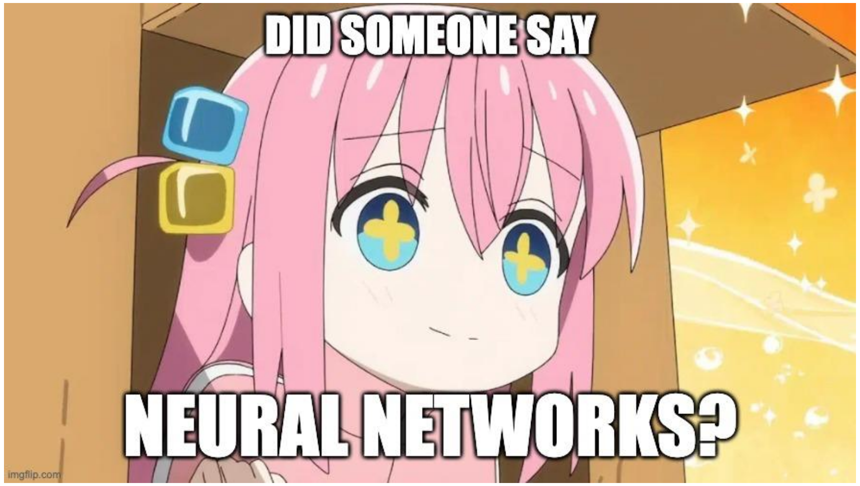
Deep tokenization

Tokenization

- Recent tokenization techniques are based on deep learning models
  - Better to handle out-of-vocabulary (OOV), misspellings, etc.

NEURAL NETWORKS

Deep learning = Deep neural networks = neural networks



Why neural networks

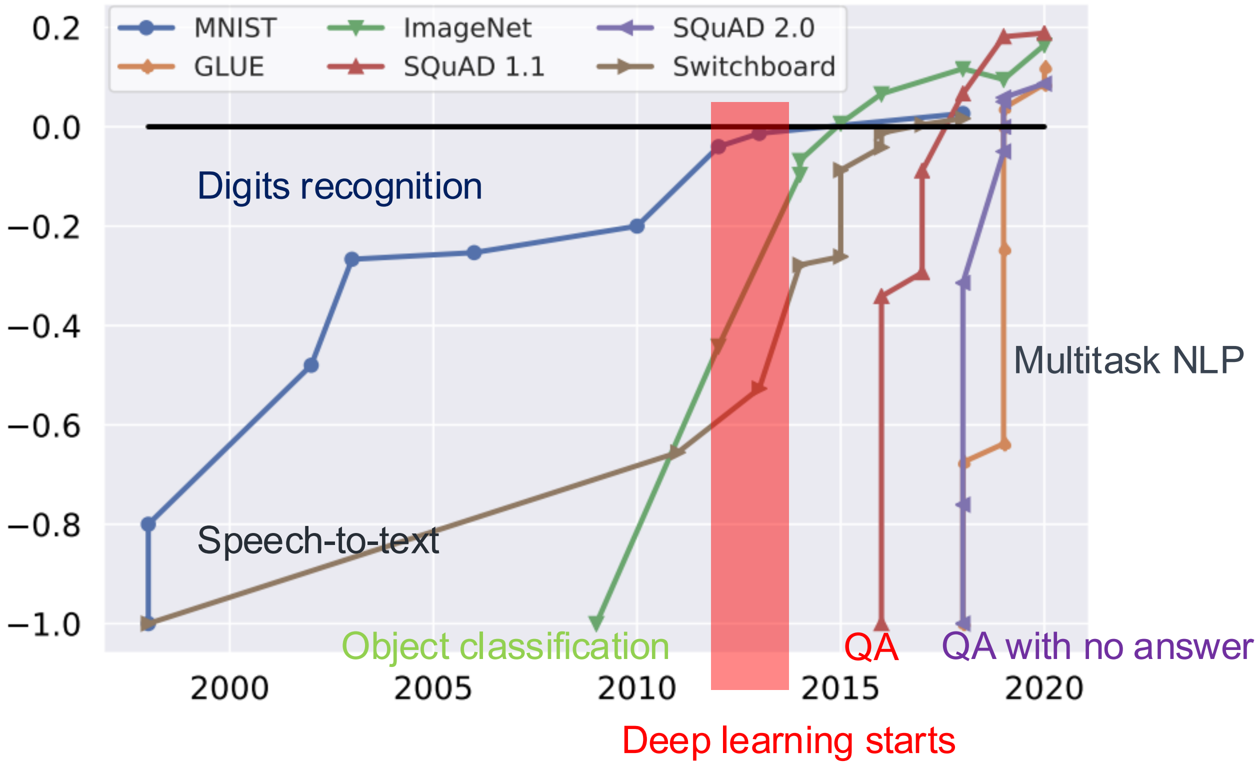
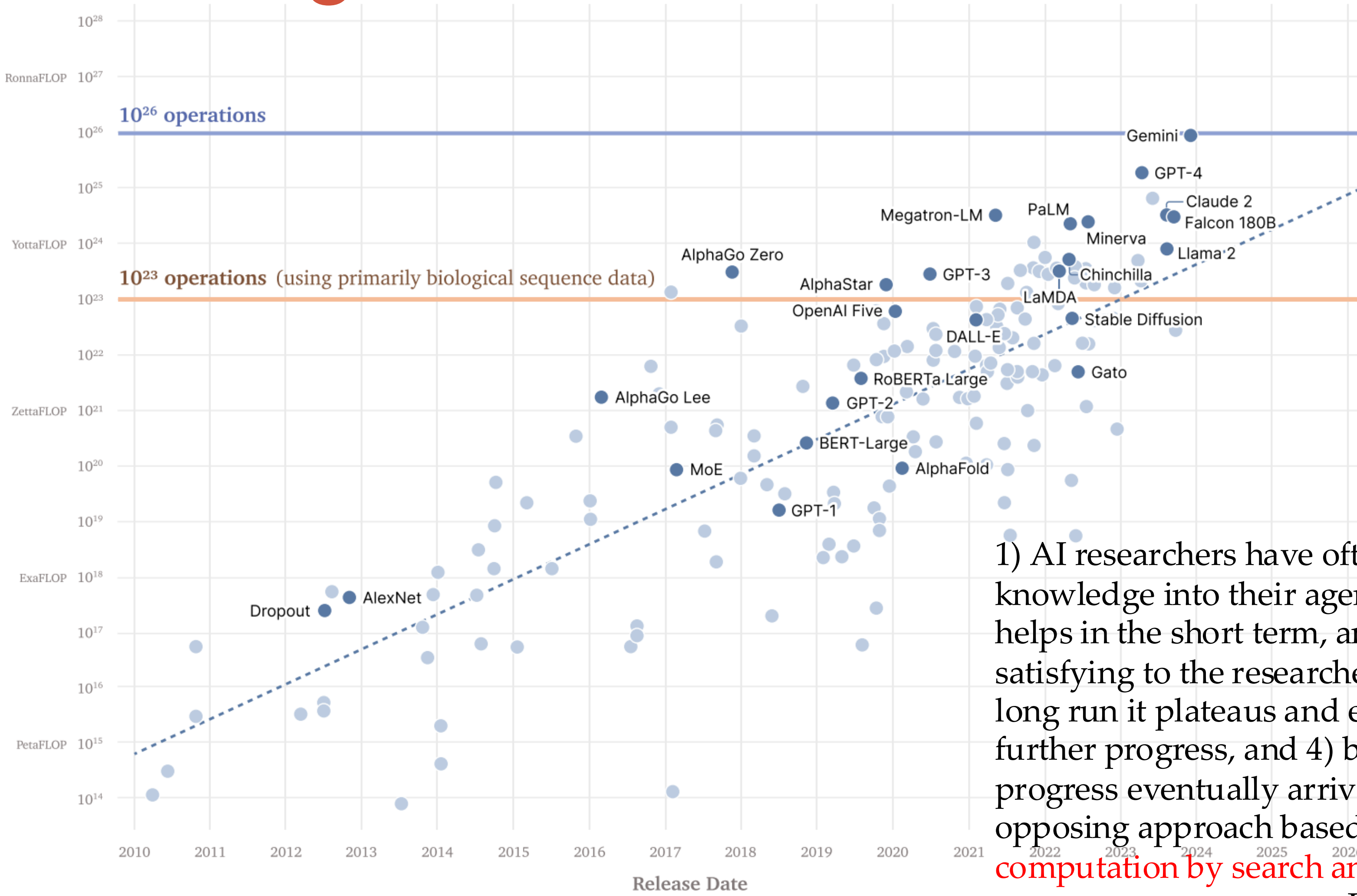


Figure 1: Benchmark saturation over time for popular benchmarks, normalized with initial performance at minus one and human performance at zero.

https://arxiv.org/abs/2006.11239

Scaling matters

https://arxiv.org/pdf/2402.08797



1) AI researchers have often tried to build knowledge into their agents, 2) this always helps in the short term, and is personally satisfying to the researcher, but 3) in the long run it plateaus and even inhibits further progress, and 4) breakthrough progress eventually arrives by an opposing approach based on scaling computation by search and learning.

- Richard Sutton
The Bitter Lesson

Figure 4: Training compute used for notable ML models has been doubling every six months since the emergence of the Deep Learning Era. *Executive Order 14110 introduced a notification requirement for models trained with more than 10^{26} operations (and 10^{23} operations if trained on using primarily biological sequence data).*

Deep learning in NLP

Easy task modest gains

	Traditional ML	Deep learning
Wisesight Sentiment (th)	72%	76% (WangchanBERTa) 71% (Phayathaibert unsup) (60% QWEN2-72B zeroshot)
Topic classification (th)	67%	70%
PoS (th)	96%	97%

Harder task larger gains

	Traditional ML	Deep learning
QA	51%*	90%
Creating image from text	???	very good

wangchanbert
https://www.aclweb.org/anthology/D16-1264/
https://openai.com/blog/dall-e/

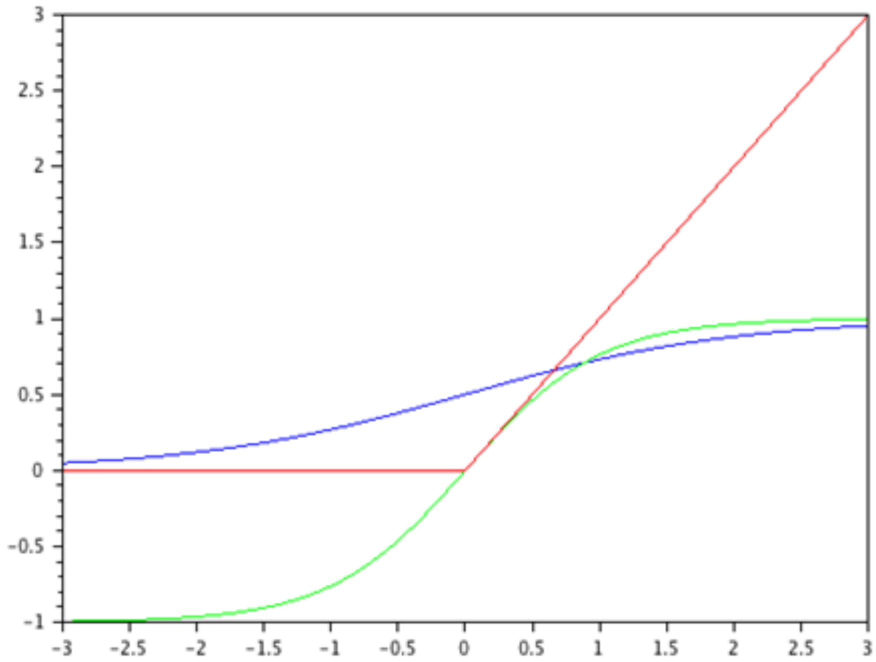
Neural networks

- Fully connected networks
  - Neuron
  - Non-linearity
  - Softmax layer
  - Dropout
  - Batchnorm
- CNN, RNN, LSTM, GRU

