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# Document Classification through Image-Based Character Embedding and Wildcard Training

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# Introduction

- Difficulty of processing Japanese / Chinese text
  - **No word boundary**
    - Word segmentation preprocess
    - Hard to segment words include coinages and slang words

| |
|---|
| メロスは激怒した。 |
| **Melos was enraged.** |

  - **Large number of different characters**
    - *More than 2,000 different characters for daily use (Japanese)*

# Introduction

- Character-level approaches to Japanese / Chinese text
  - Character-level N-gram feature
  - **Character-level Convolutional Neural Networks (CLCNN)** [Zhang et al. 2015]
    - State-of-the-art in English document classification
    - *Vectorization of character (e.g. one-hot vector, lookup table)*
    - *Data augmentation by using paraphrase*

**[Zhang et al. 2015]** X. Zhang et al. Character-level Convolutional Networks for Text Classification. In *Advances in Neural Information Processing Systems*, pp. 649–657, 2015.

# Introduction

- Character-level approaches to Japanese / Chinese text
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  - **Character-level Convolutional Neural Networks (CLCNN)** **[**Zhang et al. 2015**]**
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These strategies is NOT appropriate for Japanese and Chinese.

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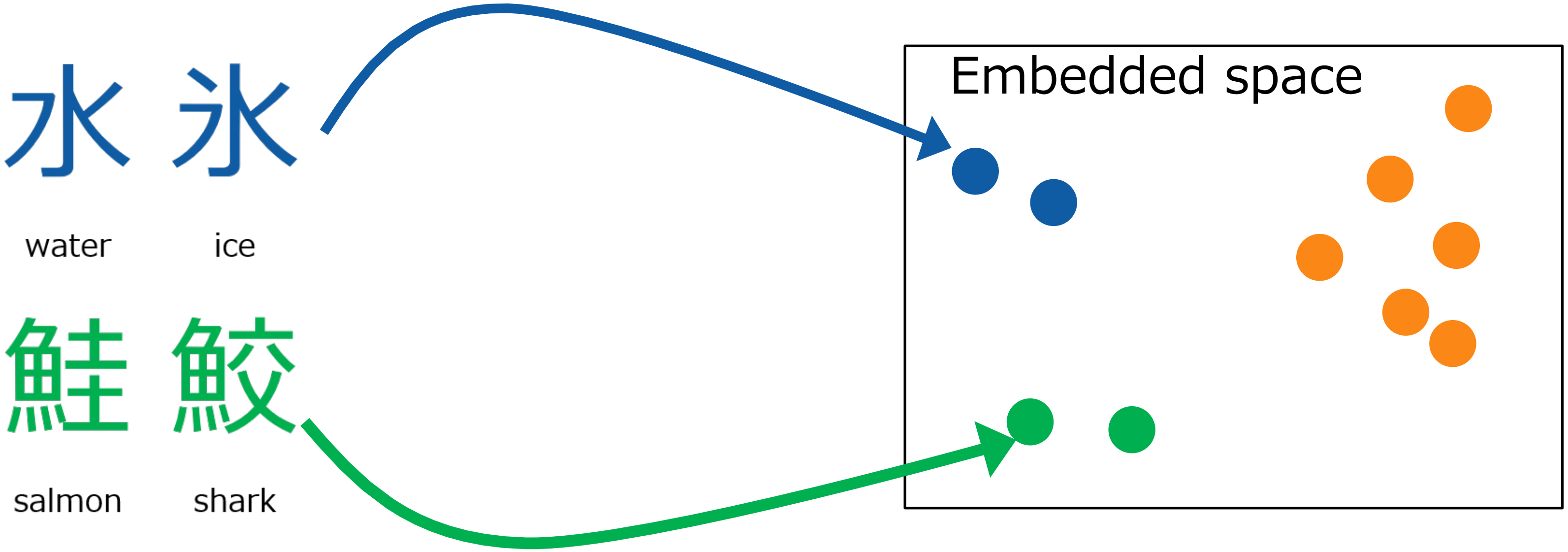
# Introduction

