NCCU, Fall 2020
PyTorch and Machine Learning

NLP: Surname Classification

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Outline

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PART II : MLP

PART III: CNN

PART IV: RNN

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Part I: Introduction & Pre-processing

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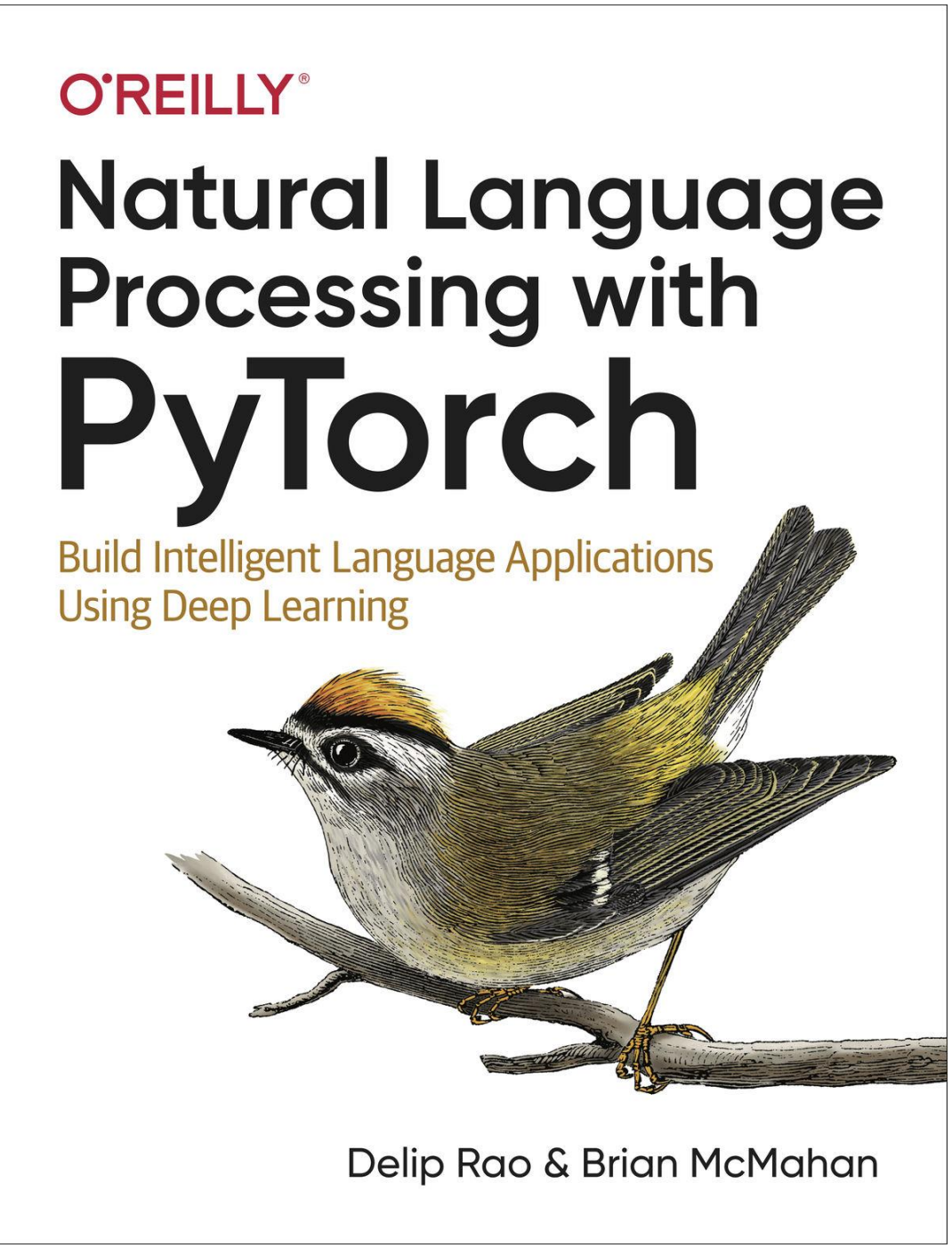
- (2) Text Pre-processing Steps for NLP & Text Mining
- (3) Data Pre-processing for this Project
- (4) One-hot Representation
- (5) The Classification Models & Baseline Models
- (6) Hyperparameter Walkthrough

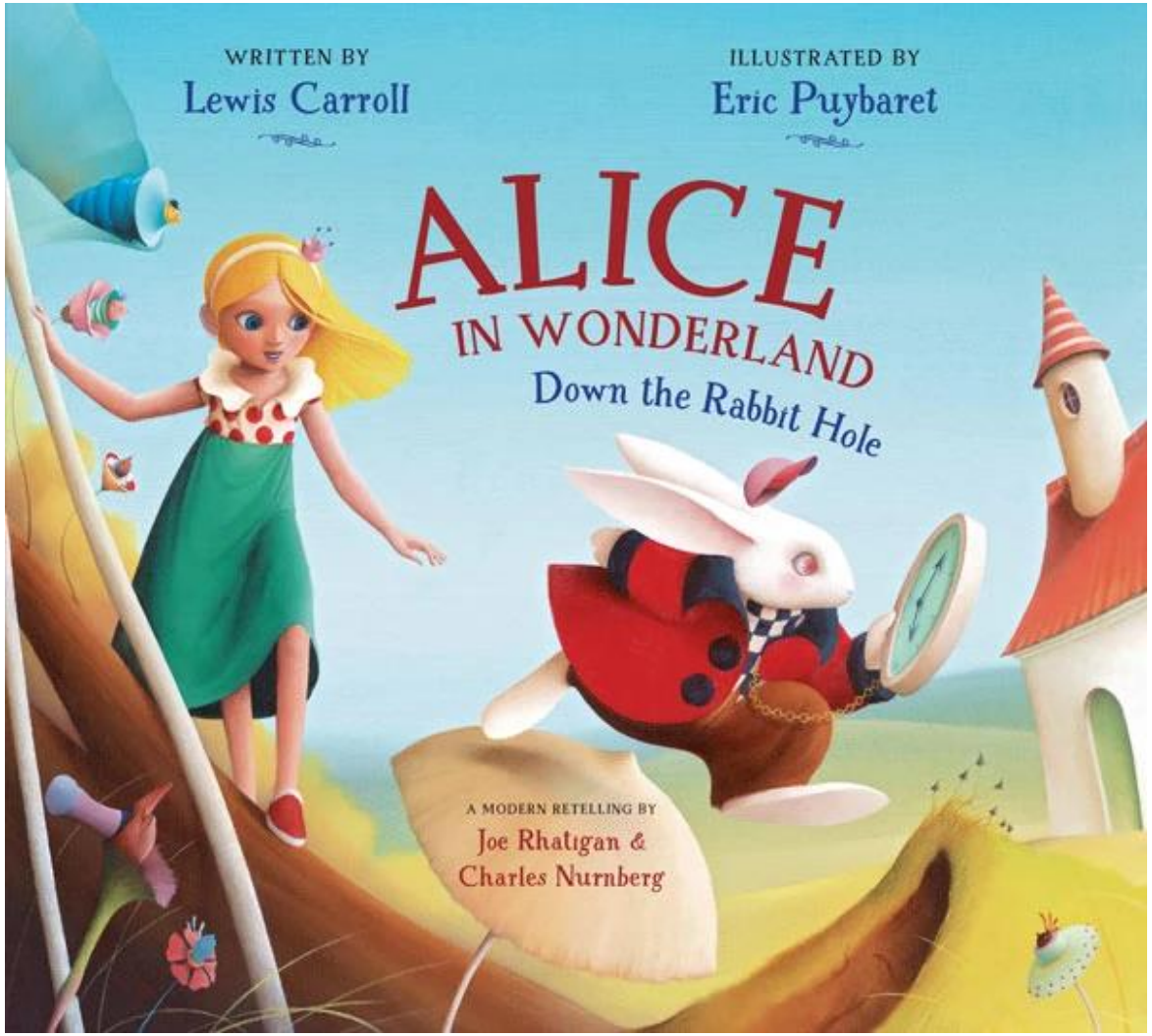


(1) Introduction to Data & Model

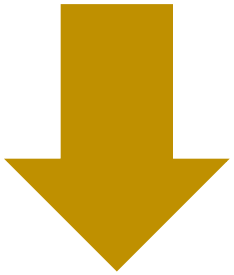
- Source : The data and models all come from *Rao, D. & McMahan, B. (2019). Natural Language Processing with PyTroch. California, CA: O'Reilly Media.*
- Data : The surname dataset, a collection of 10,000 surnames from 18 different nationalities collected by the authors from different name sources on the Internet. We split the data into 70% training data, 15% validation data, and 15% test data.
- Model : Build surname classifier through MLP, CNN and RNN.
- [Remark] The models with given parameters in this book are taken as baseline models.