- If you are unaware of these, please watch last year's Pattern lecture 7 and 7.5

Non-linearity

- The Non-linearity is important in order to stack neurons
  - If F is linear, a multi layered network can be collapsed as a single layer (by just multiplying weights together)
- Sigmoid or logistic function
- tanh
- Rectified Linear Unit (ReLU)
  - LeakyReLU, ELU, PreLU
- Sigmoid Linear Units (SiLU)
  - Swish, Mish, GELU, SwiGLU



SiLU, GELU

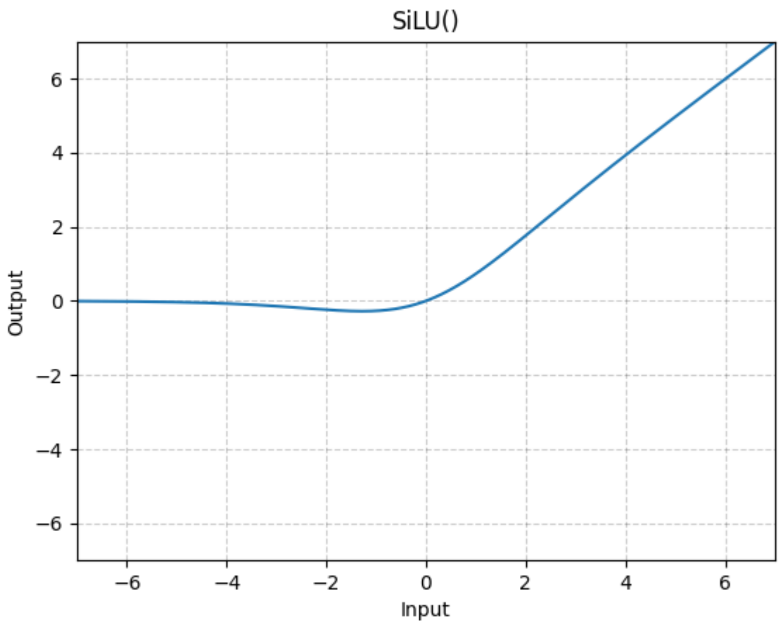
SiLU (or Swish – Swish paper comes after SiLU but is more popular)

CLASS torch.nn.SiLU(*inplace=False*) [SOURCE]

Applies the Sigmoid Linear Unit (SiLU) function, element-wise.

The SiLU function is also known as the swish function.

$$\text{silu}(x) = x * \sigma(x), \text{where } \sigma(x) \text{ is the logistic sigmoid.}$$



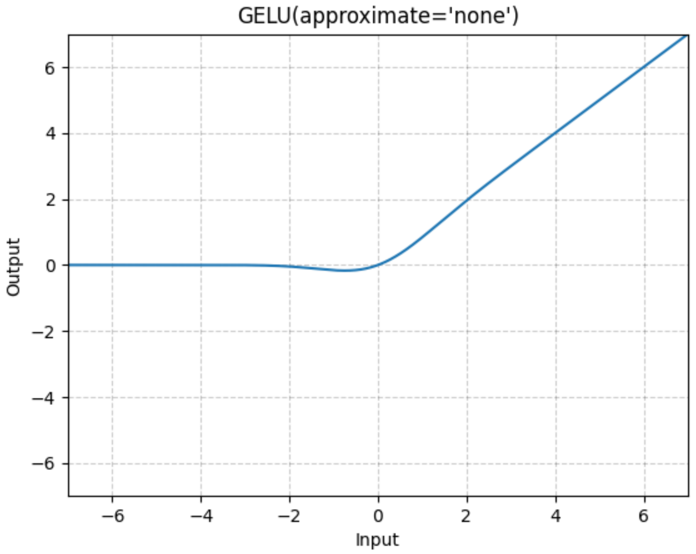
GELU

CLASS torch.nn.GELU(*approximate='none'*) [SOURCE]

Applies the Gaussian Error Linear Units function.

$$\text{GELU}(x) = x * \Phi(x)$$

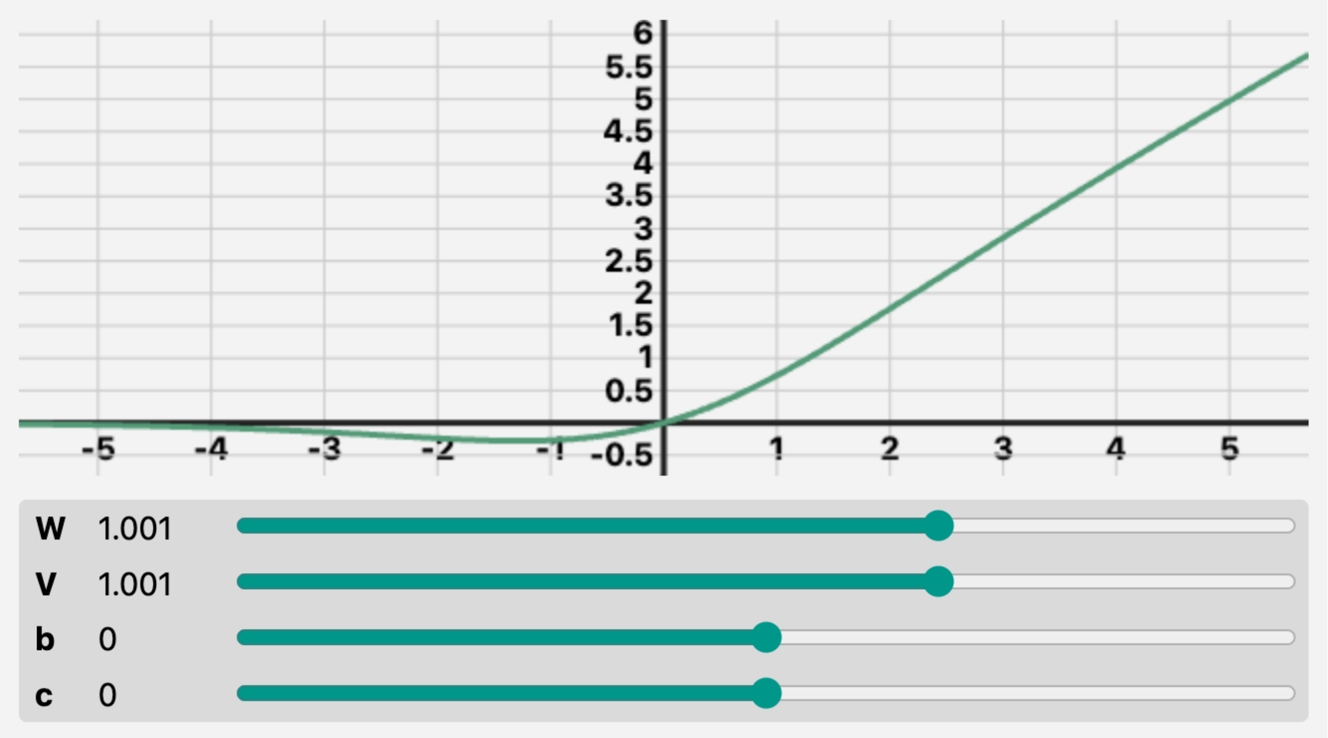
where $\Phi(x)$ is the Cumulative Distribution Function for Gaussian Distribution.



GLU (Gated Linear Unit)

- A gated dense layer

GLU(x) = (Wx+b)*sigmoid(Vx+c)



https://jcarlosroldan.com/post/348/what-is-swiglu

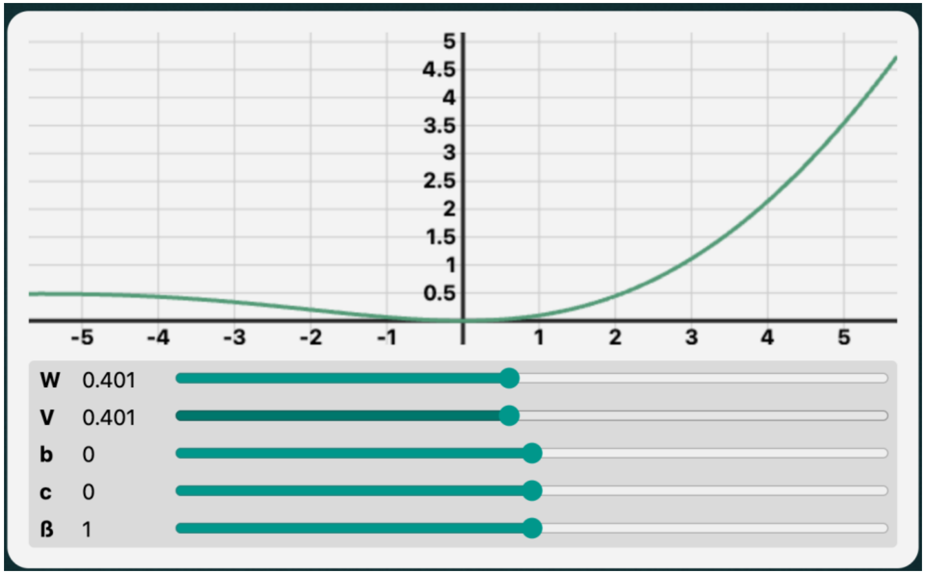
SwiGLU

- GLU with a Swish/SiLU gating function
- Many LLMs use this. Example: Llama

GLU(x) = (Wx+b)*sigmoid(Vx+c)

Swish(x) = x*sigmoid(Bx)

SwiGLU(x) = (Wx+b)*Swish(Vx+c)



https://jcarlosroldan.com/post/348/what-is-swiglu

Batch normalization

- Recent technique for (implicit) regularization
- Normalize every mini-batch at various batch norm layers to standard Gaussian (different from global normalization of the inputs)
- Place batch norm layers before non-linearities
- Faster training and better generalizations