- Two New Document Analysis Techniques for CLCNN

**i. Image-based Character Embedding**




**ii. Data augmentation without word segmentation, “wildcard training”**

**メロスは激怒した。 ⟶ メロス＊激＊した。**

# Key Concept – (i) Image-based Character Embedding

- Focus on Ideographic of Japanese / Chinese characters
  - *Most of them imply their meanings.*
  - *Similar character shapes have similar meanings to each other.*

| | | | | |
|---|---|---|---|---|
| 水 | 氷 | 「 | [ | < |
| water | ice | | | |
| 鮭 | 鮫 | ( | { | 【 |
| salmon | shark | | brackets | |

Our model handles **characters through their “images.”**

# Key Concept – (ii) Data Augmentation without Word Segmentation

- Introducing "wildcard" character —Wildcard Training
  - *Wildcard is defined as a zero-vector in the embedded space.*
  - *It replaces some input characters randomly (like dropout* [Hinton et al. 2012]*).*

| Input text | | Augmented texts |
|---|---|---|
| | → | メロス＊激＊した。 |
| メロスは激怒した。 | → | ＊ロ＊は激＊した。 |
| | → | メロスは＊怒し＊。 |

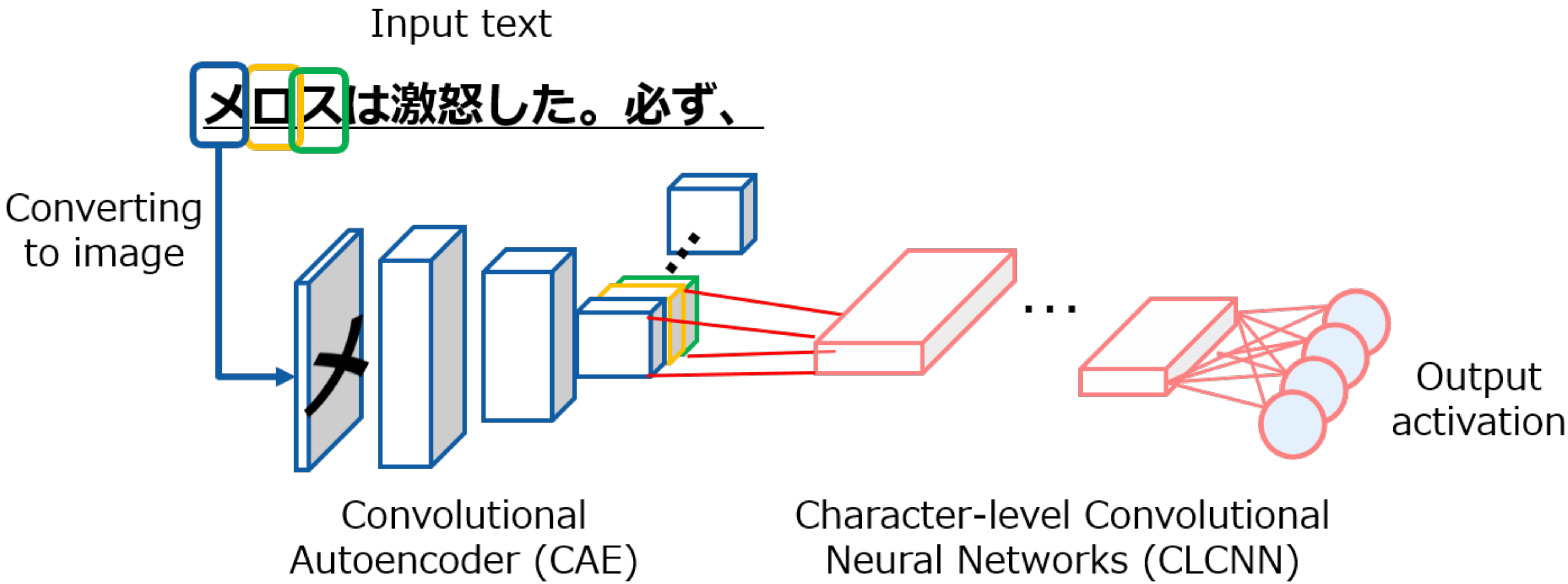
Wildcard training

**[Hinton et al. 2012]** G. Hinton et al. Improving Neural Networks by Preventing Co-adaption of Feature Detectors. *arXiv:1207.0580*, 2012.