(2) Text Pre-processing Steps for NLP & Text Mining

- 1. Expanding Contractions
- 2. Lower Case Transformation
- 3. Removing Non-alphabet Characters
- 4. Tokenization
- 5. Removing Stopwords
- 6. Lemmatization OR Stemming



- “I’m sure those are not the right words,” said poor Alice, and her eyes filled with tears again as she went on, “I must be Mabel after all, and I shall have to go and live in that poky little house, and have next to no toys to play with, and oh! ever so many lessons to learn! No, I’ve made up my mind about it; if I’m Mabel, I’ll stay down here!



Text Preprocessing

- [‘sure’, ‘right’, ‘word’, ‘say’, ‘poor’, ‘alice’, ‘eye’, ‘fill’, ‘tear’, ‘go’, ‘must’, ‘mabel’, ‘shall’, ‘go’, ‘live’, ‘poky’, ‘little’, ‘house’, ‘next’, ‘toy’, ‘play’, ‘oh’, ‘ever’, ‘many’, ‘lesson’, ‘learn’, ‘make’, ‘mind’, ‘mabel’, ‘stay’]

Ref: Sarkar, D. (2019). Text Analytics with Python (2nd ed.). Karnataka, India: Apress.
Kuo, M. (2021). ML16: Hands-on Text Preprocessing. Retrieved from https://bit.ly/2KRsCNC

(3) Data Pre-processing for this Project

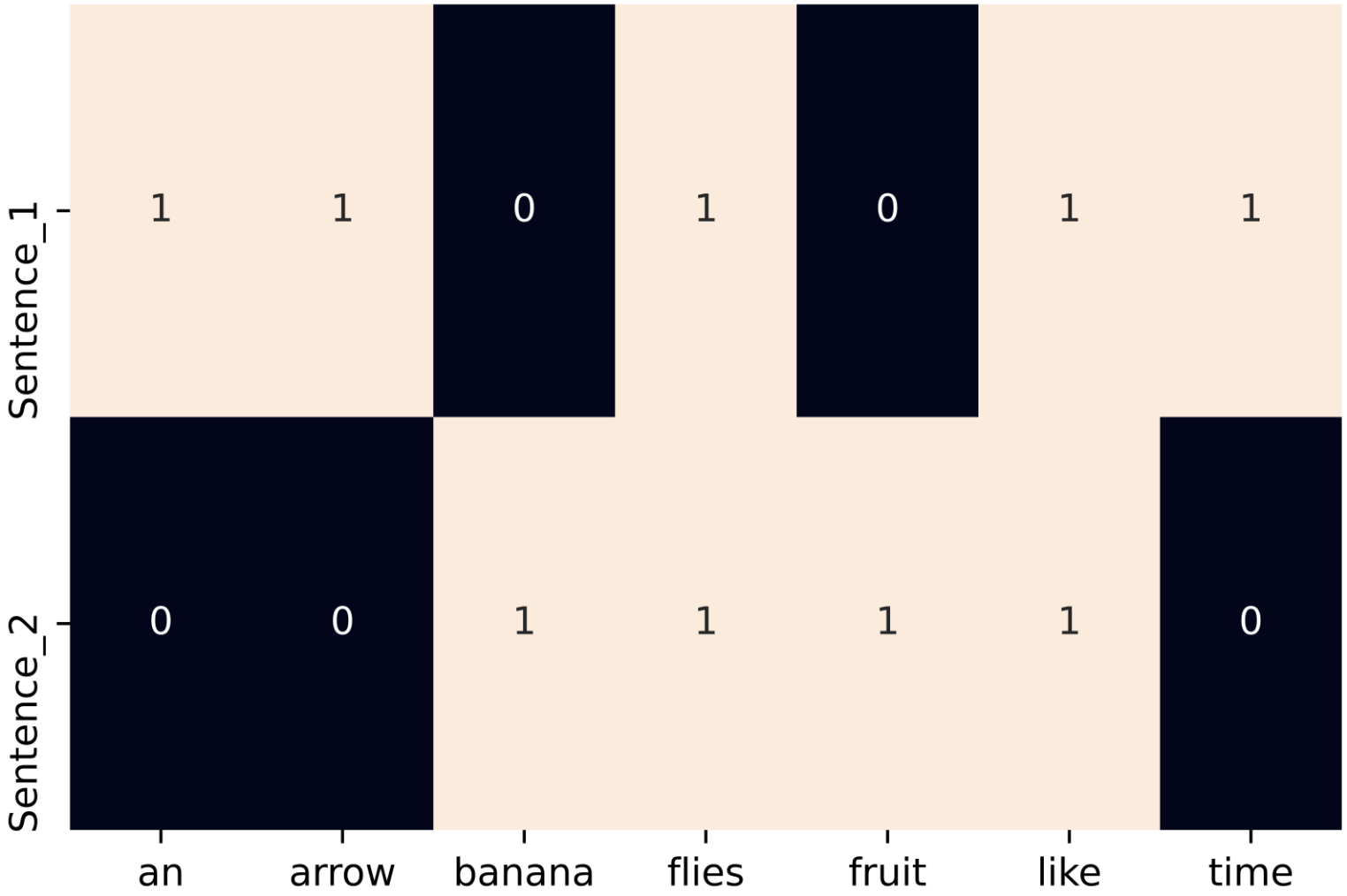
Prepro code on Colab

1	surname	nationality
2	Woodford	English
3	Coté	French
4	Kore	English
5	Koury	Arabic
6	Lebzak	Russian
7	Obinata	Japanese
8	Rahal	Arabic
9	Zhuan	Chinese

1	nationality	nationality_index	split	surname
2	Arabic	15	train	Totah
3	Arabic	15	train	Abboud
4	Arabic	15	train	Fakhoury
5	Arabic	15	train	Srour
6	Arabic	15	train	Sayegh
7	Arabic	15	train	Cham
8	Arabic	15	train	Haik

The surname dataset is spitted into 70% training, 15% validation, 15% test data. Then, we vectorize the surnames using one-hot encoding. We utilize two variants— "collapsed one-hot vector" and "one-hot matrix".

(4) One-hot Representation



- S_1: Time flies like an arrow.
- S_2: Fruit flies like a banana.

Ref: Rao, D. & McMahan, B. (2019). Natural Language Processing with PyTroch. California, CA: O'Reilly Media.

(5) The Classification Models & Baseline Models

We try to classify surnames from 18 different nationalities using NLP. Specifically, we leverage MLP, CNN, RNN (Elman RNN) to accomplish that. Then, we quickly walk through the basic concepts.

- **Neuron:** A minimum unit of neural network.
- **Perceptron:** A single-layer neural network.
- **FNN(feedforward neural network)**: MLP(multilayer perceptron, also called “fully-connected” network), CNN(convolutional neural network).
- **RNN(recurrent neural network)**: RNN, LSTM(long short-term memory), GRU(gated recurrent unit).
- **Baseline Models**: The MLP, CNN, RNN model retrieved from the book, only change the *drop probability* of RNN from 50% to 0%.

(6) Tuning Deep Networks — 1

1. Activators : sigmoid(), tanh(), ReLU() [fast], PReLU(), LeakyReLU(), ELU(), SELU(), Softmax()
2. Optimizers: SGD, Momentum, AdaGrad, RMSprop, Adam, Nadam, AdaMax
3. Batch Normalization (BN) : Introduced by Ioffe & Szegedy in 2015, allowing models to be *less sensitive to initialization of the parameters* and *simplifies the tuning of learning rates*.