For each mini-batch that goes through batch norm

1. Normalize by the mean and variance of the mini-batch for each dimension
2. Shift and scale by learnable parameters

Replaces dropout in some networks

$$\hat{x} = \frac{x - \mu_b}{\sigma_b}$$

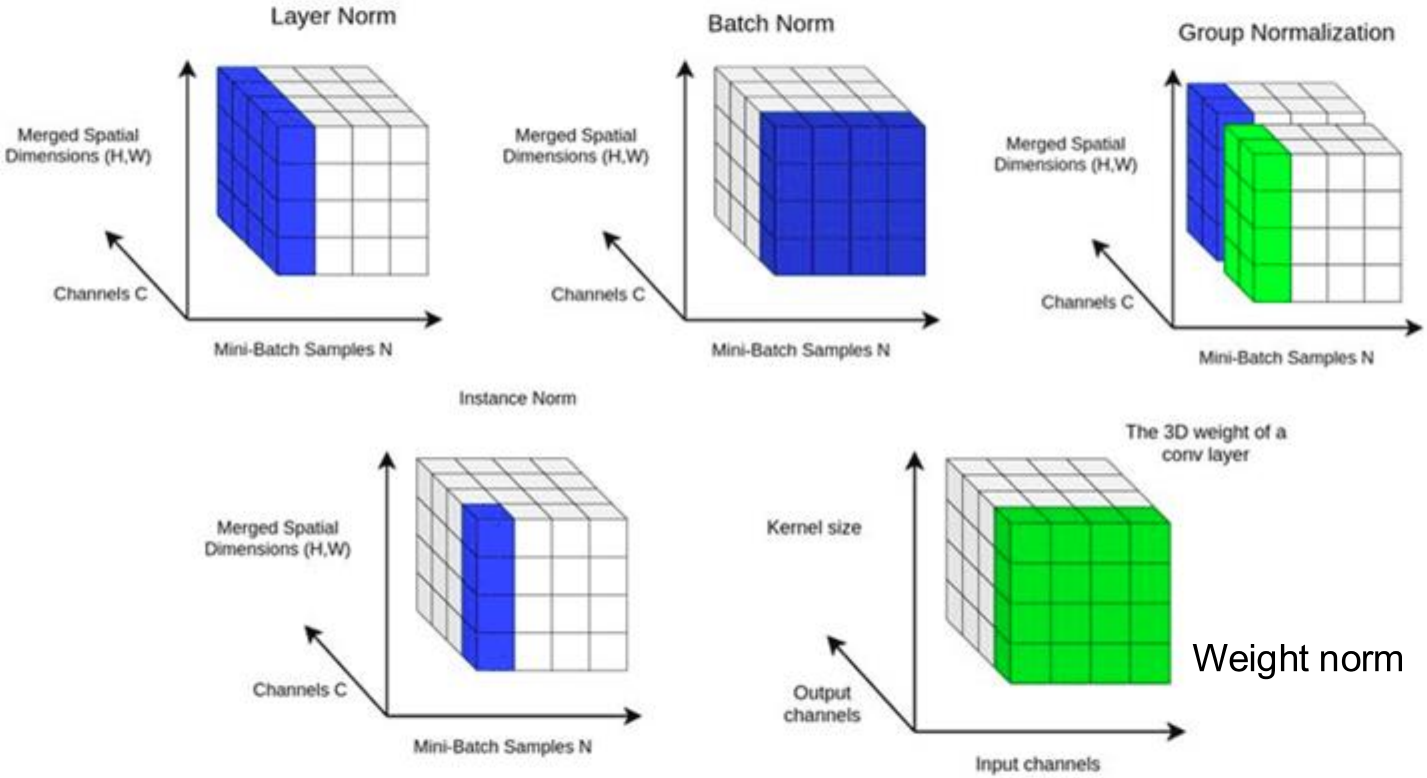
$$y = \alpha\hat{x} + \beta$$

https://arxiv.org/abs/1502.03167

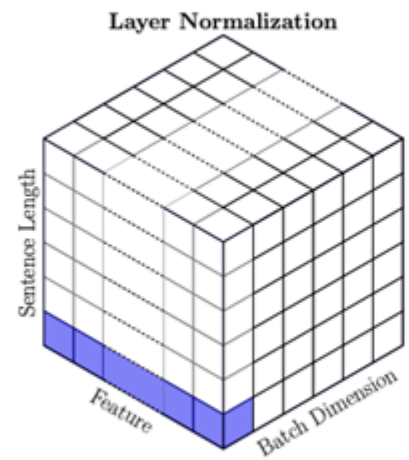
Other normalizations

- Other normalizations are out there

NLP and CV layer norm are not the same (In NLP, layer norm is applied separately for each element in the sequence)



Layer norm in transformers

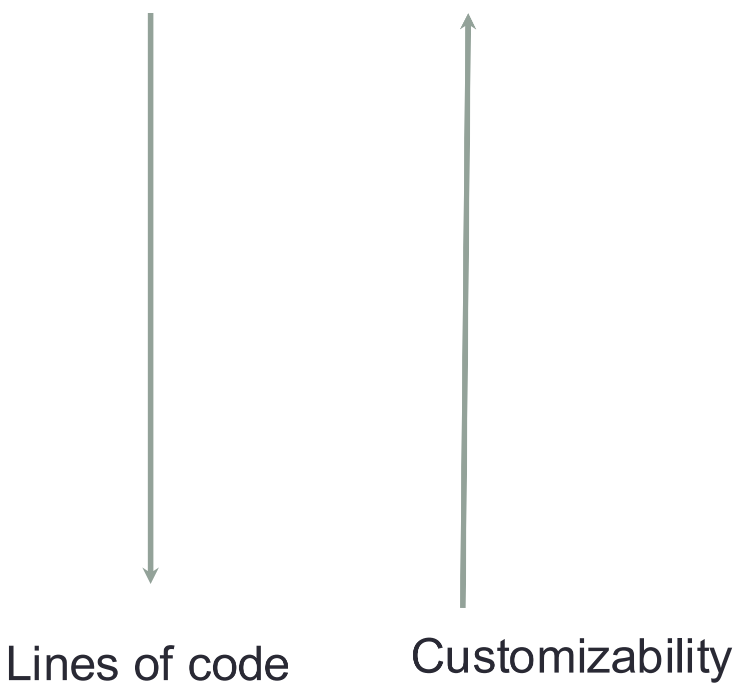


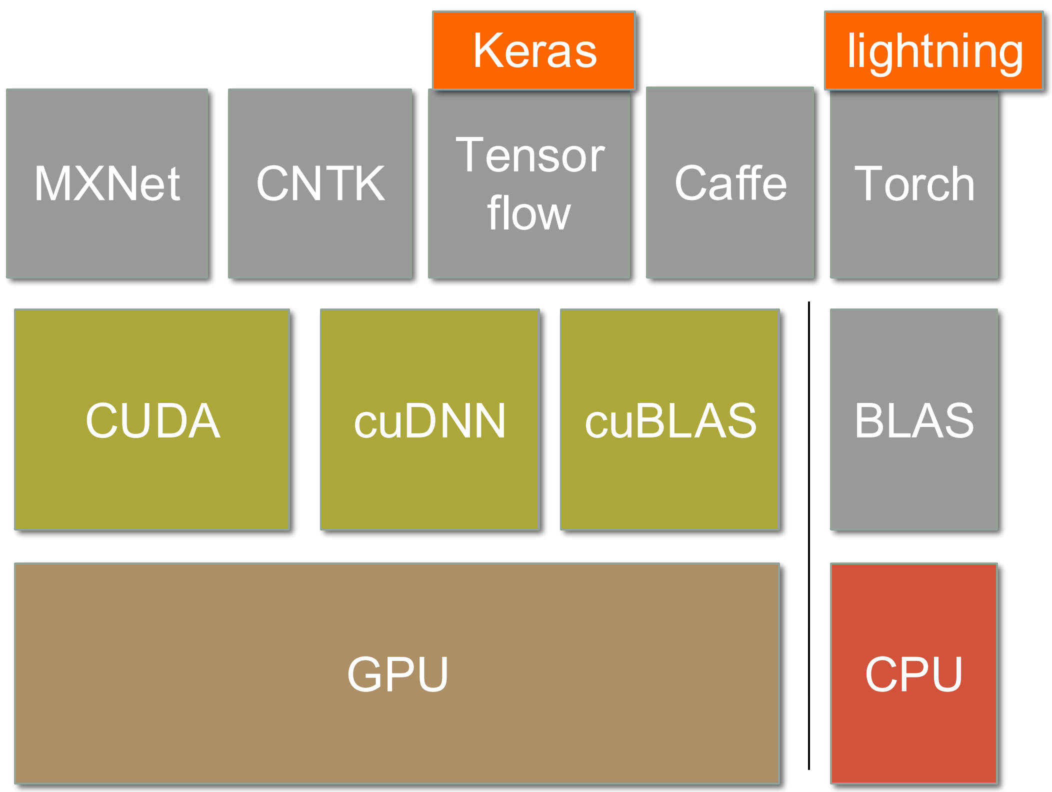
https://theaisummer.com/normalization/

https://proceedings.mlr.press/v119/shen20e/shen20e.pdf

What toolkit

Tradeoff between customizability and ease of use





Pytorch steps

- Setting up dataloader
  - Gives minibatch
- Define a network
  - Init weights
  - Define computation graph
- Setup optimization method
  - Pick LR scheduler
  - Pick optimizer
- Training loop
  - Forward (compute Loss)
  - Backward (compute gradient and apply gradient)

- Let’s demo

Lightning

- Setting up dataloader
  - Gives minibatch
- Define a network
  - Init weights
  - Define computation graph
- Setup optimization method
  - Pick LR scheduler
  - Pick optimizer
- Training loop
  - Forward (compute Loss)
  - Backward (compute gradient and apply gradient)