# The Proposed Method

a. Image-based Character Embedding (CAE)

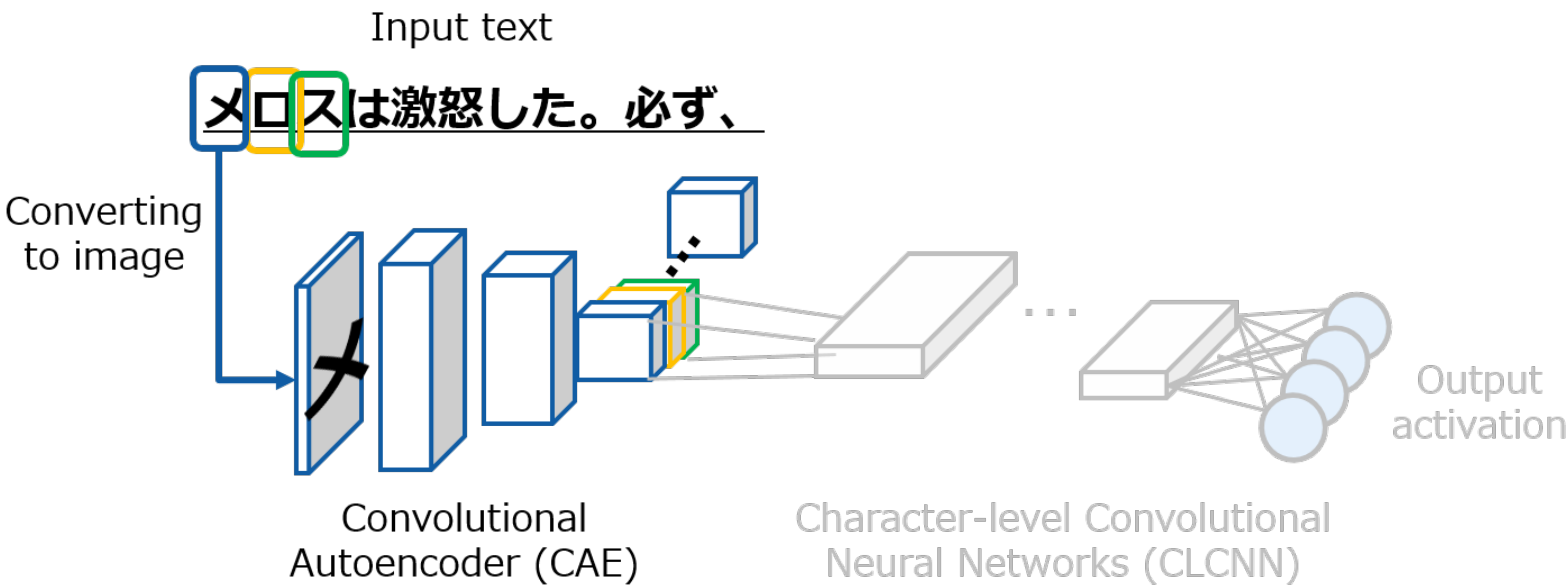
b. Character-level Classifier with Wildcard Training (CLCNN)