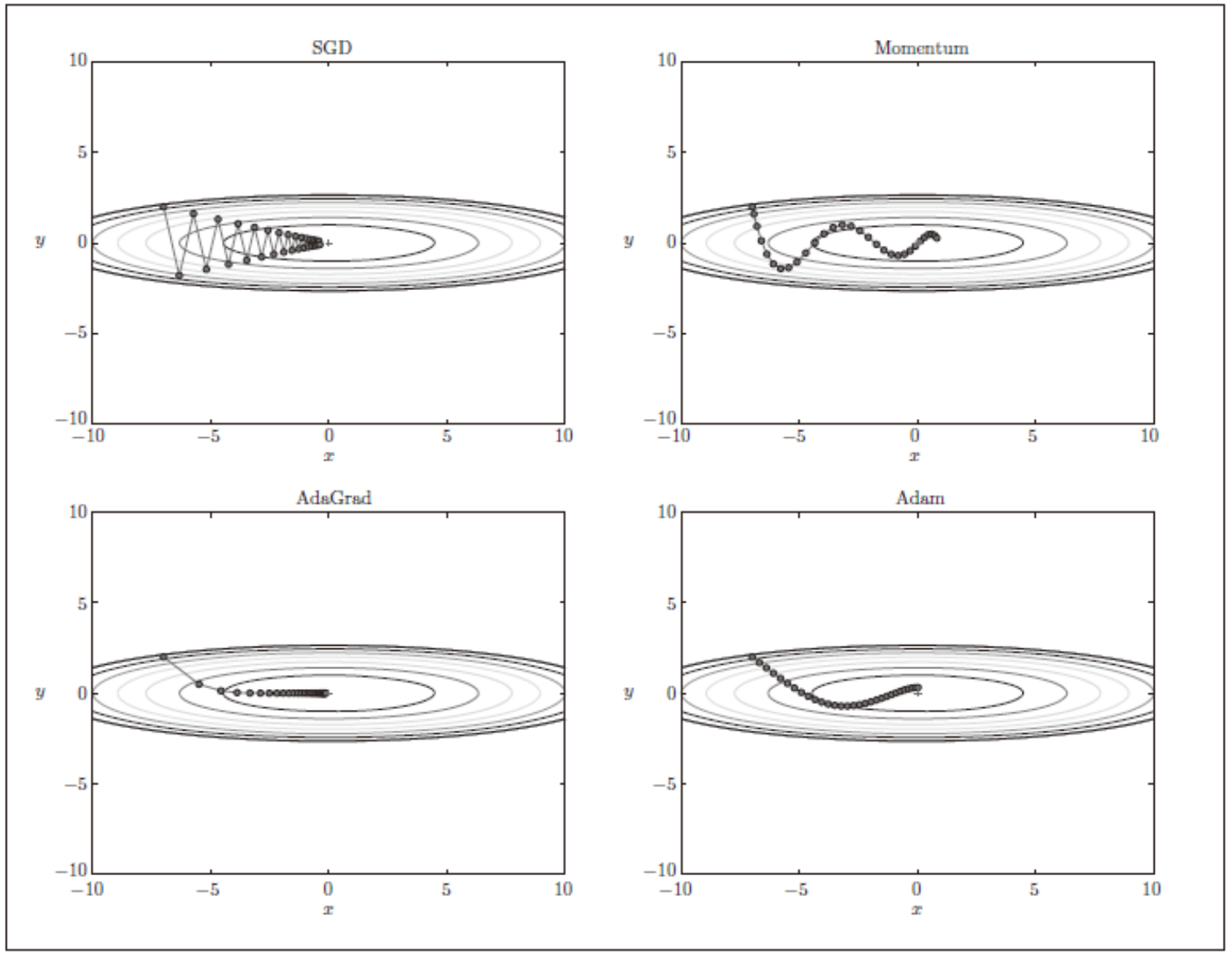


图6-8 最优化方法的比较：SGD、Momentum、AdaGrad、Adam

Ref: Rao, D. & McMahan, B. (2019). Natural Language Processing with PyTroch. California, CA: O'Reilly Media.
Géron, A. (2019). Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). California, CA: O'Reilly Media.
斎藤康毅 (2016). ゼロから作るDeep Learning —Pythonで学ぶディープラーニングの理論と実. Japan, JP: O'Reilly Japan.

(6) Tuning Deep Networks — 2

4. Epochs and Mini-Batch Size – 1

- ✓ The relationship between how fast our algorithm can learn the model is typically **U-shaped** (batch size versus training speed). This means that initially **as the batch size becomes larger, the training time will decrease**. Eventually, we'll see the training time begin to increase when we exceed a certain batch size that is too large.
- ✓ A **larger mini-batch size** means **smoother gradients**.
- ✓ For performance (this is most important in the case of GPUs), we **should use a multiple of 32 for the batch size**, or multiples of 16, 8, 4, or 2 if multiples of 32 can't be used (or result in too large a change given other requirements). In short, the reason for this is simple: **memory access and hardware design are better optimized** for operating on arrays **with dimensions that are powers of two**, compared to other sizes. For example, we should use a layer size of 128 over size 125, or size 256 over size 250, and so on.

Ref: Patterson, J. & Gibson, A. (2017). Deep Learning: A Practitioner's Approach. California, CA: O'Reilly Media.

(6) Tuning Deep Networks — 3

4. Epochs and Mini-Batch Size – 2

- ✓In practice, 32 to 256 is common for CPU training, and **32 to 1,024** is common for GPU training. Usually, something in this range is good enough for smaller networks, though you should probably test this for larger ones (where training time can be prohibitive).
- ✓ The Relationship Between Mini-Batch Size and Epochs: If we increase our mini-batch size by a factor of two, we **need to increase the number of epochs by a factor of two** in order **to maintain the same number of parameter updates**. The number of parameter updates per epoch is just the total number of examples in our training set divided by the mini-batch size.
- ✓ Using a larger mini-batch size might help our network to learn in some difficult cases, such as for noisy or imbalanced datasets.

Ref: Patterson, J. & Gibson, A. (2017). Deep Learning: A Practitioner's Approach. California, CA: O'Reilly Media.

(6) Tuning Deep Networks — 4

5. Dropout : Introduced by Hinton in 2012. Usually 10% ~ 50%. In CNN, often 40% ~ 50%. In RNN, usually 20% ~ 30%.

- ✓ Dropout & weight decay are all regularization techniques.
- ✓ The resulting neural network can be seen as an **averaging ensemble** of all these smaller neural networks.
- ✓ Sometimes we'll use **no dropout at all on the input**, especially for noisy or sparse datasets.
- ✓ It is **not common to use dropout on the output layer**.
- ✓ Dropout in all hidden layers works more effectively than in only one hidden layer.
- ✓ Dropout also tends to make the activations of hidden units **sparse** even when other regularization techniques are absent, leading to **sparse representations**.

Ref: Patterson, J. & Gibson, A. (2017). Deep Learning: A Practitioner's Approach. California, CA: O'Reilly Media.
Géron, A. (2019). Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). California, CA: O'Reilly Media.

(6) Tuning Deep Networks — 5

6. Weight Decay : L1 (Lasso) or L2(Ridge) regularization. In *torch.optim*, the parameter *weight_decay (float, optional)* adopts L2.

- ✓ Dropout & weight decay are all regularization techniques.
- ✓ L1: **Sparse models**. L1 has less of a penalty for large weights, but leads to many weights being driven to 0 (or very close to 0), meaning that the resultant weight vector can be sparse.
- ✓ L2: **Dense models**. L2 more heavily penalizes large weights, but doesn't drive small weights to 0.
- ✓ In practice, we see **L2 regularization give better performance** over L1 outside of explicit feature selection.
- ✓ We can combine L1 and L2 in the one network, i.e., Elastic Net (Zou et al., 2005).
- ✓ For cases in which we're using early stopping, we might not want to use L2 regularization at all, because **early stopping is more efficient at performing the same mechanics as L2** (Bengio, 2012).

Ref: Patterson, J. & Gibson, A. (2017). Deep Learning: A Practitioner's Approach. California, CA: O'Reilly Media.
Géron, A. (2019). Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). California, CA: O'Reilly Media.

Part II: MLP

MLP code on Colab

- Baseline Model
- How to Improve the Model
- Best Model

[Remark] At pre-processing stage of MLP, we utilize "collapsed one-hot vector", which do not count the frequency of characters and only record the character appearing or not. Also, this approach ***ignores*** *the sequential information*.