Pytorch Lightning helps with this and much more

- Let's demo

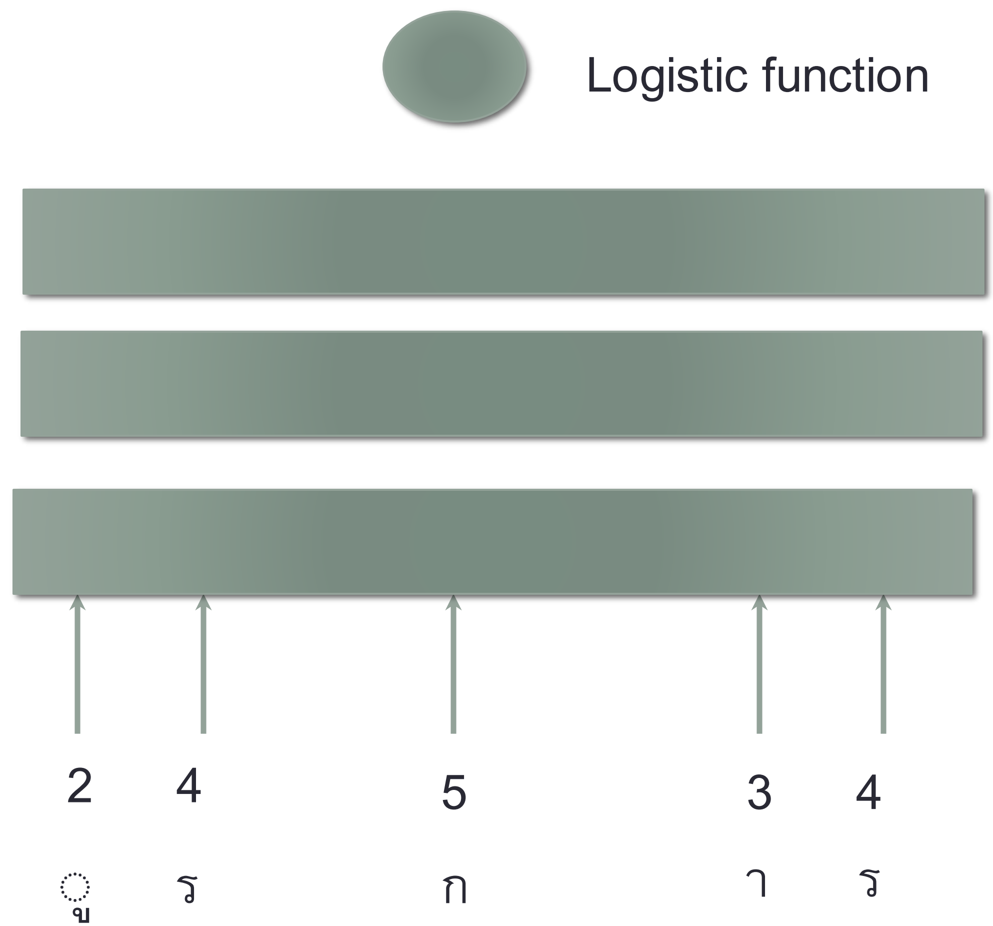
Lab/HW

- Word segmentation using pytorch
- Given a letter with 10 letters before and after, determine whether it's a start of a word

ท ร ง อ ย่ า ง แ บ ด แ ซ อ ย่ า ง บd

Word segmentation with fully connected networks

1 = word beginning, 0 = word middle



Embeddings

- A way to encode information to a lower dimensional space
  - We can learn about this lower dimensional space through data

DOG

[68, 79, 71]

PIG
[80, 73, 71]

CAT

[67, 65, 84]

CAP

[67, 65, 80]

One hot encoding

- Categorical representation is usually represented by one hot encoding

- Categorical representations examples:
    - Words in a vocabulary, characters in Thai language

Apple -> 1 -> [1, 0, 0, 0, …]

Bird -> 2 -> [0, 1, 0, 0, …]

Cat -> 3 -> [0, 0, 1, 0, …]

- Sparse representation
    - Spare means most dimension are zero

One hot encoding

- Sparse – but lots of dimension
  - Curse of dimensionality
- Does not represent meaning.

Apple -> 1 -> [1, 0, 0, 0, …]

Bird -> 2 -> [0, 1, 0, 0, …]

Cat -> 3 -> [0, 0, 1, 0, …]

|Apple – Bird| = |Bird – Cat|

Getting meaning into the feature vectors

- You can add back meanings by hand-crafted rules
- Old-school NLP is all about feature engineering
- Word segmentation example:
  - Cluster Numbers
  - Cluster letters
- Concatenate them
- 1 = [0 0 0 0 1 0 0 0, 1, 0]
- ก = [0 0 0 1 0 0 0 0, 0, 1]
- า = [1 0 0 0 0 0 0 0, 0, 2]
- Which rules to use?
  - Try as many as you can think of, and do feature selection or use models that can do feature selection

Dense representation

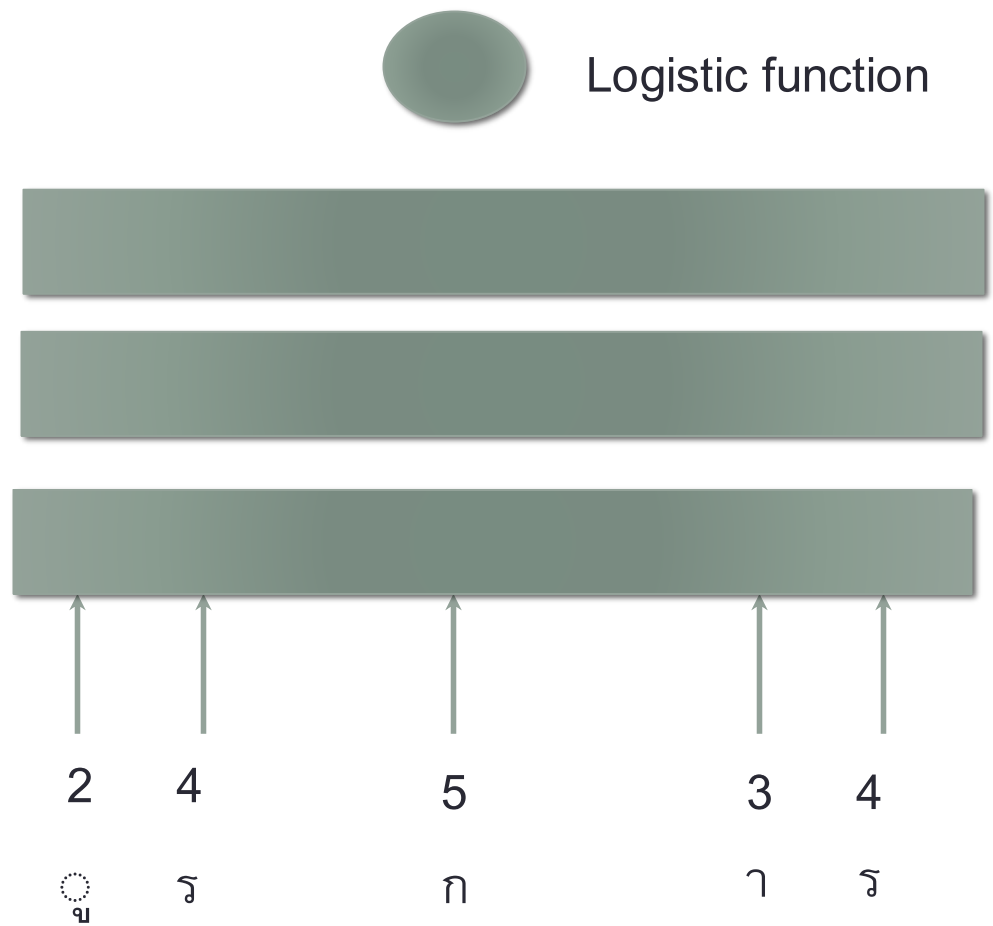
- We can encode sparse representation into a lower dimensional space
  - F: R^N -> R^M, where N>M

Apple -> 1 -> [1, 0, 0, 0, …] -> [2.3, 1.2]
Bird -> 2 -> [0, 1, 0, 0, …] -> [-1.0, 2.4]
Cat -> 3 -> [0, 0, 1, 0, …] -> [-3.0, 4.0]

- We can do this by using an embedding layer
  - This is just a (learnable) lookup table!