# The Proposed Method

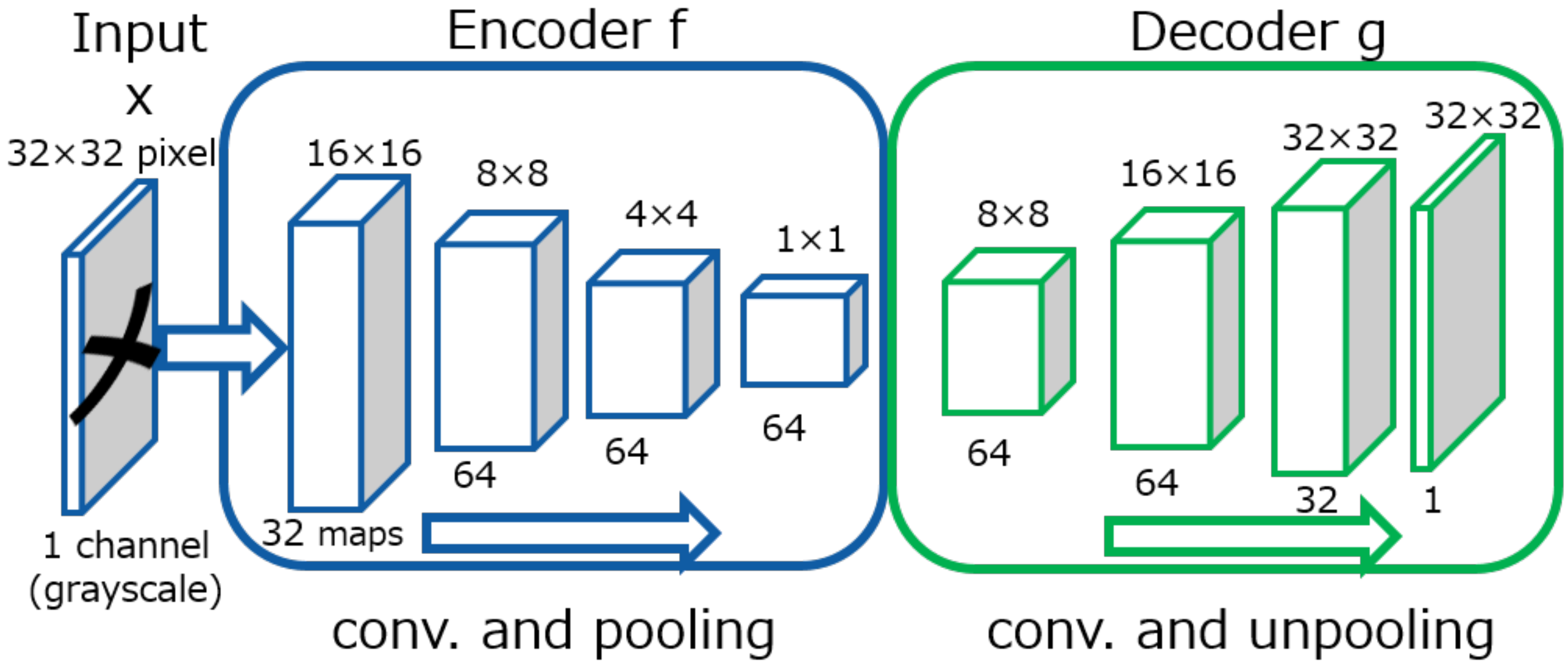
## a. Image-based Character Embedding (CAE)

b. Character-level Classifier with Wildcard Training (CLCNN)



# a. Image-based Character Embedding

- Convolutional Autoencoder (CAE) [Masci et al. 2011] is composed of Encoder and Decoder have conv. and pooling layers.
- CAE is trained by reconstruction loss beforehand.
- Our CAE encodes 6,631 character images into 64-dimensional space.