(1) MLP: Baseline Model

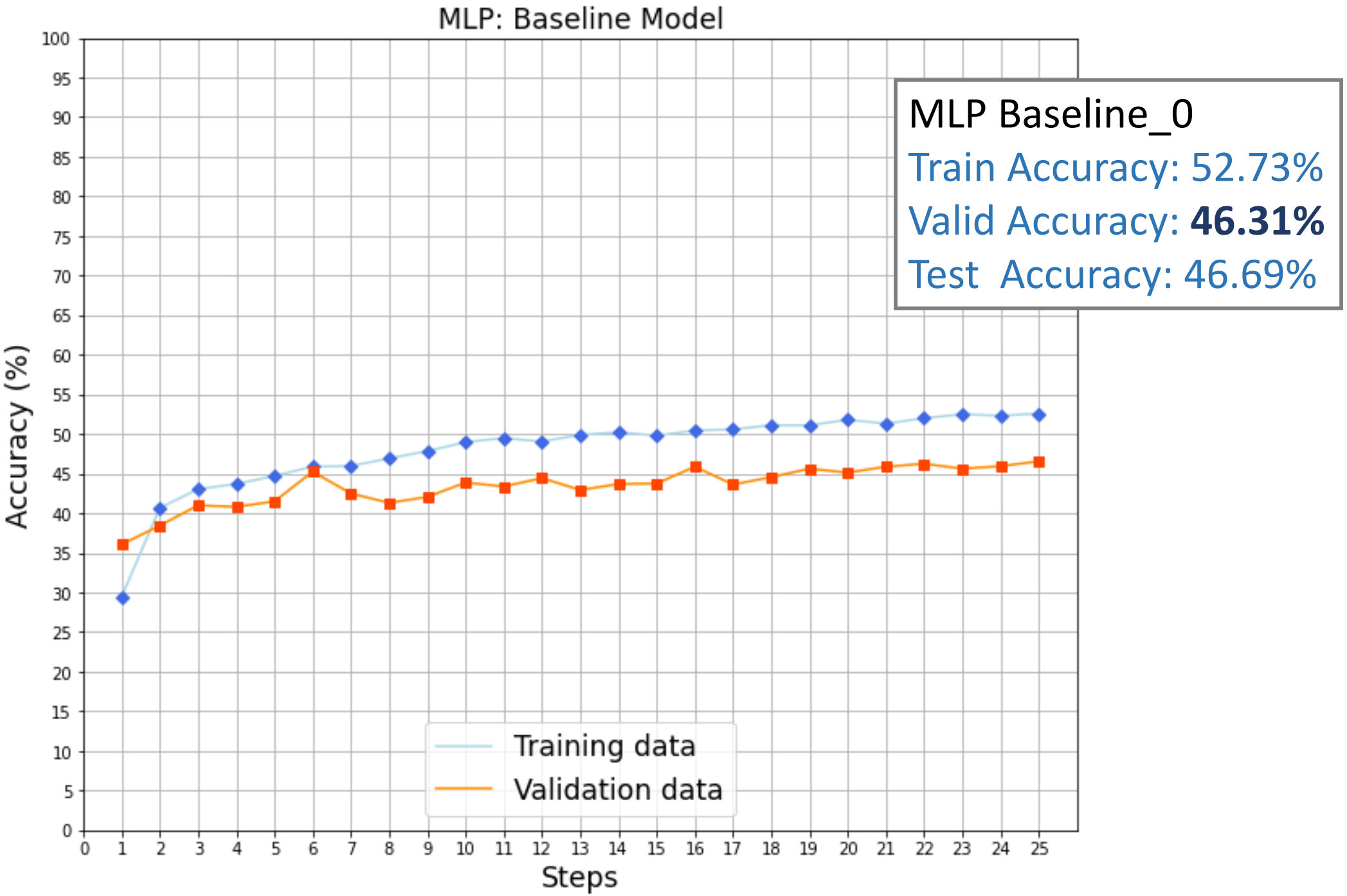
MLP Baseline_0
Train Accuracy: 52.73%
Valid Accuracy: **46.31%**
Test Accuracy: 46.69%

MLP Baseline Model structure
(0): Linear(input_dim, hidden_dim, bias=True)
(1): ReLU()
(2): Linear(hidden_dim, output_dim, bias=True)

Parameters of MLP Baseline Model

- Epoch = 25
- Hidden layer dimension = 300 (only one hidden layer)
- Batch Size = 64
- Activator = ReLU()
- Optimizer = Adam
- Learning rate = 0.001 (commonly recommended)
- Learning rate schedule: lr_scheduler.ReduceLROnPlateau()
- No batch normalization, dropout, weight decay

Ref: Géron, A. (2019). Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). California, CA: O'Reilly Media.


MLP: Baseline Model
Accuracy (%)
Steps
Training data
Validation data
MLP Baseline_0
Train Accuracy: 52.73%
Valid Accuracy: 46.31%
Test Accuracy: 46.69%

(2) MLP: Improving Baseline Model

What could we do to further improve the baseline model?

MLP Baseline Model structure

(0): Linear(input_dim, hidden_dim, bias=True)
(1): ReLU()
(2): Linear(hidden_dim, output_dim, bias=True)

1. Nonlinear Activators : Without nonlinearity between two *Linear* layers, two Linear layers in sequence are mathematically equivalent to a single *Linear* layer.
2. Batch Normalization (BN) : Introduced by Ioffe & Szegedy in 2015, allowing models to be *less sensitive to initialization of the parameters* and *simplifies the tuning of learning rates*.
3. Dropout : Introduced by Hinton in 2012. Usually 10% ~ 50%. In CNN, often 40% ~ 50%. In RNN, usually 20% ~ 30%. It's just like operating ensemble learning by a NN.
4. Weight Decay : Use L1 (Lasso) or L2(Ridge) regularization. In general, L2 is recommended. In *torch.optim*, the parameter *weight_decay (float, optional)* adopts L2.

Ref: Rao, D. & McMahan, B. (2019). Natural Language Processing with PyTroch. California, CA: O'Reilly Media.
Géron, A. (2019). Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). California, CA: O'Reilly Media.
斎藤康毅 (2016). ゼロから作るDeep Learning —Pythonで学ぶディープラーニングの理論と実. Japan, JP: O'Reilly Japan.

(3) MLP: Batch Size

Given the parameter below, we switched batch.

- Epoch = 100
- Hidden layer dimension = 300 (only one hidden layer)
- Activator = ReLU()
- Optimizer = Adam
- Learning rate = 0.001 (commonly recommended)
- Learning rate schedule: lr_scheduler.ReduceLROnPlateau()
- No batch normalization, dropout, weight decay

model	hidden_dim	batch_size	running_time (s)	train_acc (%)	valid_acc (%)	test_acc (%)
MLP_basline_0	300	64	152.80	52.73%	46.31%	46.69%
MLP_basline_1	300	32	176.52	56.85%	49.39%	50.12%
MLP_basline_2	300	16	225.27	63.66%	54.11%	53.46%
MLP_basline_3	300	8	317.39	72.27%	57.87%	59.72%
MLP_basline_4	300	4	497.12	79.21%	61.71%	64.16%
MLP_basline_5	300	2	856.73	86.07%	**64.51%**	***66.99%***

(4) MLP: Neurons of Hidden Layer

Given the parameter below, we switched neurons of the hidden layer.

- Epoch = 100
- Batch Size = 64
- Activator = ReLU()
- Optimizer = Adam
- Learning rate = 0.001 (commonly recommended)
- Learning rate schedule: lr_scheduler.ReduceLROnPlateau()
- No batch normalization, dropout, weight decay

model	hidden_dim	batch_size	running_time (s)	train_acc (%)	valid_acc (%)	test_acc (%)
MLP_basline_0	300	64	152.80	52.73%	46.31%	46.69%
MLP_basline_6	500	64	153.02	53.41%	46.38%	47.56%
MLP_basline_7	800	64	152.85	62.10%	52.56%	53.38%
MLP_basline_8	1000	64	153.96	66.64%	53.75%	55.88%
MLP_basline_9	1500	64	153.57	66.24%	53.81%	54.06%
MLP_basline_10	2000	64	153.49	70.98%	**56.50%**	***58.63%***
MLP_basline_11	2500	64	153.63	69.27%	55.63%	56.94%

(5) MLP: Batch Size & Neurons of Hidden Layer

Given the parameter below, we switched batch size & neurons of the hidden layer.

- Epoch = 100
- Hidden layer dimension = 300 (only one hidden layer)
- Activator = ReLU()
- Optimizer = Adam
- Learning rate = 0.001 (commonly recommended)
- Learning rate schedule: lr_scheduler.ReduceLROnPlateau()
- No batch normalization, dropout, weight decay

model	hidden_dim	batch_size	running_time (s)	train_acc (%)	valid_acc (%)	test_acc (%)
MLP_basline_0	300	64	152.80	52.73%	46.31%	46.69%
MLP_basline_12	300	2	856.73	86.07%	64.51%	***66.99%***
MLP_basline_13	500	2	801.12	88.18%	65.12%	65.42%
MLP_basline_14	600	2	795.99	88.35%	65.43%	66.57%
MLP_basline_15	1000	2	800.24	90.64%	65.30%	66.51%
MLP_basline_16	1500	2	809.44	92.88%	66.46%	66.45%
MLP_basline_17	2000	2	865.50	93.79%	**66.71%**	66.81%

(6) MLP: Conclusion to this point

So far, I found that:

✓Batch Size ↓ →→ Validation Accuracy ↑

✓Hidden Layer Dimension ↑ →→ Validation Accuracy ↑

The steps above are trivial so we will skip this basic steps afterward.

The best validation accuracy we get is **66.71%** with test accuracy ***66.81%***.