Word segmentation with fully connected networks

1 = word beginning, 0 = word middle

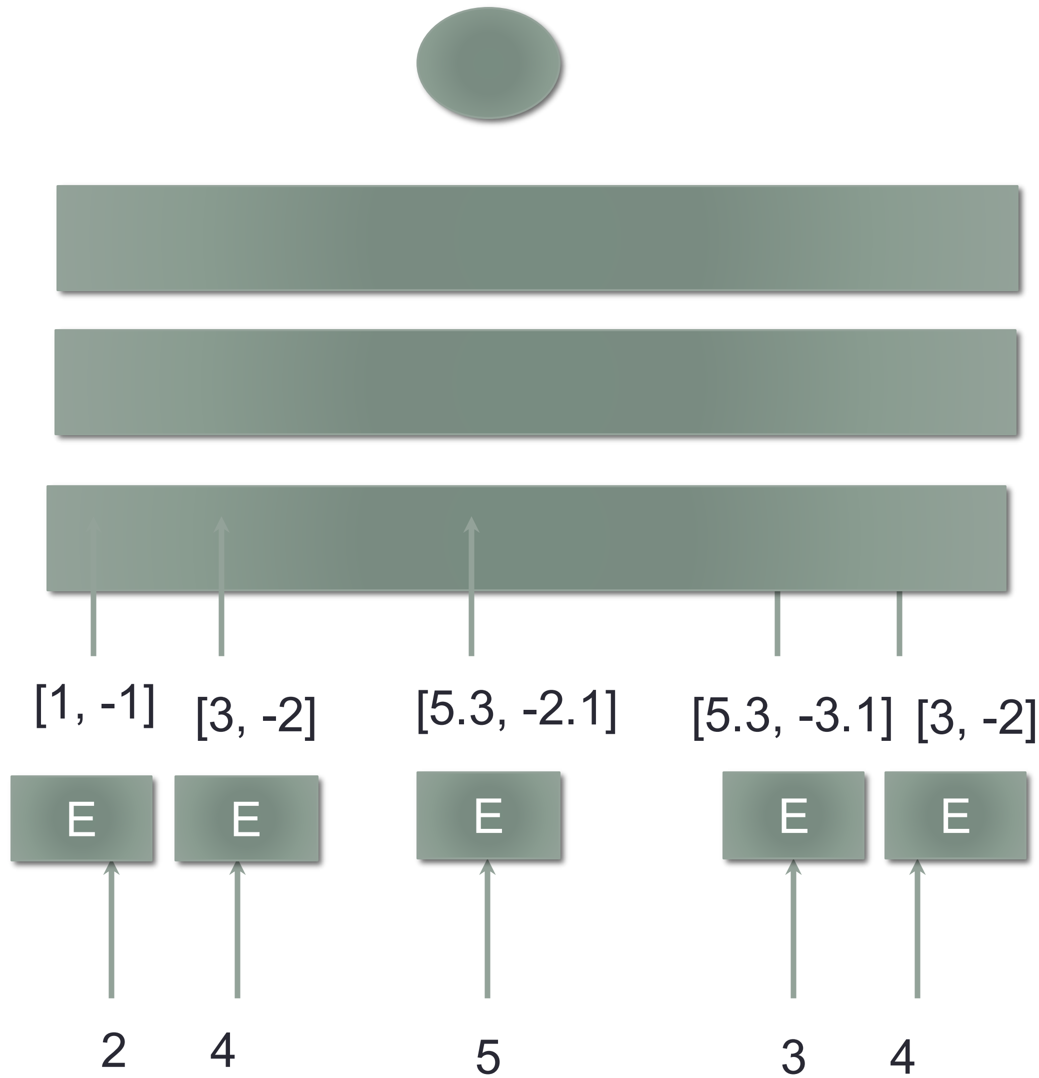


Adding embedding layer

Embedding layer shares the same weights

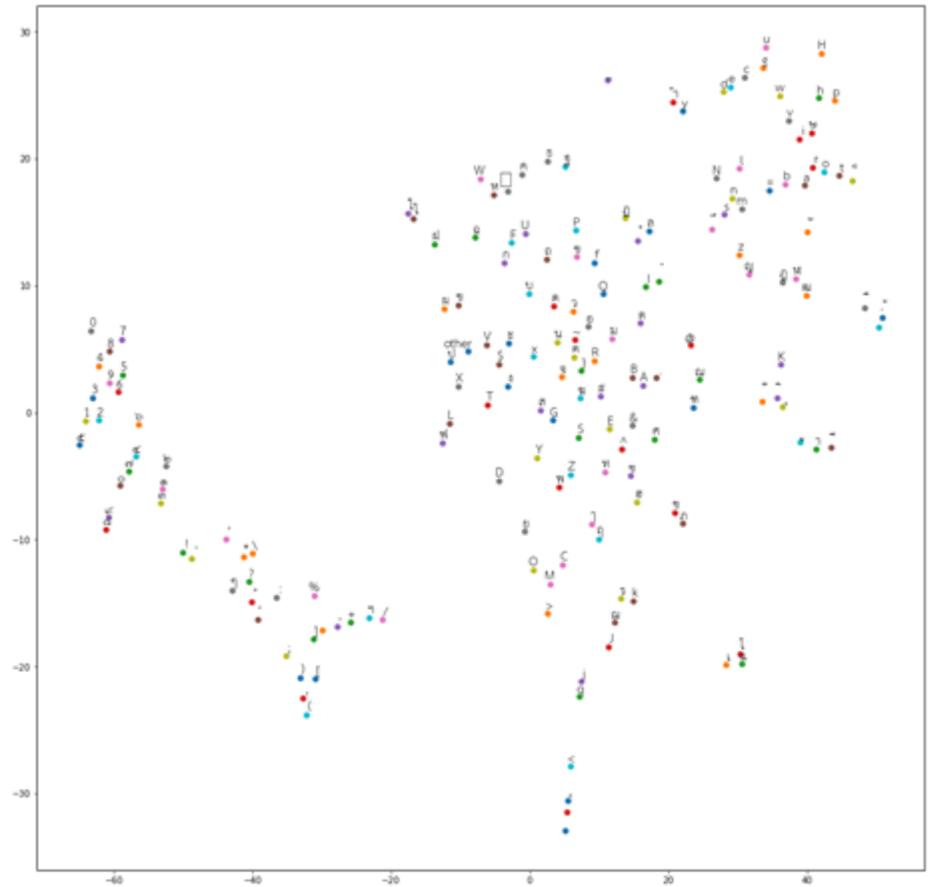
Parameter sharing!

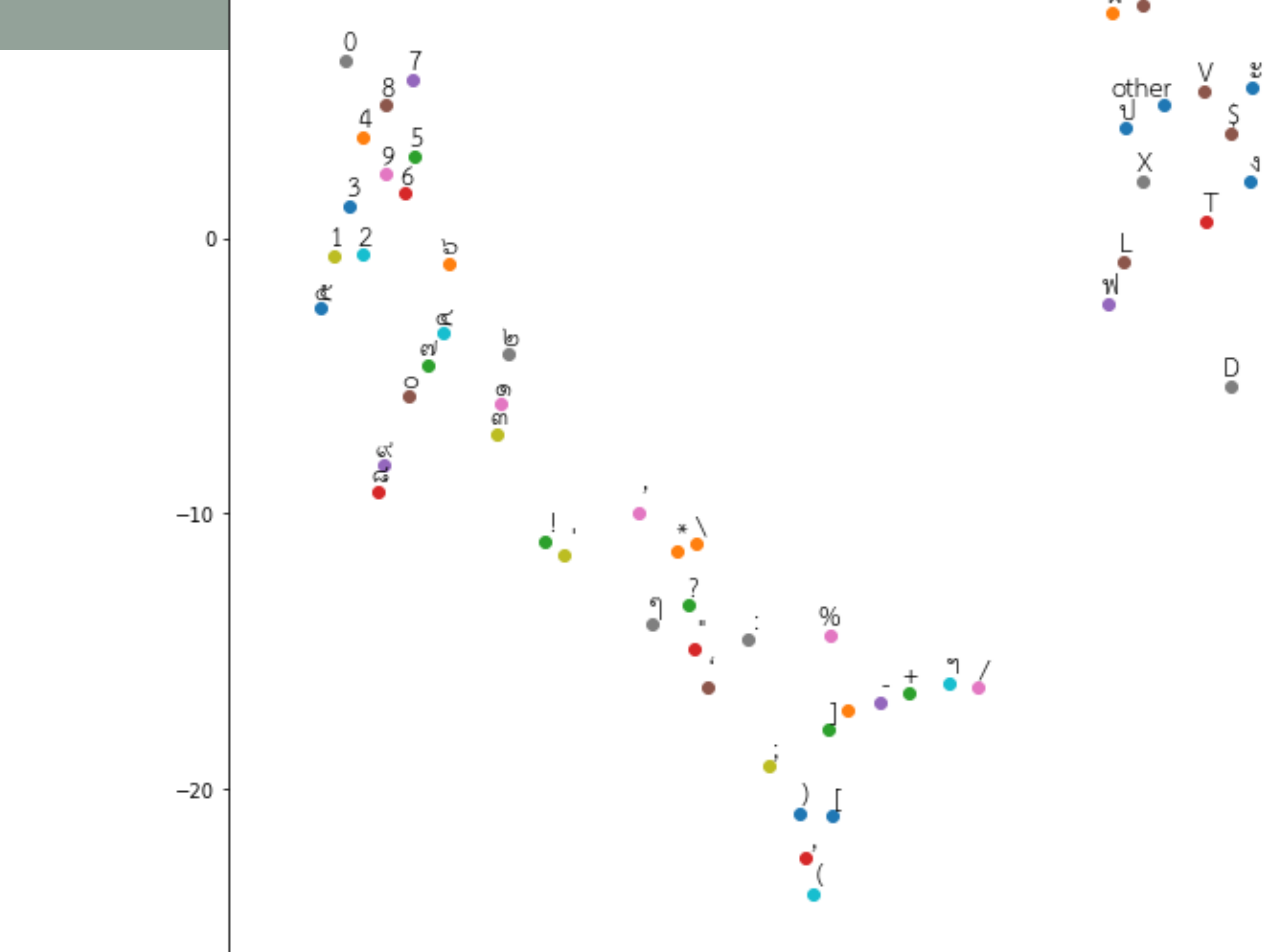
More on embeddings in the next two lectures!



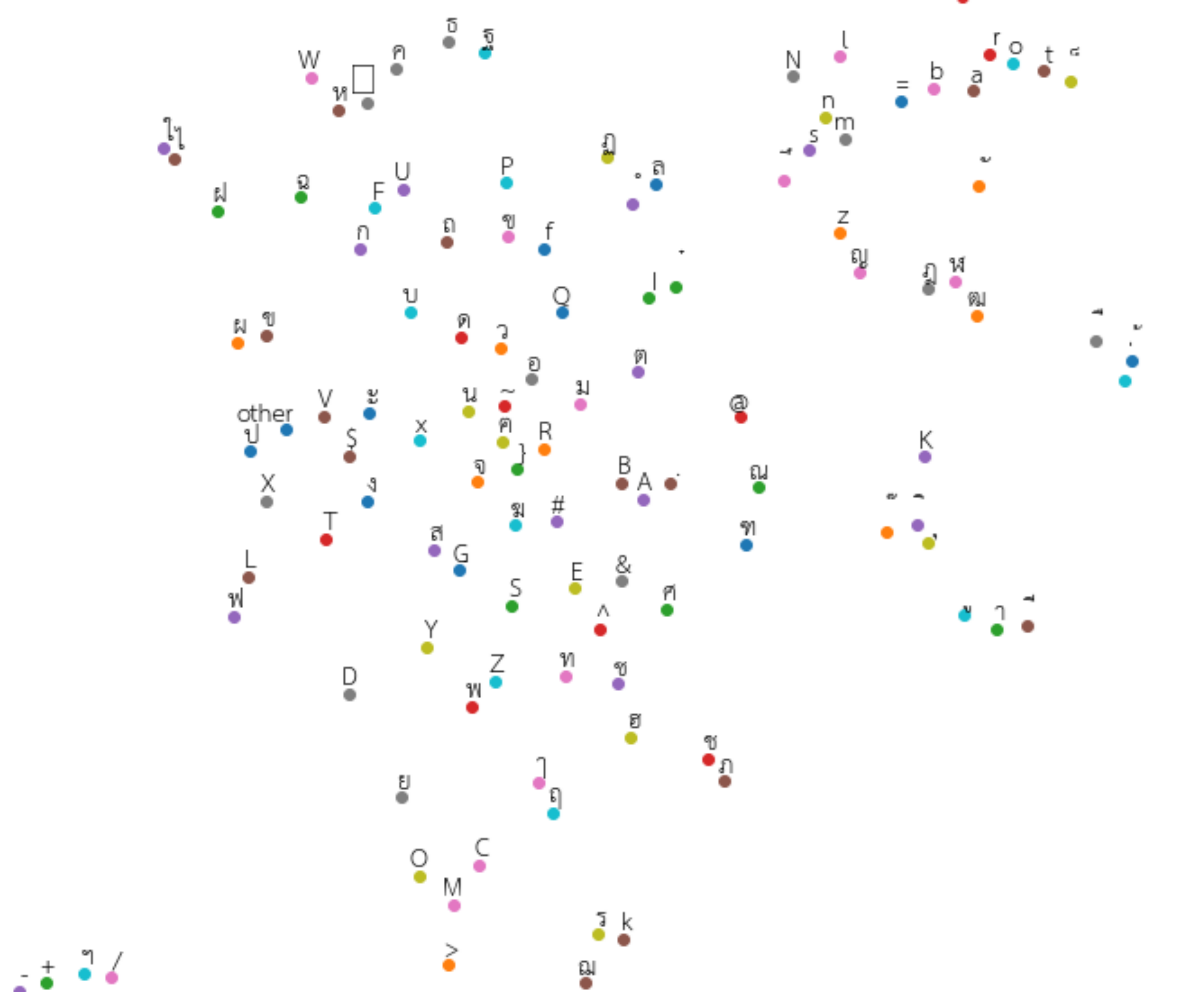
Embedding and meaning (semantics)

- Meaning is inferred from the task
- Embedding of 32 dimensions -> t-SNE into 2 dimension for visualization
- Automatically!