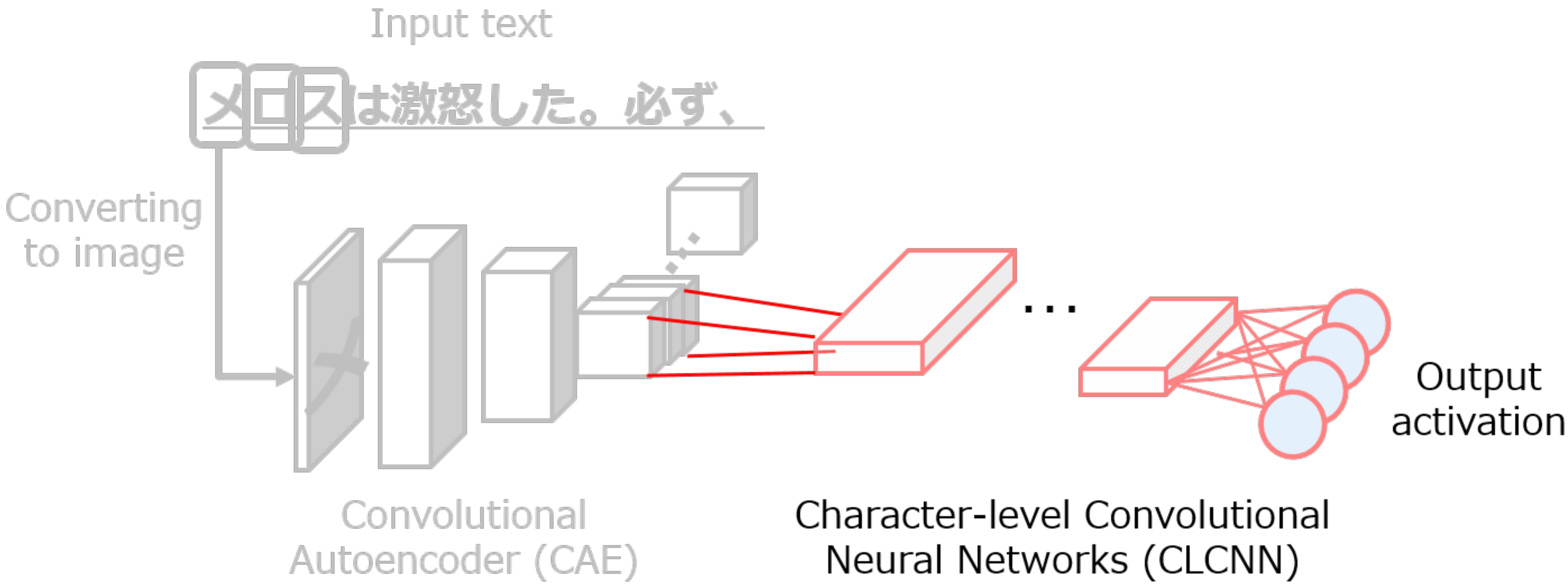



**[Masci et al. 2011]** J. Masci et al. Stacked convolutional auto-encoders for hierarchical feature extraction. *Lectures Notes in Computer Science*, vol. 6791, pp. 52–59, 2011.

# The Proposed Method

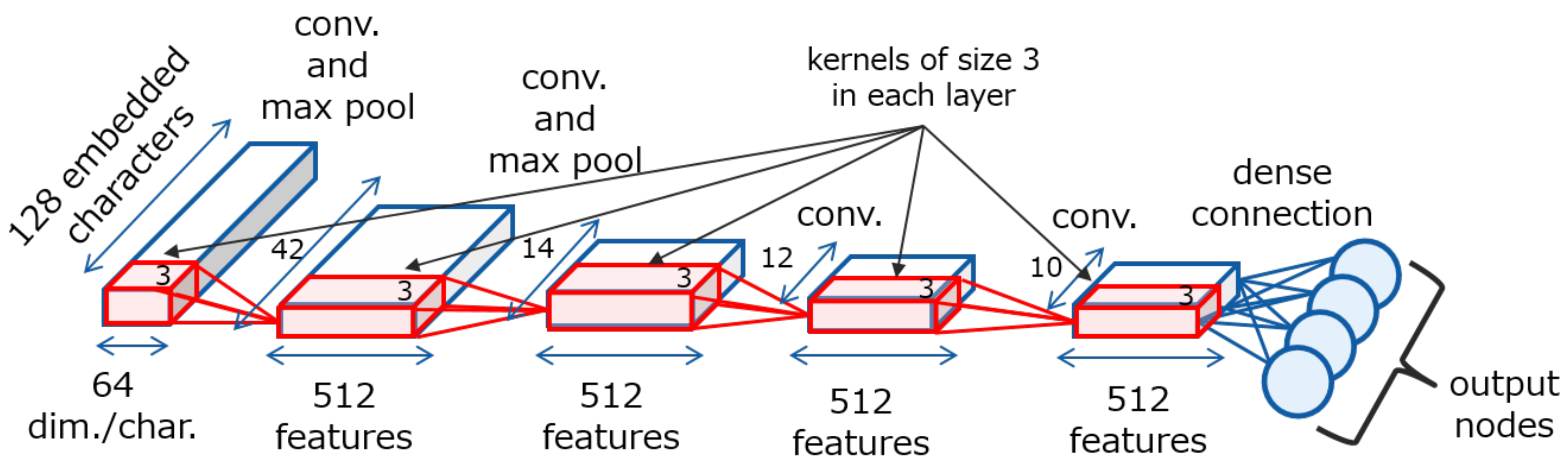
a. Image-based Character Embedding (CAE)