After the quick walkthrough of basics, let's dive deep into model building & parameter tuning. That is, improving the model in the following aspects:

- Nonlinear Activator
- Batch Normalization (BN)
- Dropout
- Weight Decay (using L1 & L2 regularization)
- Activator

(7) MLP: Best Model

- After trial and error, the best model and parameters is as follows:

MLP Best
Train Accuracy: 93.63%
Valid Accuracy: **67.26%**
Test Accuracy: 66.87%

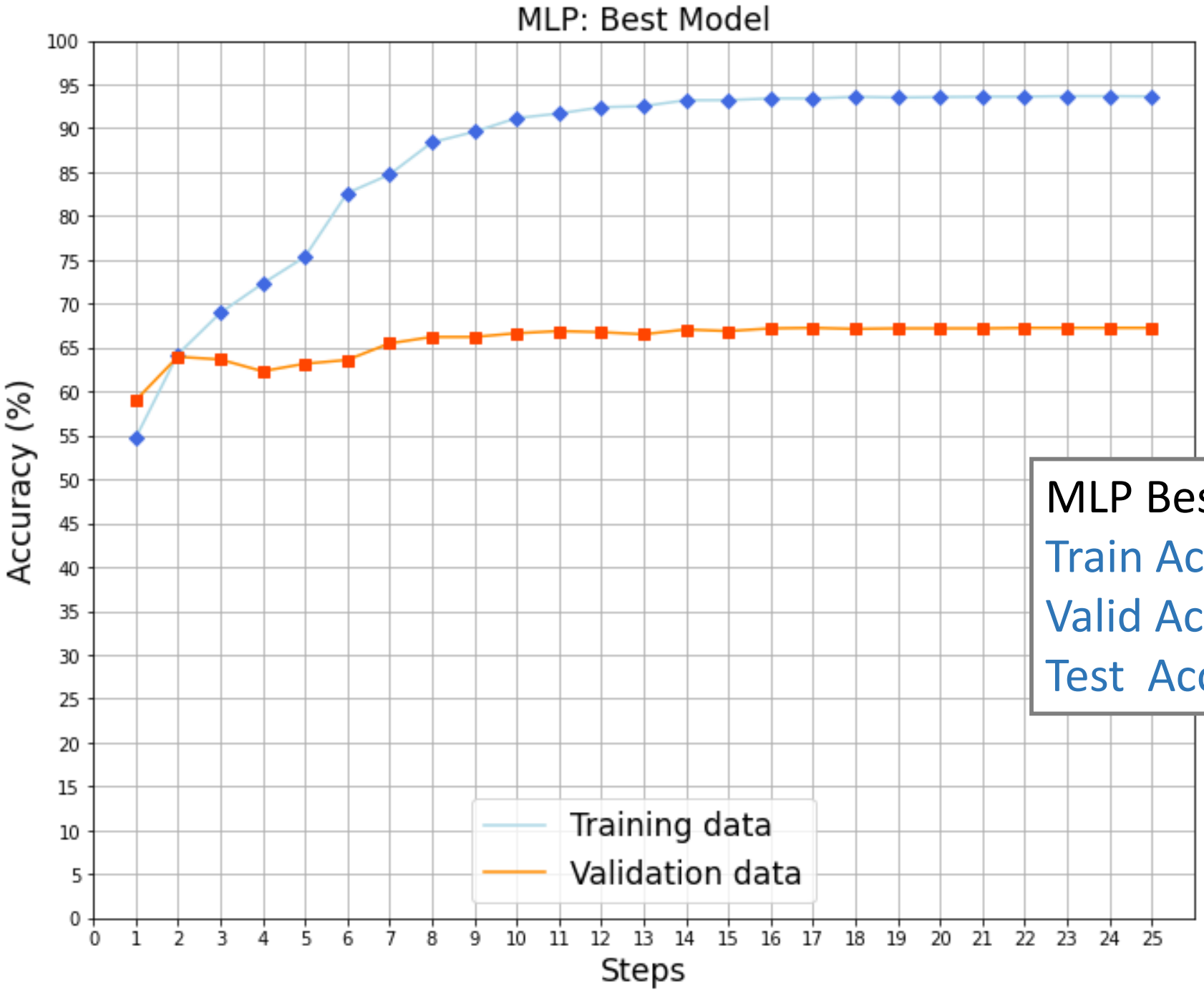
- We tried *batch norm*, *dropout*, *weight decay* and *adding a hidden layer*, but oddly none of these offer us better performance.
- We found *LeakyReLU()* performs better than *PReLU()* and *ReLU()*.

FNN/MLP Best Model structure

(0): Linear(input_dim, hidden_dim, bias=True)
(1): LeakyReLU()
(2): Linear(hidden_dim, output_dim, bias=True)

Parameters of FNN/MLP Best Model

- Epoch = 25
- Hidden layer dimension = 1000 (only one hidden layer)
- Batch Size = 2
- Activator = LeakyReLU()
- Optimizer = Adam
- Learning rate = 0.001 (commonly recommended)
- Learning rate schedule: lr_scheduler.ReduceLROnPlateau()
- No batch normalization
- Dropout = 0.0
- Weight decay = 0.0



MLP Best

Train Accuracy: 93.63%

Valid Accuracy: **67.26%**

Test Accuracy: 66.87%

(8) MLP: Summary

Regularization approaches (dropout & weight decay using L2) don't help at all! They are all 0 in the best MLP model.

Probably since the surname dataset is not big enough to generate overfitting!

MLP Baseline_0
Train Accuracy: 52.73%
Valid Accuracy: **46.31%**
Test Accuracy: 46.69%

MLP Validation Accuracy
MLP_basline_0: 46.31%
MLP_basline_17: 66.71%
MLP_best: 67.26%

MLP Best
Train Accuracy: 93.63%
Valid Accuracy: **67.26%**
Test Accuracy: 66.87%

Part III: CNN

CNN code on Colab

- Baseline Model
- Best Model

[Remark] At pre-processing stage of CNN, we utilize "one-hot matrix", which ***retains*** *the sequential information*.

(1) CNN: Baseline Model — 1

CNN: Baseline
Train Accuracy: 68.83%
Valid Accuracy: **57.16%**
Test Accuracy: 56.38%

CNN Baseline Model structure

(0): Conv1d(in_channels, num_channels, bias=True, kernel_size=3)
(1): ELU()
(2): Conv1d(num_channels, num_channels, bias=True, kernel_size=3, stride=2)
(3): ELU()
(4): Conv1d(num_channels, num_channels, bias=True, kernel_size=3, stride=2)
(5): ELU()
(6): Conv1d(num_channels, num_channels, bias=True, kernel_size=3)
(7): ELU()
(8): Linear(num_channels, num_classes)

