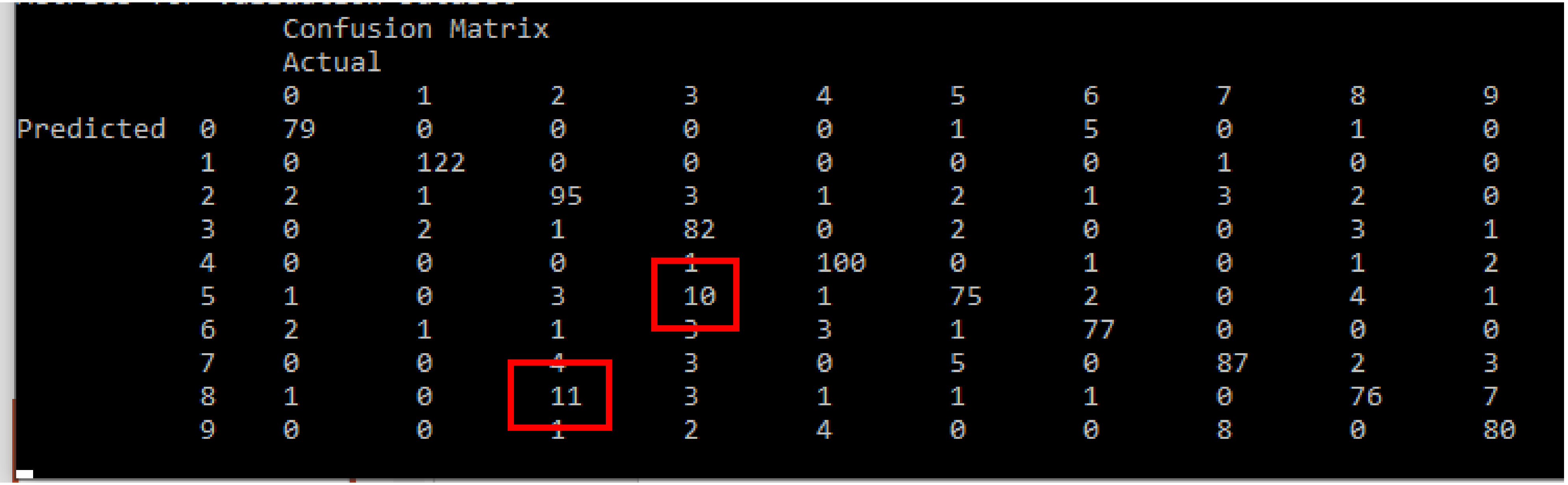






Digit Classification – Summary of Results

- Confusion Matrix:
  - Actual 2 is predicted as 8 on 11 occasions (roughly 10% of time)
  - Actual 3 is predicted as 5 on 10 occasions (roughly 10% of time)



```
                Confusion Matrix
                Actual
                0       1       2       3       4       5       6       7       8       9
Predicted  0    79      0       0       0       0       1       5       0       1       0
           1    0       122     0       0       0       0       0       1       0       0
           2    2       1       95      3       1       2       1       3       2       0
           3    0       2       1       82      0       2       0       0       3       1
           4    0       0       0       1       100     0       1       0       1       2
           5    1       0       3       10      1       75      2       0       4       1
           6    2       1       1       3       3       1       77      0       0       0
           7    0       0       4       3       0       5       0       87      2       3
           8    1       0       11      3       1       1       1       0       76      7
           9    0       0       1       2       4       0       0       8       0       80
```

New Code for Digits Classification

Method	Input	Description
load_mnist	ntrain (integer) nvalid (integer)	Loads MNIST database Return: Xtrain, Ytrain, Xvalid, Yvalid
driver_casestudy_mnist		Driver for performing mnist training
plot_results_mnist_animation	X (numpy array) Y (numpy array) Y_pred (numpy array) Afinal (numpy array) nframe (integer)	Shows animation of digit images (X), actual label (Y) and predicted label (Y_pred), as well as probabilities for each digit as represented in results of activation at final layer Afinal. Nframe is number of frames to show in animation. Return: nothing

7.3 MNIST Digits Classification DEMO

- Code located at: IntroML/Code/Version4.1
- Data located at: IntroML/Code/Data_MNIST
- How to proceed:
  - Using information from previous videos, see if you can create functions for loading and processing data and a driver starting with an original Version3.3 of the code
  - Alternatively, watch this video, which walks through the changes and then use as a guide to make changes
  - The examples in the Jupyter notebooks are a useful resource showing how to use pandas and numpy functionality to load and process data

Course Resources at:

- https://github.com/satishchandrareddy/IntroML/