**b. Character-level Classifier with Wildcard Training (CLCNN)**



## b. Character-level Convolutional Neural Networks (CLCNN)

- CLCNN performs hierarchical feature extraction and classification.
- It takes image-based embedded characters as input.
- It's trained with ***wildcard training (WT)***, dropping some characters randomly.
    - Wildcard training augments the combinations of characters.



# Experiments and Results

## (1) Author Estimation of Japanese Novels (10 classes)

- 104 novels written by 10 authors (almost 10 each)
- Training Dataset: 81 novels (2,010,000 characters)

## (2) Publisher Estimation from Japanese Newspaper Articles (4 classes)

- 22,440 articles from four major newspapers (5,610 each) from economics, politics, international sections
- Training Dataset: 17,952 articles (55,420,000 characters)

**Comparative approaches**

- Character-level N-gram + TF-IDF + Logistics Regression (LR)
- Word segmentation + TF-IDF + LR
- Latent Semantic Indexing (LSI) / Latent Dirichlet Allocation (LDA) + LR

# Experiments and Results

## (1) Author Estimation of Japanese Novels

| Methods | Accuracy [%] |
|---|---|
| (proposed) CAE + CLCNN + WT | 69.57 |
| (proposed) CAE + CLCNN w/o WT | 52.17 |
| (proposed) Lookup Table + CLCNN + WT | 69.57 |
| Lookup Table + CLCNN w/o WT | 65.22 |
| Character-level 3-gram* + TF-IDF | 56.52 |
| Word segmentation* + TF-IDF | 47.83 |
| **LSI (# topics = 60)** | **73.90** |
| LDA (# topics = 30) | 52.10 |

* 3-gram and Word segmentation use top-50,000 most frequently tokens.

- In spite of no preprocessing, our method shows the second-best.
- Wildcard training (WT) raises the performance of CLCNN.
  - ◆ Wildcard training is effective for eliminating overfitting in the classifier

# Experiments and Results

## (2) Publisher Estimation from Japanese Newspaper Articles

| Methods | Accuracy [%] |
|---|---|
| **(proposed) CAE + CLCNN + WT** | **86.72** |
| (proposed) CAE + CLCNN w/o WT | 80.95 |
| (proposed) Lookup Table + CLCNN + WT | 79.66 |
| Lookup Table + CLCNN w/o WT | 73.13 |
| Character-level 3-gram* + TF-IDF | 84.27 |
| Word segmentation** + TF-IDF | 67.22 |
| LSI (# topics = 2,000) | 84.00 |
| LDA (# topics = 70) | 56.10 |