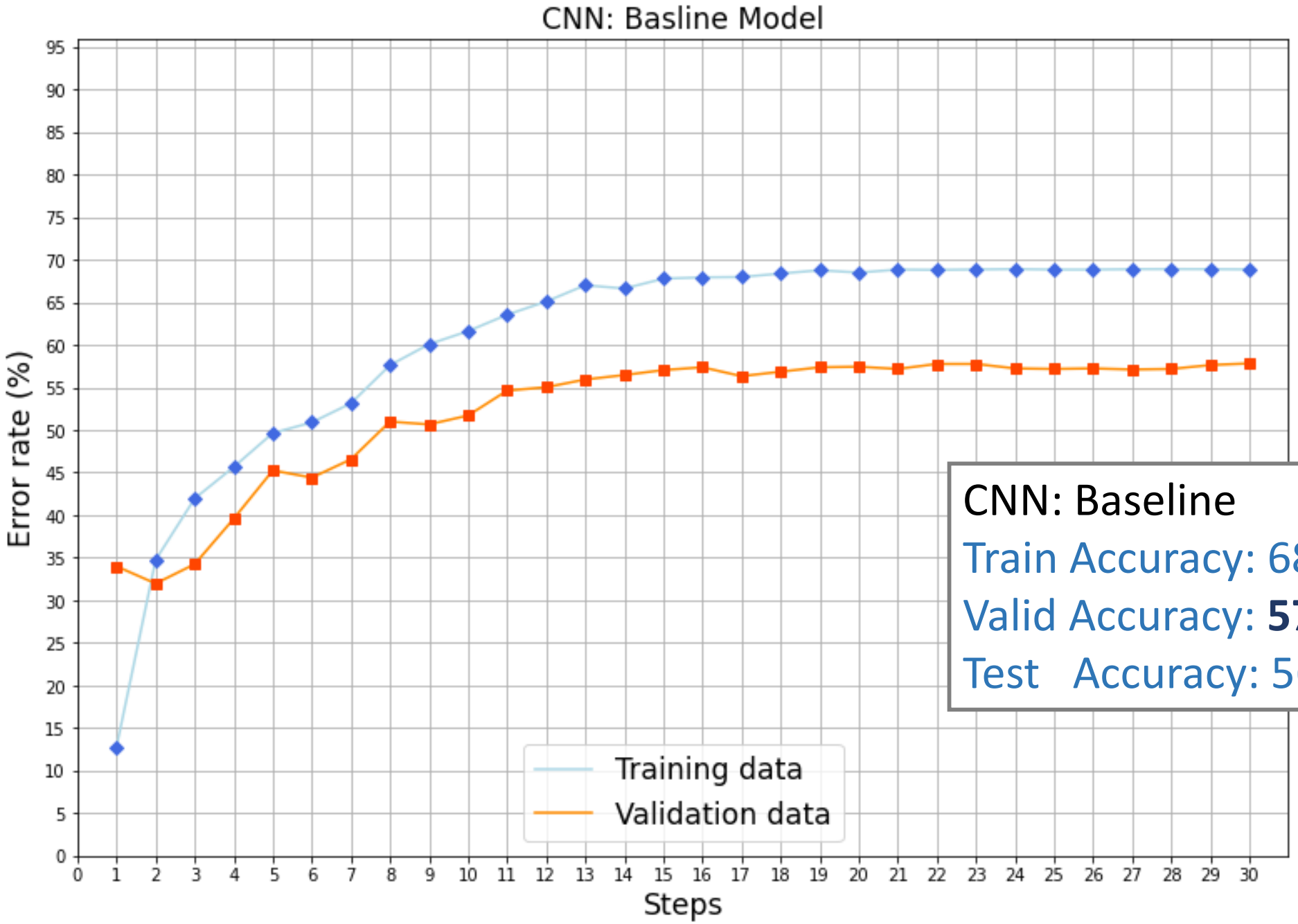
(2) CNN: Baseline Model — 2

CNN: Baseline
Train Accuracy: 68.83%
Valid Accuracy: **57.16%**
Test Accuracy: 56.38%

Parameters of CNN Baseline Model

- Epoch = 30
- Number of channel = 256
- Batch Size = 128
- Activator = ELU()
- Optimizer = Adam
- Learning rate = 0.001 (commonly recommended)
- Learning rate schedule: lr_scheduler.ReduceLROnPlateau()
- No dropout, weight decay

Ref: Géron, A. (2019). Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). California, CA: O'Reilly Media.



CNN: Baseline

Train Accuracy: 68.83%

Valid Accuracy: **57.16%**

Test Accuracy: 56.38%

(3) CNN: Best Model — 1

CNN Best
Train Accuracy: 90.66%
Valid Accuracy: **76.46%**
Test Accuracy: 71.20%

CNN Best Model structure

```
(  0): Conv1d(in_channels, num_channels, bias=True, kernel_size=3)
(  1): BatchNorm1d(num_channels)
(  3): ELU()
(  4): Conv1d(num_channels, num_channels, bias=True, kernel_size=3, stride=2)
(  5): BatchNorm1d(num_channels)
(  6): ELU()
(  7): Conv1d(num_channels, num_channels, bias=True, kernel_size=3, stride=2)
(  8): BatchNorm1d(num_channels)
(  9): ELU()
(10): Conv1d(num_channels, num_channels, bias=True, kernel_size=3)
(11): BatchNorm1d(num_channels)
(12): ELU()
(13): Linear(num_channels, num_classes)
```

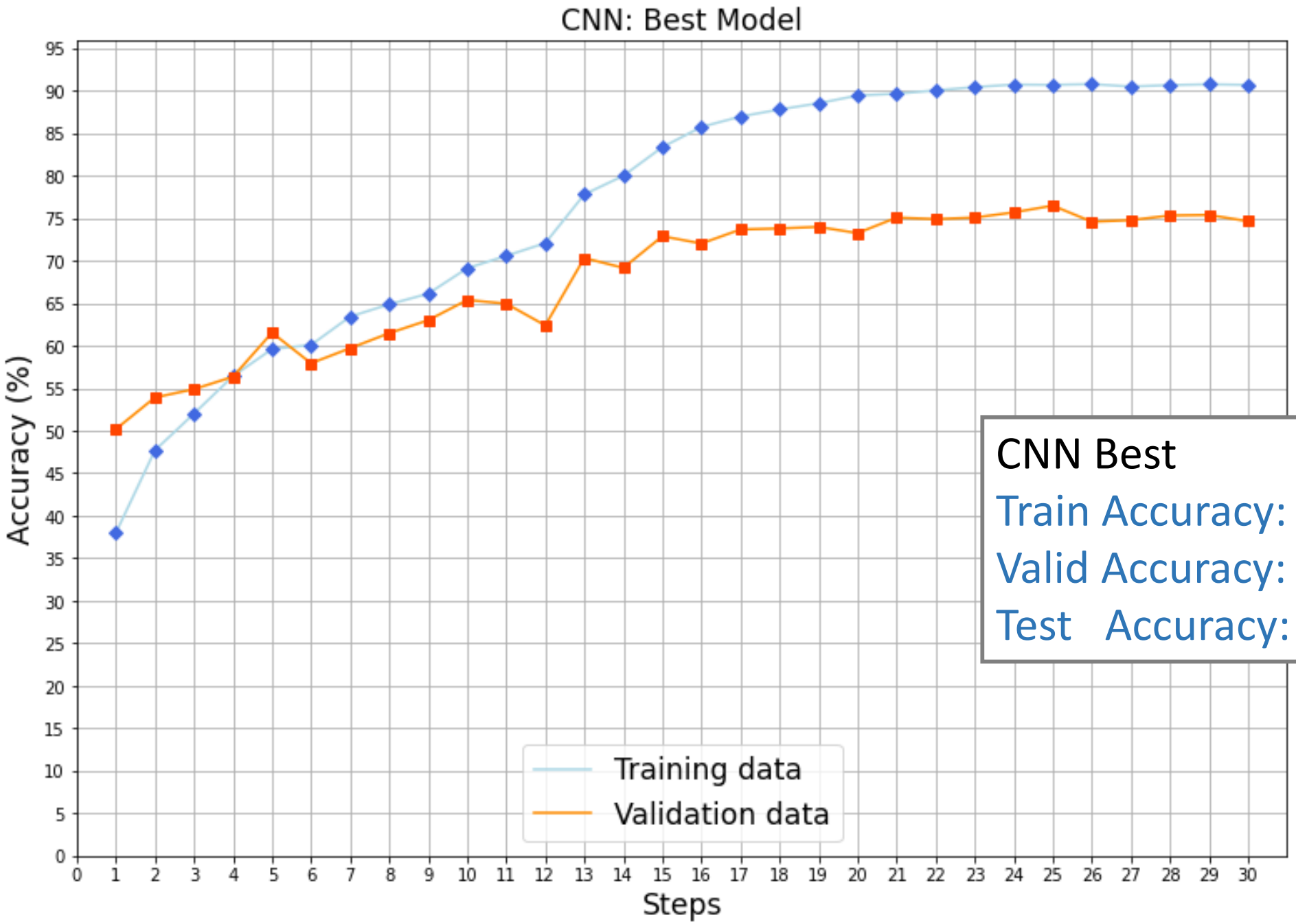
(4) CNN: Best Model — 2

CNN Best
Train Accuracy: 90.66%
Valid Accuracy: **76.46%**
Test Accuracy: 71.20%

Parameters of CNN Baseline Model

- Epoch = 30
- Number of channel = **280**
- Batch Size = **8**
- Activator = ELU()
- Optimizer = Adam
- Learning rate = 0.001 (commonly recommended)
- Learning rate schedule: lr_scheduler.ReduceLROnPlateau()
- Weight decay = **5e-5** (L2 regularization)
- Dropout = 0.0

Ref: Géron, A. (2019). Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). California, CA: O'Reilly Media.



CNN Best

Train Accuracy: 90.66%

Valid Accuracy: **76.46%**

Test Accuracy: 71.20%

(5) CNN: Summary

Regularization approaches (dropout & weight decay using L2) barely help! In the best CNN model,

- Drop probability = 0
- Weight decay = 5e-5

Probably since the surname dataset is not big enough to generate overfitting!

CNN Baseline
Train Accuracy: 68.83%
Valid Accuracy: **57.16%**
Test Accuracy: 56.38%

CNN Best
Train Accuracy: 90.66%
Valid Accuracy: **76.46%**
Test Accuracy: 71.20%

Part IV: RNN

RNN code on Colab

- Baseline Model
- Best Model

[Remark] At pre-processing stage of RNN, we utilize "one-hot matrix", which ***retains*** *the sequential information*.