0
−10
−20
other



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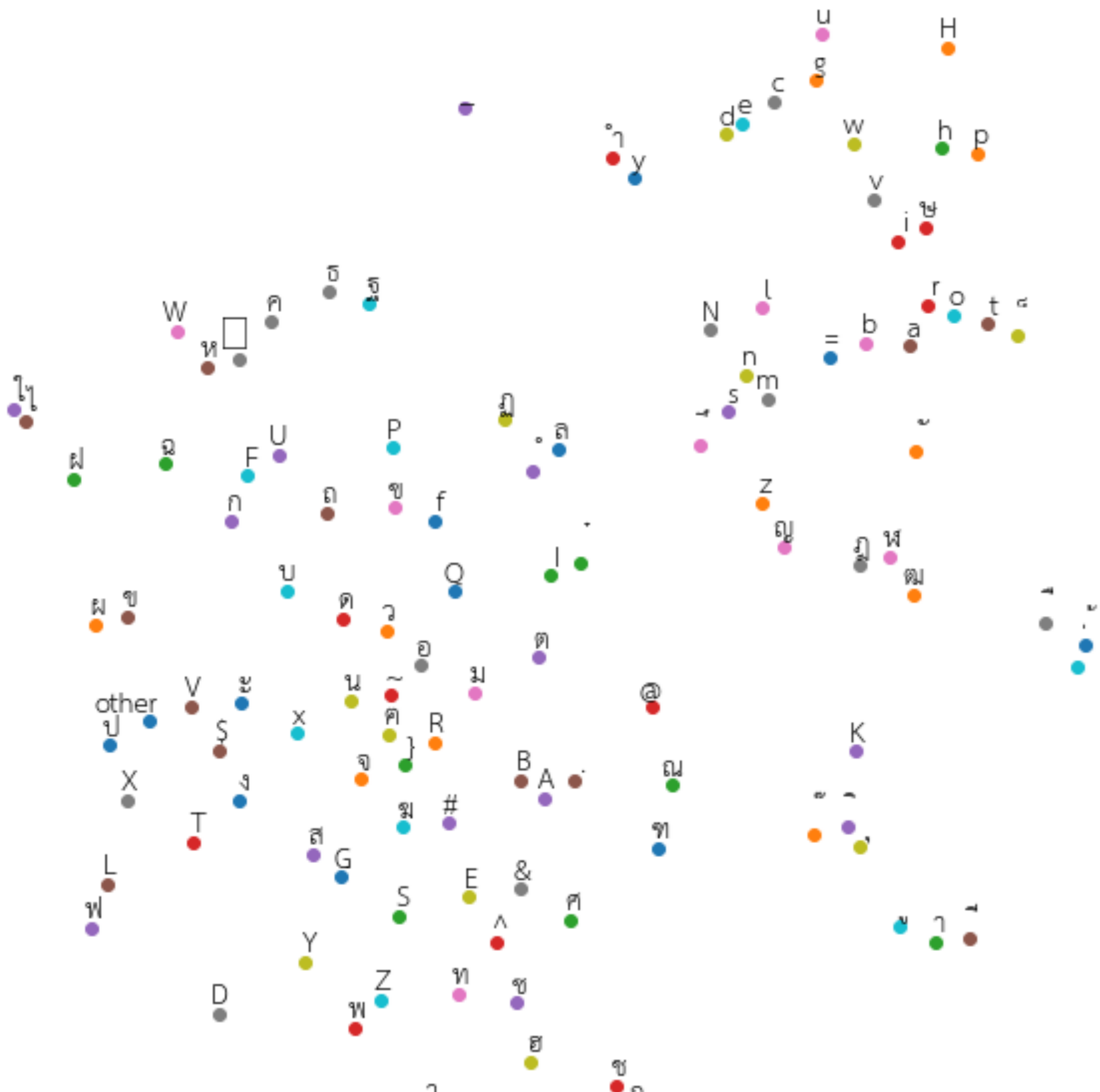


Debugging guide

- https://uvadlc-notebooks.readthedocs.io/en/latest/tutorial_notebooks/guide3/Debugging_PyTorch.html
  has list of common errors and best practices
- http://karpathy.github.io/2019/04/25/recipe/
  has guide for end-to-end model building (start simple and go more advance)

Back to tokenization…

TABLE II
RESULTS OF THE SIX BEST TEAMS

Type of participants	F-Measure (%)	Time (mm:ss)
Non-Students[a]	97.94937	00:47
Non-Students	97.84097	02:46
Non-Students	97.18822	00:26
Bachelor Students[b]	95.78162	01:08
Master Students	95.56670	12:14
PhD+Master Students	92.02067	02:28

[a]Best of the BEST 2009 Award Winner
[b]BEST Student 2009 Award Winner

BEST 2009 : Thai word segmentation software contest
http://ieeexplore.ieee.org/document/5340941/
https://sertiscorp.com/thai-word-segmentation-with-bi-directional_rnn/

Best 2009 standard

- Based on “Minimal Integrity Unit”
- A compound that its meaning is not so different from its part should be segmented.

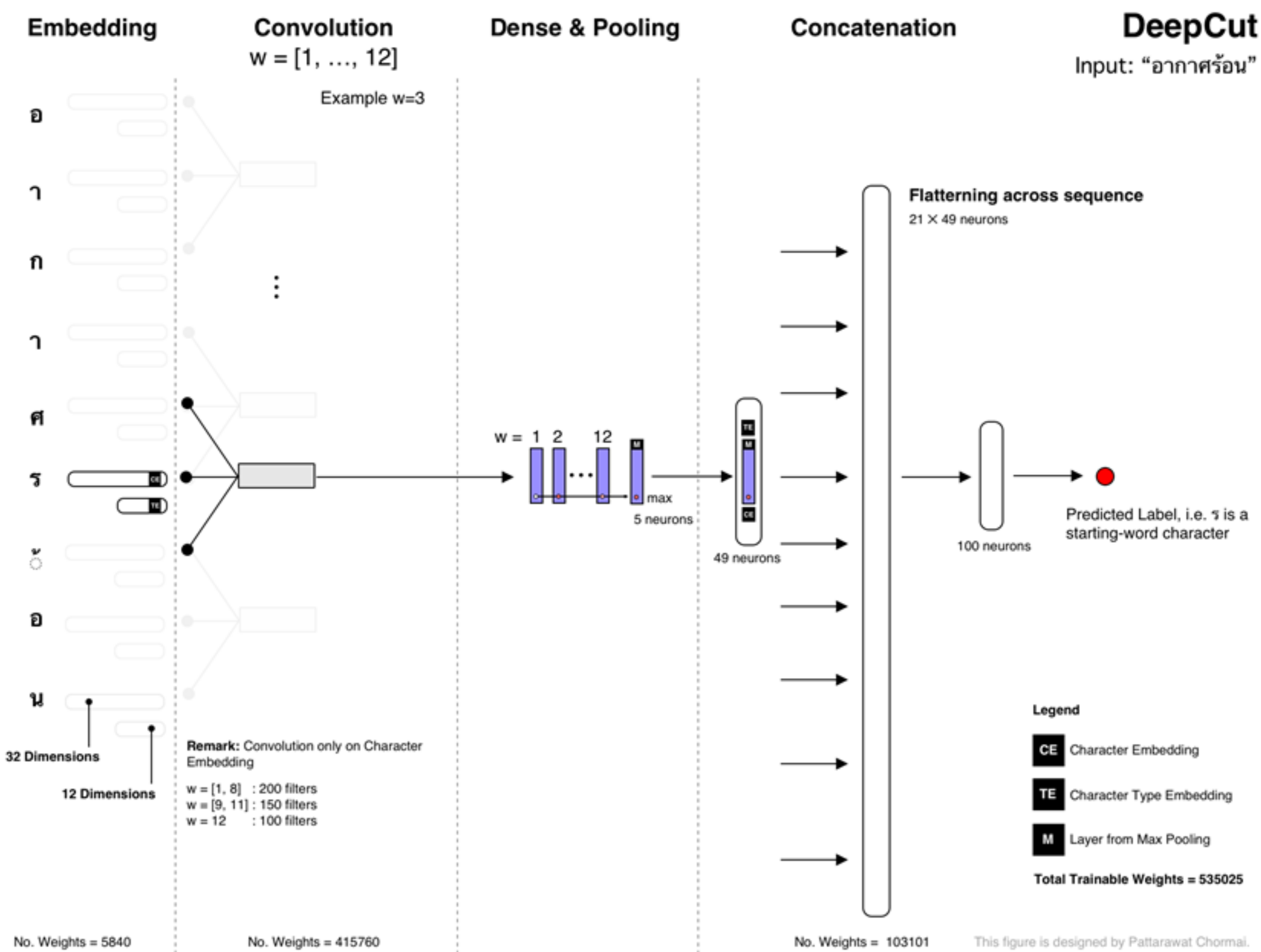
Segmented into single words

แม่น้ำ-‘river’ ≠ แม่-‘mother’ + น้ำ-‘water’
ยินดี-‘glad’ ≠ ยิน-‘hear’ + ดี-‘good’
หายใจ-‘breath’ ≠ หาย-‘lost’ + ใจ-‘heart’

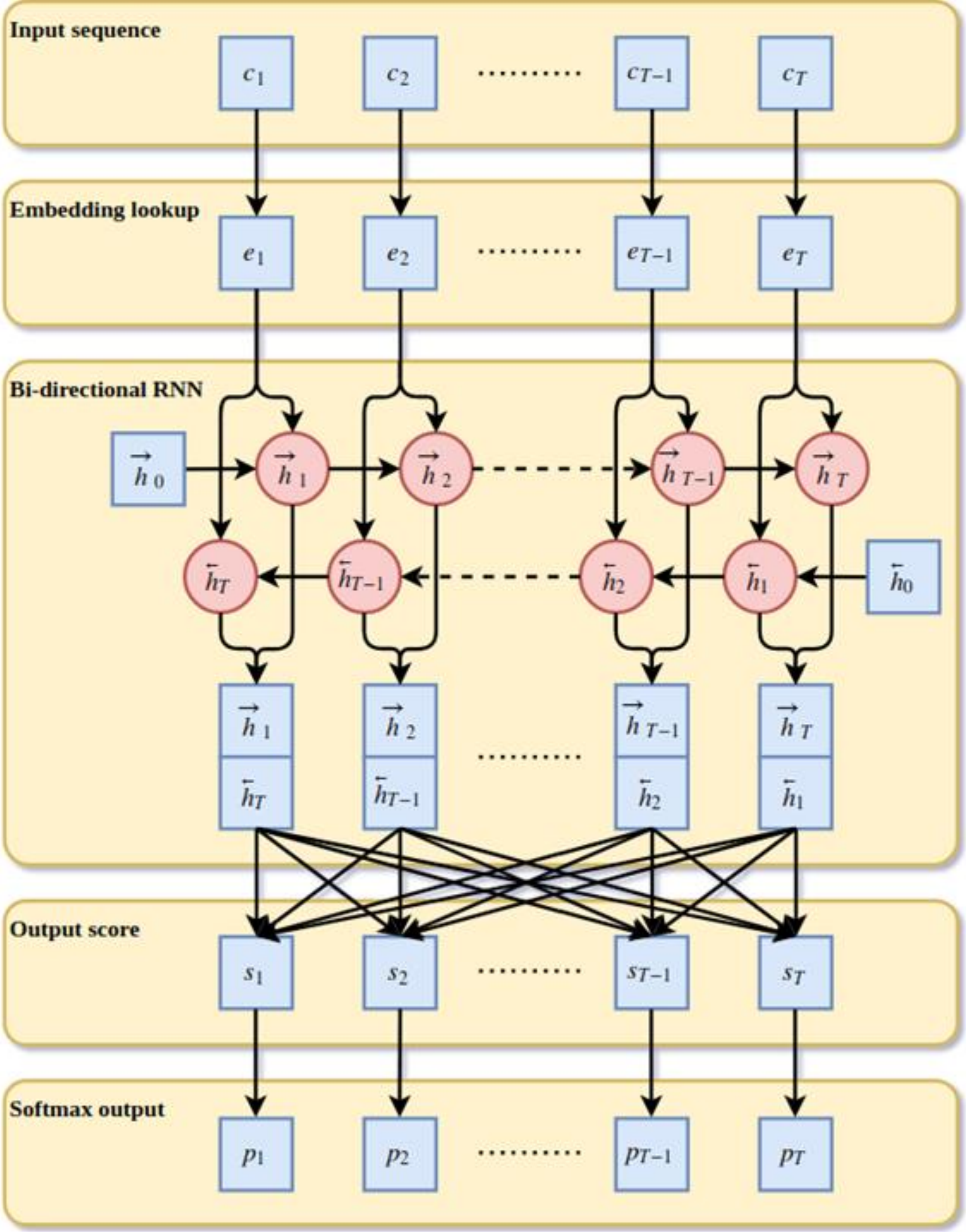
Segmented into multiple words

หมอฟัน-‘dentist’ ≈ หมอ-‘specialist’+ฟัน-‘dental’
กระเป๋าเดินทาง-‘luggage’ ≈กระเป๋า-‘bag’+เดินทาง-‘travel’
เครื่องตัดหญ้า-‘lawnmower’ ≈ เครื่อง-‘machine’+ตัด-‘cut’+หญ้า-‘grass’