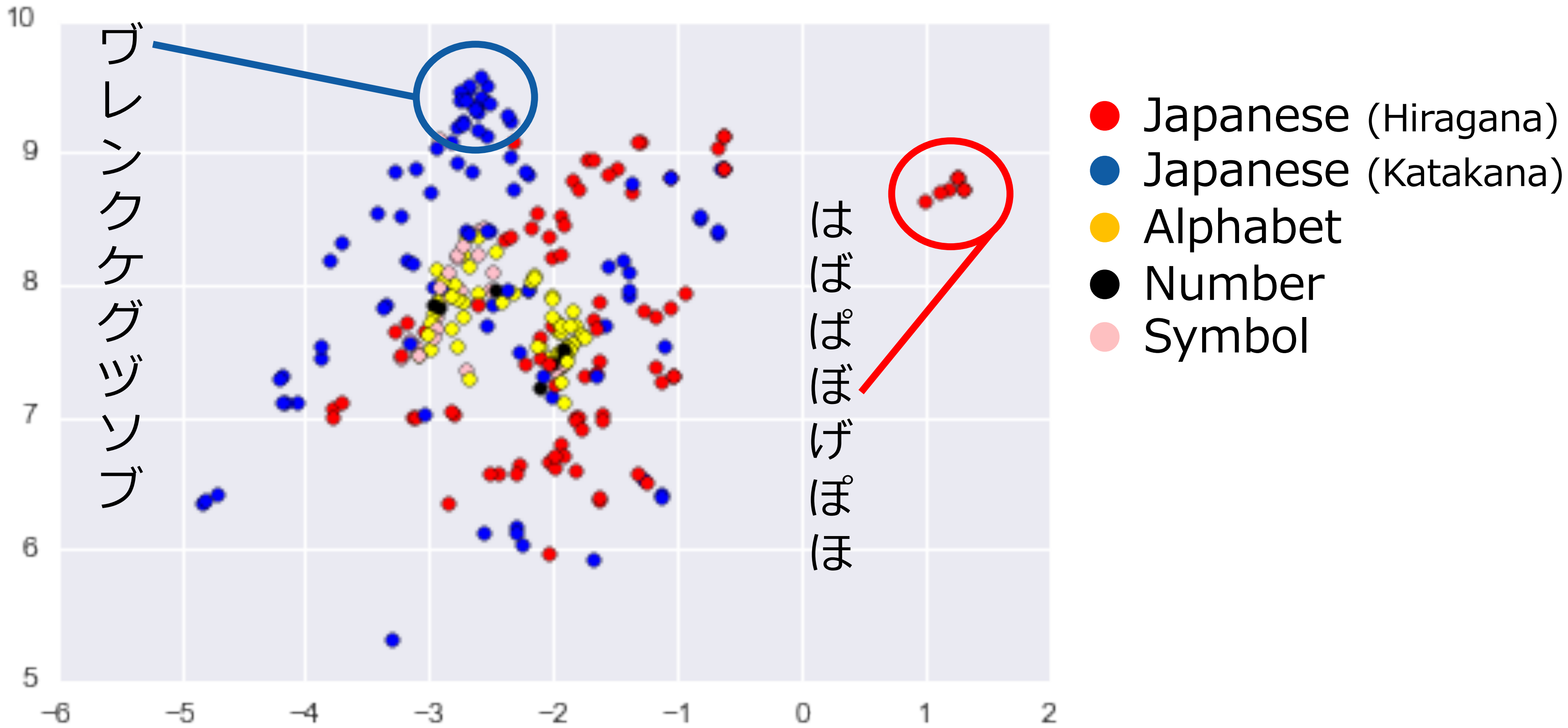
* 3-gram approach uses top-30,000 most frequently tokens.

** Word segmentation approach uses all of morphemes in training data.

- Our methods shows the best score in this task.
- Other character-level methods also shows higher score.
  - ◆ Newspaper text is hard to segment words because of many coinages.

# Experiments and Results

2-D Mapping of Embedded Character Vectors by t-SNE




- Some characters form clusters.

- Similar shape characters have similar vector representation.

# Conclusion and Future works

- A new document analysis method for Japanese
  - Tackling much larger number of characters with "Image-based embedding"
  - Data augmentation without word segmentation
- Towards applying to different languages / NLP tasks
  - Chinese, Korean etc.
  - Tasks that need normalization process (e.g. Entity-linking)

# Appendix | Loss Curve of CLCNN Training (Author Estimation)

# Appendix | Loss Curve of CLCNN Training (Publisher Estimation)