(1) RNN: Baseline Model — 1

RNN Baseline
Train Accuracy: 65.25%
Valid Accuracy: **56.81%**
Test Accuracy: 56.38%

RNN Baseline Model structure

(1): nn.Embedding(num_embeddings=num_embeddings, embedding_dim=embedding_size, padding_idx=padding_idx)

(2): ElmanRNN(input_size=embedding_size, hidden_size=rnn_hidden_size, batch_first=batch_first)

(4): nn.Linear(in_features=rnn_hidden_size,out_features=rnn_hidden_size)
(5): nn.ReLU()

(6): nn.Linear(in_features=rnn_hidden_size, out_features=num_classes)

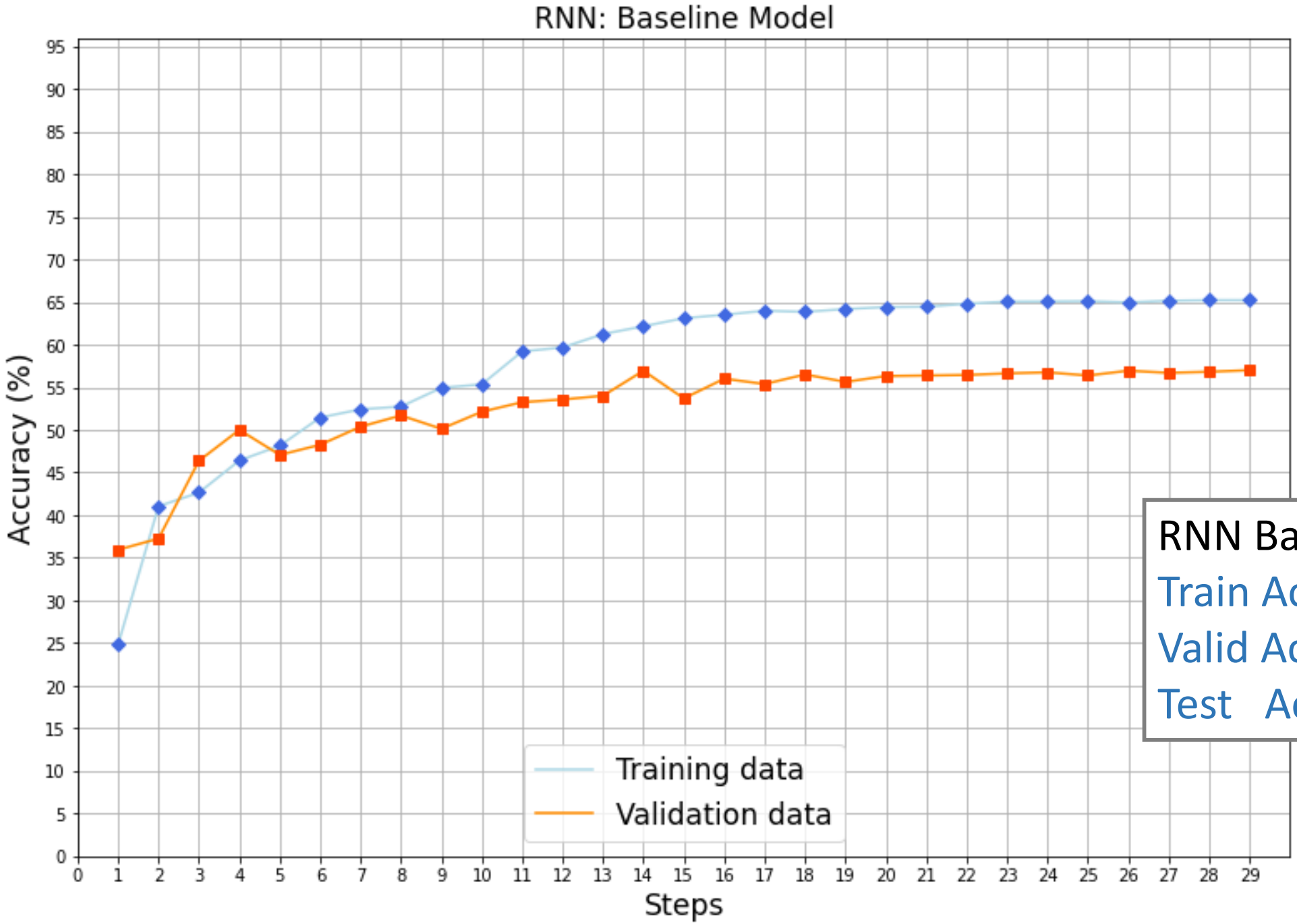
(2) RNN: Baseline Model — 2

RNN Baseline
Train Accuracy: 65.25%
Valid Accuracy: **56.81%**
Test Accuracy: 56.38%

Parameters of RNN Baseline Model

- Epoch = 30
- char_embedding_size= **100**
- rnn_hidden_size= **64**
- Batch Size = **64**
- Activator = **ReLU()**
- Optimizer = Adam
- Learning rate = 1e-3 (commonly recommended)
- Learning rate schedule: lr_scheduler.ReduceLROnPlateau()
- Weight decay = **0** (L2 regularization)
- Dropout = **0.0** (Originally 0.5 but 0.5 results in worse outcome, so I make it 0.)
- **No** batch normalization

Ref: Géron, A. (2019). Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). California, CA: O'Reilly Media.



RNN Baseline

Train Accuracy: 65.25%

Valid Accuracy: **56.81%**

Test Accuracy: 56.38%

(3) RNN: Best Model — 1

RNN Best
Train Accuracy: 94.23%
Valid Accuracy: **72.37%**
Test Accuracy: 63.91%

RNN Baseline Model structure

(1): nn.Embedding(num_embeddings=num_embeddings, embedding_dim=embedding_size, padding_idx=padding_idx)

(2): ElmanRNN(input_size=embedding_size, hidden_size=rnn_hidden_size, batch_first=batch_first)

(4): nn.Linear(in_features=rnn_hidden_size,out_features=rnn_hidden_size)
(5): nn.BatchNorm1d(rnn_hidden_size)
(6): nn.LeakyReLU()

(7): nn.Linear(in_features=rnn_hidden_size, out_features=num_classes)