https://web.archive.org/web/20240608223632/https://pioneer.chula.ac.th/~awirote/ling/snlp2007-wirote.pdf



https://github.com/rkcosmos/deepcut



https://www.sertiscorp.com/november-20-2017

$$e_t = W_c c_t$$

$$z_t = \text{sigmoid}\left(W_z e_t + U_z h_{t-1} + b_z\right)$$

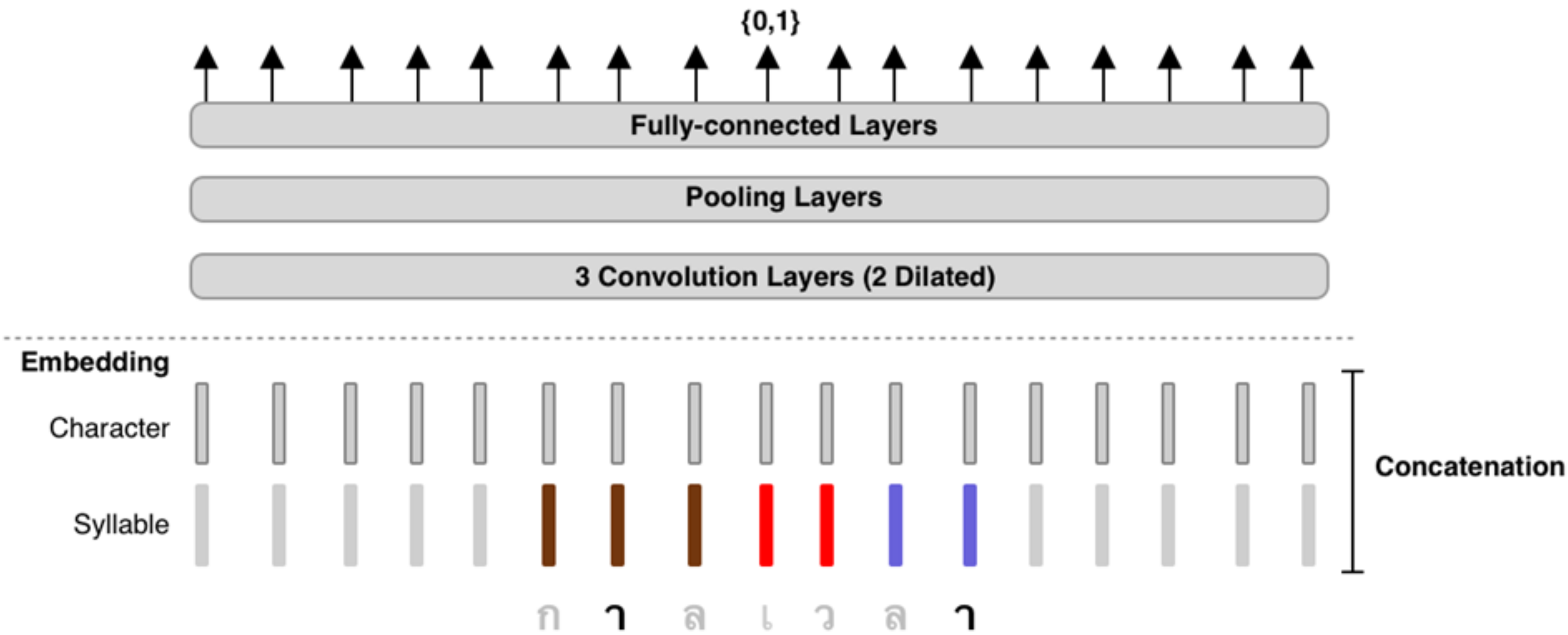
$$r_t = \text{sigmoid}\left(W_r e_t + U_r h_{t-1} + b_r\right)$$

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tanh\left(W_h e_t + U_h\left(r_t \odot h_{t-1}\right) + b_h\right)$$

$$H_t = \left[\overrightarrow{h}_t, \overleftarrow{h}_{T-t+1}\right]$$

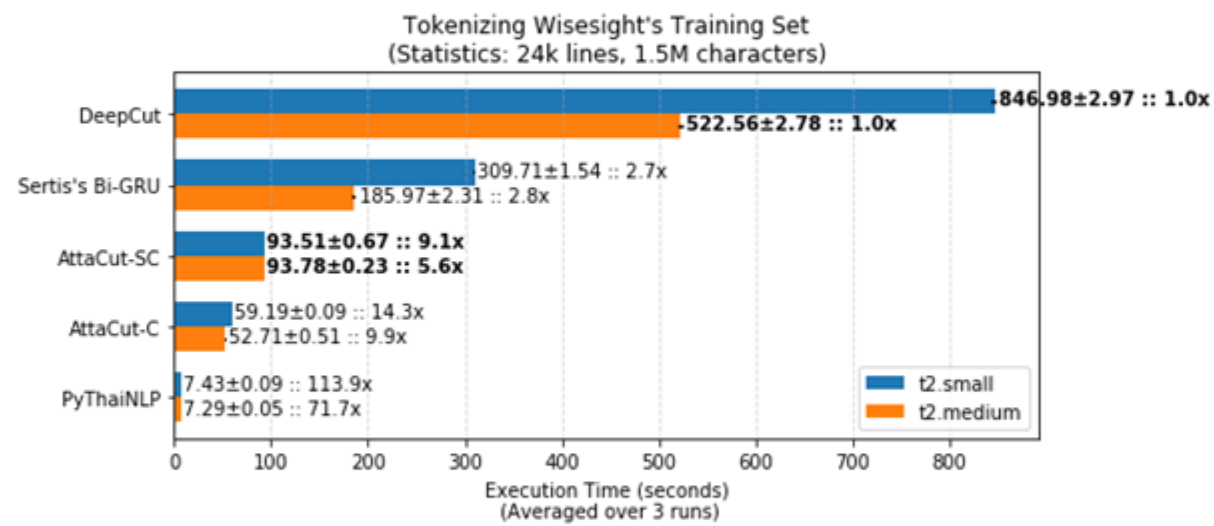
$$s_t = H_t W_s + b_s^{\top}$$

$$p_t = \frac{\exp(s_t)}{\exp(s_{t1}) + \exp(s_{t2})}$$



https://github.com/PyThaiNLP/attacut

Last Updated: 29/08/2019		Others			Ours	
		PyThaiNLP newmm	Sertis Bi-GRU	DeepCut	AttaCut-C	AttaCut-SC
BEST Validation Set						
Character-Level	precision	0.94±0.11	0.95±0.10	0.99±0.05	0.97±0.07	0.98±0.05
	recall	0.83±0.09	0.99±0.02	0.99±0.03	0.98±0.04	0.99±0.03
	f1	0.88±0.08	0.97±0.07	**0.99±0.04**	0.98±0.05	0.99±0.04
Word-Level	precision	0.73±0.16	0.91±0.14	0.97±0.07	0.94±0.10	0.96±0.08
	recall	0.65±0.16	0.94±0.10	0.97±0.07	0.94±0.09	0.97±0.08
	f1	0.68±0.15	0.93±0.12	**0.97±0.07**	0.94±0.10	**0.97±0.08**
BEST Test Set						
Character-Level	precision	0.91±0.15	0.92±0.11	0.96±0.08	0.94±0.10	0.95±0.09
	recall	0.85±0.09	0.98±0.04	0.98±0.04	0.98±0.04	0.98±0.04
	f1	0.86±0.11	0.95±0.08	**0.97±0.06**	0.96±0.07	0.96±0.07
Word-Level	precision	0.70±0.19	0.85±0.18	0.92±0.14	0.88±0.17	0.91±0.15
	recall	0.64±0.18	0.90±0.14	0.93±0.12	0.91±0.14	0.92±0.13
	f1	0.67±0.19	0.87±0.16	**0.93±0.13**	0.89±0.16	0.91±0.14



https://github.com/PyThaiNLP/attacut

ผมเห็นคนวงการนี้เมื่อ 20-30 ปีที่แล้วทำเรื่องตัดคำ วงการนี้มันไม่ไปไหนเลยใช่ไหมเนี่ย

มิตรสหาย Business Development ท่านนึง

Words of caution

Statistical tokenizers fail on mismatched data

A tokenizer trained on social text might not be able to cut simple words like

https://www.aclweb.org/anthology/2020.emnlp-main.315/
https://github.com/mrpeerat/OSKut

มะม่วง มะละกอ

	WS160	TNHC
Deepcut	93.8	93.5
Attacut	93.5	80.8

Statistical tokenizers fails unpredictably

หมูกรอบ => |หมู|กรอบ|

ข้าวผัดคะน้าหมูกรอบหนึ่งจาน => |ข้าวผัด|คะน้า|หมูก|รอบ|หนึ่ง|จาน|

Might need rule-based to override (Deepcut has this)

For speed, maximal matching (newmm) is reliable.

- drawbacks?