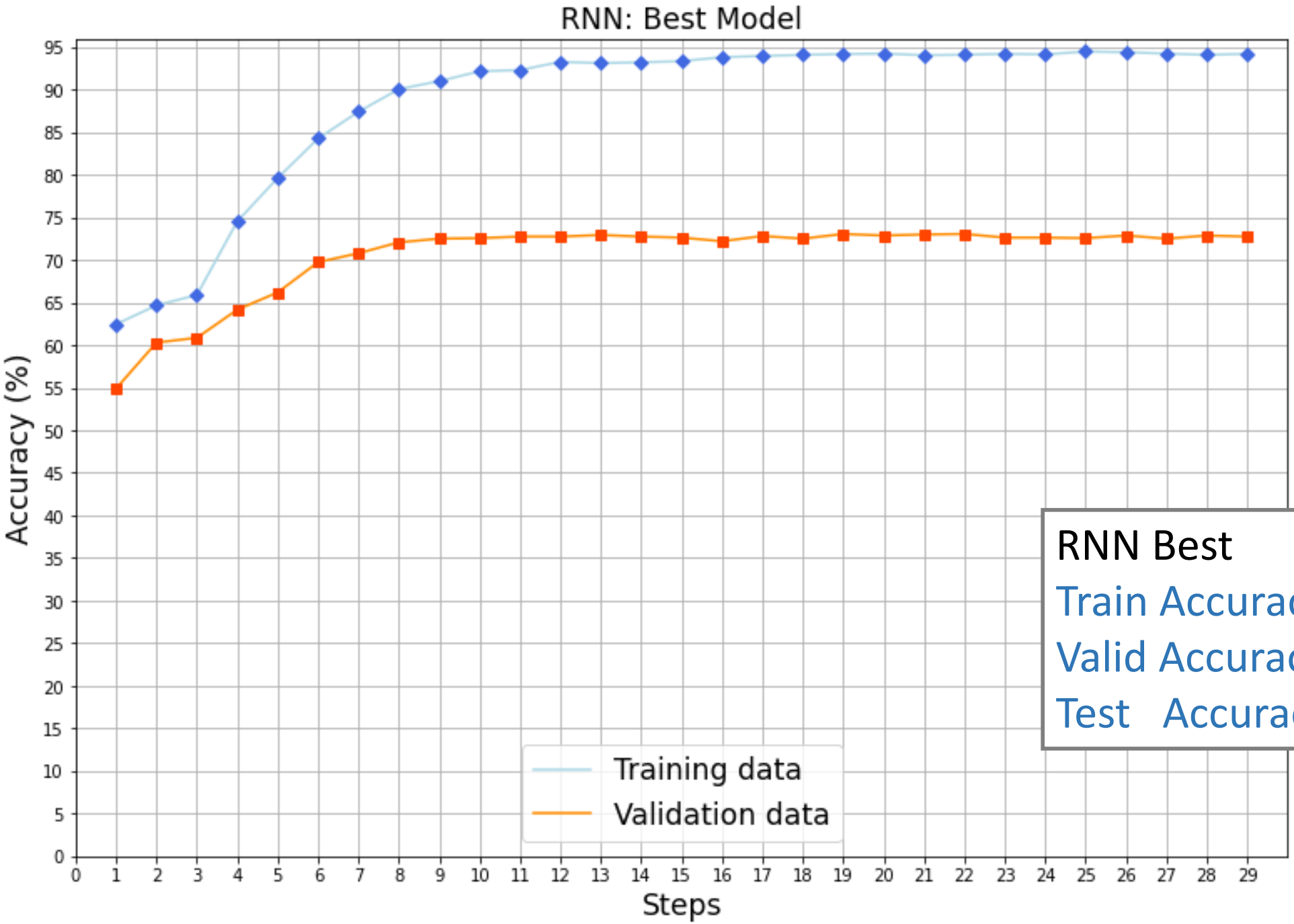
(4) RNN: Best Model — 2

RNN Best
Train Accuracy: 94.23%
Valid Accuracy: **72.37%**
Test Accuracy: 63.91%

Parameters of RNN Baseline Model

- Epoch = 30
- char_embedding_size= **300**
- rnn_hidden_size= **900**
- Batch Size = **32**
- Activator = **LeakyReLU()**
- Optimizer = Adam
- Learning rate = 1e-3 (commonly recommended)
- Learning rate schedule: lr_scheduler.ReduceLROnPlateau()
- Weight decay = **1e-4** (L2 regularization)
- Dropout = **0.0**

Ref: Géron, A. (2019). Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). California, CA: O'Reilly Media.



RNN Best

Train Accuracy: 94.23%

Valid Accuracy: **72.37%**

Test Accuracy: 63.91%

(5) RNN: Summary

Regularization approaches (dropout & weight decay using L2) barely help! In the best RNN model,

- Drop probability = 0
- Weight decay = 1e-4

Probably since the surname dataset is not big enough to generate overfitting!

RNN Baseline
Train Accuracy: 65.25%
Valid Accuracy: **56.81%**
Test Accuracy: 56.38%

RNN Best
Train Accuracy: 94.23%
Valid Accuracy: **72.37%**
Test Accuracy: 63.91%

Part V: Conclusion

- MLP, CNN, RNN — Comparison
- MLP, CNN, RNN — Ensemble Learning
- Prospect
- Code

(1) **Conclusion**: MLP vs. CNN

MLP Baseline_0	CNN Baseline	RNN Baseline
Train Accuracy: 52.73%	Train Accuracy: 68.83%	Train Accuracy: 65.25%
Valid Accuracy: **46.31%**	Valid Accuracy: **57.16%**	Valid Accuracy: **56.81%**
Test Accuracy: 46.69%	Test Accuracy: 56.38%	Test Accuracy: 56.38%



MLP Best	CNN Best	RNN Best
Train Accuracy: 93.65%	Train Accuracy: 90.66%	Train Accuracy: 94.23%
Valid Accuracy: **67.26%**	Valid Accuracy: **76.46%**	Valid Accuracy: **72.37%**
Test Accuracy: **66.87%**	Test Accuracy: **71.20%**	Test Accuracy: **63.91%**
Epoch: 25	Epoch: 30	Epoch: 30
Running Time: 231.21 s	Running Time: 203.15 s	Running Time: 146.82 s

Compared to a fully connected layer, a convolution layer in a CNN has a *much smaller number of parameters*. This allows us to build deeper models without worrying about **memory overflow**. Also, deeper models usually lead to better performance.

Ref: Ganegedara, T. (2018). Natural Language Processing with TensorFlow. Birmingham, UK: Packt Publishing.

(2) **Conclusion**: CNN vs. RNN

MLP Baseline_0	CNN Baseline	RNN Baseline
Train Accuracy: 52.73%	Train Accuracy: 68.83%	Train Accuracy: 65.25%
Valid Accuracy: **46.31%**	Valid Accuracy: **57.16%**	Valid Accuracy: **56.81%**
Test Accuracy: 46.69%	Test Accuracy: 56.38%	Test Accuracy: 56.38%



MLP Best	CNN Best	RNN Best
Train Accuracy: 93.65%	Train Accuracy: 90.66%	Train Accuracy: 94.23%
Valid Accuracy: **67.26%**	Valid Accuracy: **76.46%**	Valid Accuracy: **72.37%**
Test Accuracy: **66.87%**	Test Accuracy: **71.20%**	Test Accuracy: **63.91%**
Epoch: 25	Epoch: 30	Epoch: 30
Running Time: 231.21 s	Running Time: 203.15 s	Running Time: 146.82 s

One-dimensional convolutions ***sometimes perform better*** than RNNs and are ***computationally cheaper***.

Ref: Subramanian, V. (2018). Deep Learning with PyTorch. Birmingham, UK: Packt Publishing.

(3) **Conclusion**: MLP, CNN, RNN — Ensemble Learning

MLP Baseline_0
Train Accuracy: 52.73%
Valid Accuracy: **46.31%**
Test Accuracy: 46.69%

CNN Baseline
Train Accuracy: 68.83%
Valid Accuracy: **57.16%**
Test Accuracy: 56.38%

RNN Baseline
Train Accuracy: 65.25%
Valid Accuracy: **56.81%**
Test Accuracy: 56.38%

MLP Best
Train Accuracy: 93.65%
Valid Accuracy: **67.26%**
Test Accuracy: **66.87%**
Epoch: 25
Running Time: 231.21 s

CNN Best
Train Accuracy: 90.66%
Valid Accuracy: **76.46%**
Test Accuracy: **71.20%**
Epoch: 30
Running Time: 203.15 s

RNN Best
Train Accuracy: 94.23%
Valid Accuracy: **72.37%**
Test Accuracy: **63.91%**
Epoch: 30
Running Time: 146.82 s

"MLP Best", "CNN Best" and "RNN best" seem to fit distinct patterns of "surname classification" respectively, so ensemble learning would help generating a more performant NN model.

(4) **Conclusion**: Prospect

To achieve better test accuracy, we may do as follows:

- ✓ 1. **MLP**: Making a deeper MLP.
- ✓ 2. **CNN**: Choose more complex CNN architecture, like ResNet.
- ✓ 3. **RNN**: The RNN we utilize is a vanilla RNN: *Elman RNN*. LSTM and GRU would probably perform better than Elman RNN.
- ✓ 4. **Optimizer**: We used *Adam* here, and we could try others.
- ✓ 5. **Activator**: We used *ReLU()*, *LeakyReLU()*, *ELU()*. We may try others.
- ✓ 6. **Regularization**: We found the surname dataset is not huge enough to yield overfitting, so no need to spend time on this.

Code on Colab

1. Preprocessing:
https://bit.ly/3hGWYhs

2. MLP:
https://bit.ly/3nTLxpf

3. CNN:
https://bit.ly/3rwRCKr

4. RNN:
https://bit.ly/3ptfcG8

Thank you !

https://morton-kuo.medium.com/

Reference

1. Géron, A. (2019). Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). California, CA: O'Reilly Media.
2. Rao, D. & McMahan, B. (2019). Natural Language Processing with PyTroch. California, CA: O'Reilly Media.
3. Sarkar, D. (2019). Text Analytics with Python (2nd ed.). Karnataka, India: Apress.
4. Ganegedara, T. (2018). Natural Language Processing with TensorFlow. Birmingham, UK: Packt Publishing.
5. Subramanian, V. (2018). Deep Learning with PyTorch. Birmingham, UK: Packt Publishing.
6. Patterson, J. & Gibson, A. (2017). Deep Learning: A Practitioner's Approach. California, CA: O'Reilly Media.
7. 斎藤康毅 (2016). ゼロから作るDeep Learning ―Pythonで学ぶディープラーニングの理論と実. Japan, JP: O'Reilly Japan.
8. Kuo, M. (2021). ML16: Hands-on Text Preprocessing. Retrieved from https://medium.com/analytics-vidhya/ml16-ef6105b5bb34#6ef4