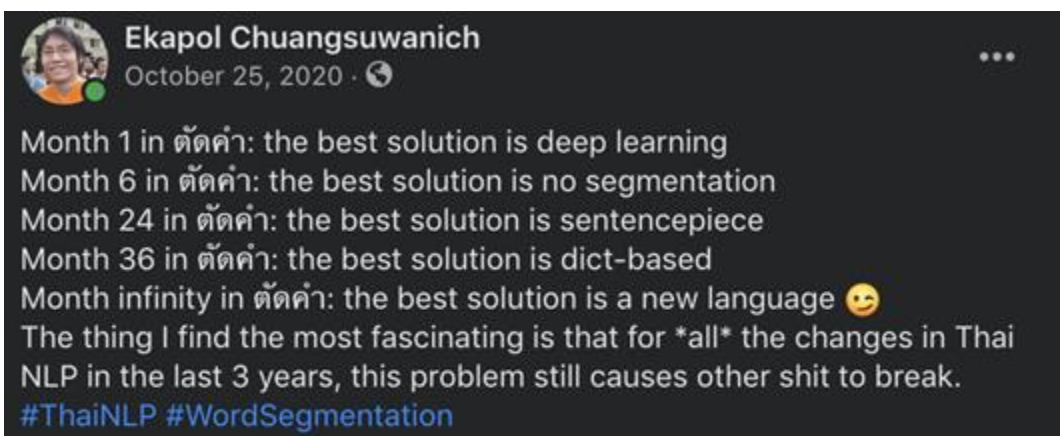
Words of caution

Tokenization performance effects downstream task performance

Can be small (1%) or large (10%)

Specialized tokenizer can help your downstream task

Example: e-commerce search |หู|ฟัง| |ต่าง|หู|


Ekapol Chuangsuwanich
October 25, 2020 ·

Month 1 in ตัดคำ: the best solution is deep learning
Month 6 in ตัดคำ: the best solution is no segmentation
Month 24 in ตัดคำ: the best solution is sentencepiece
Month 36 in ตัดคำ: the best solution is dict-based
Month infinity in ตัดคำ: the best solution is a new language 😉
The thing I find the most fascinating is that for *all* the changes in Thai NLP in the last 3 years, this problem still causes other shit to break.
#ThaiNLP #WordSegmentation

Words of caution

Be careful of what tokenization you used to train the model.

If there's a mismatch in training and testing tokenization, the results can be devastating.

TrueVoice

Training	Testing tokenization			
Deepcut	Deepcut	Longest matching+ noise0.1	Longest matching+ noise0.4	Longest matching+ noise0.7
	76.8	60.4	50.9	42

Wisesight1000

Training	Testing			
Manual	Manual	Longest matching+ noise0.1	Longest matching+ noise0.4	Longest matching+ noise0.7
	52.1	48.2	38.1	32.7

https://ieeexplore.ieee.org/document/9836268

Another important note

- In Thai, due to visualization magic, these are the same
  - น + ◌ำ + น้
  - น + น้ + ◌ำ
  - เ + เ + ก
  - แ + .ı
  - ก + ก้ + ก้ + ก้ + ก้
  - ก + ก้
- You migh

pythainlp.util.normalize(*text: str*)→ str [source]

Normalize and clean Thai text with normalizing rules as follows:

- Remove zero-width spaces
- Remove duplicate spaces
- Reorder tone marks and vowels to standard order/spelling
- Remove duplicate vowels and signs
- Remove duplicate tone marks
- Remove dangling non-base characters at the beginning of text

Tokenization - English

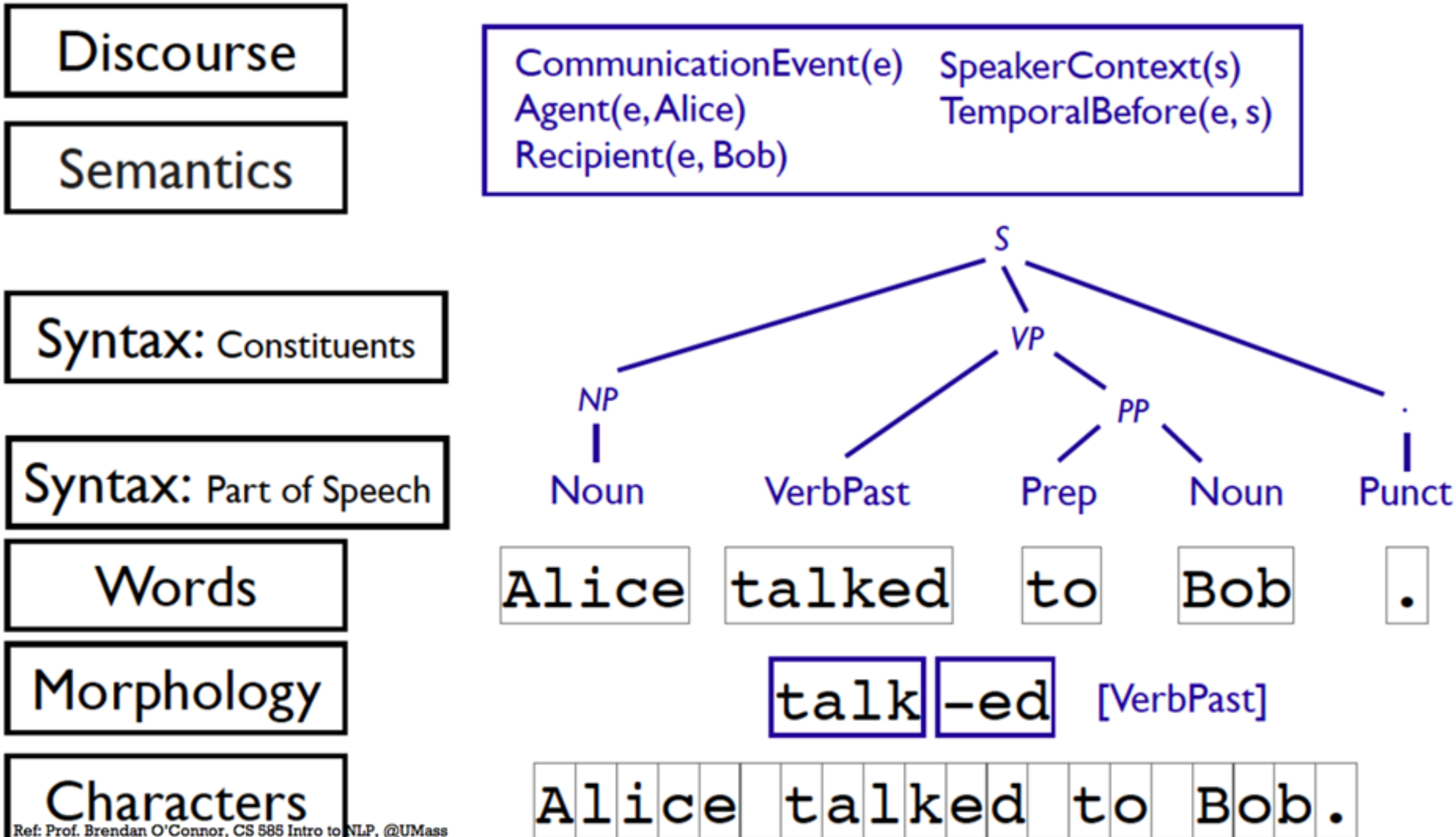
- Even English has tokenization issues!
  - Space is usually not enough
  - aren’t
    - are + n’t
    - aren’t
    - arent
    - aren t
    - are + not
  - San Francisco

- Usually includes the text normalization step
- This depends on application
  - “aren’t” might be different from “are not” for sentiment analysis

End-to-end models

- Classical machine learning systems usually break the problem into smaller subtasks
  - Self-driving:
    - Image -> objects detection -> path finding -> steering
  - Speech2speech translation:
    - Speech A -> text A -> text B -> Speech B
- End-to-end models use one large neural networks process the input and generate the desired output
  - Image -> steering
  - Speech A -> Speech B

End-to-end NLP?



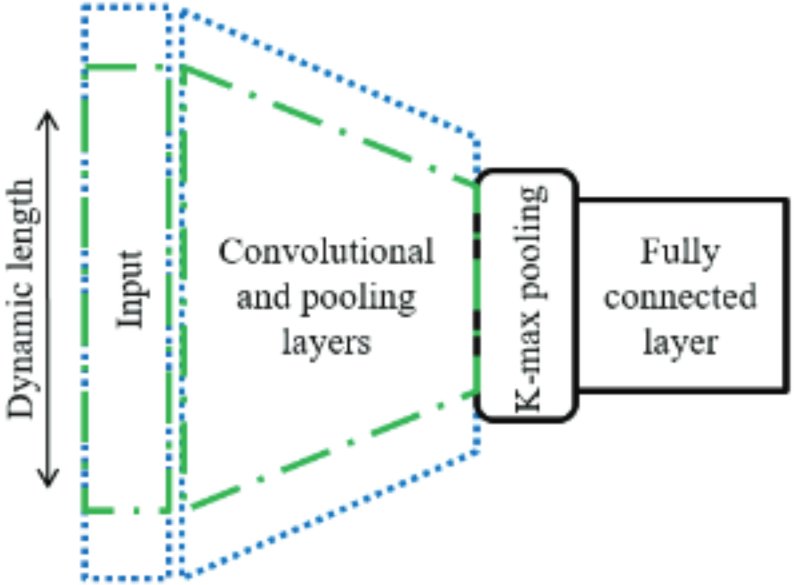
Ref: Prof. Brendan O'Connor, CS 585 Intro to NLP, @UMass

Towards no tokenization

- Text classification using charCNN on Thai

Method	Accuracy (%)	F_1 (%)
Naïve Bayes, BoW	87.2	87.1
Naïve Bayes, TF-IDF	89.0	88.9
Logistic Regression, BoW	94.8	94.8
Logistic Regression, TF-IDF	94.7	94.7
SVM, BoW	93.7	93.7
SVM, TF-IDF	95.2	95.2
DCNN (Kalchbrenner et al., 2014)	**95.9**	**95.9**
Proposed Char-CNN	95.4	95.4

Word-based methods



A character-level convolutional neural network with dynamic input length for Thai text categorization
http://ieeexplore.ieee.org/document/7886102/

Caveats of end-to-end models

- Requires lots of data for the specific task
- Hard to fix specific mistakes by the model

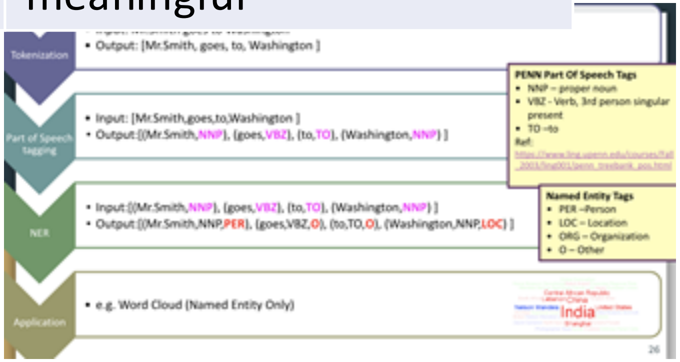
Things to consider when thinking about tokenization

Know your use cases

Large embedding lookup table

Word	Subword	Character
Large vocabulary (100k)	Medium vocabulary (20k)	Small vocabulary (100)
Can use simpler model	Moderate complexity in modeling	Needs a powerful model to learn long range influences
High OOVs	Few OOVs	No OOVs
Individual tokens are meaningful	Individual tokens might be meaningful	Individual tokens are not meaningful

Note: to handle multilingual data, some models use bytes as tokens



Conclusion

- Tokenization is far from solved but don’t let this discourage you
  - No tokenization is perfect
  - Pick one that is suited for your task
    - Speed
    - Robustness to misspelling and unseen words
    - Consistency
    - Certain tools assume you are using a particular type of tokenization, check!