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# Reducing Human Assessment of Machine Translation Quality to Binary Classifiers

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# Assessment of Machine Translation Quality



| | Document | Sentence |
|---|---|---|
| | • set of sentence translations | • translation of a single input |
| Human | • average of sentence-level grades | • discrete evaluation grade<br>• median score of multiple human grades |
| | | ***metrics***: fluency, adequacy, … |
| Machine | • comparison to (multiple) reference translations<br>• assign single numerical score | • confidence estimation<br>• machine learning approach to predict human grades |
| | ***metrics***: BLEU, METEOR, … | ***classifiers***: SVM, DT, … |

# Assessment of Machine Translation Quality

| | Document | Sentence |
|---|---|---|
| **Usage** | • evaluation of MT system development progress<br>• MT system comparison (NIST, IWSLT, …) | • usability of given translation in a real-world application (post-editing, dialog translation, …) |
| **Problems** | • quality/coverage of reference translations<br>• "meaning" of (numerical) automatic evaluation scores | • **complexity of evaluation task (multi-class classification)**<br>• granularity of evaluation grades |

# Outline of Talk

## 1. Prediction of Sentence-Level Translation Quality:

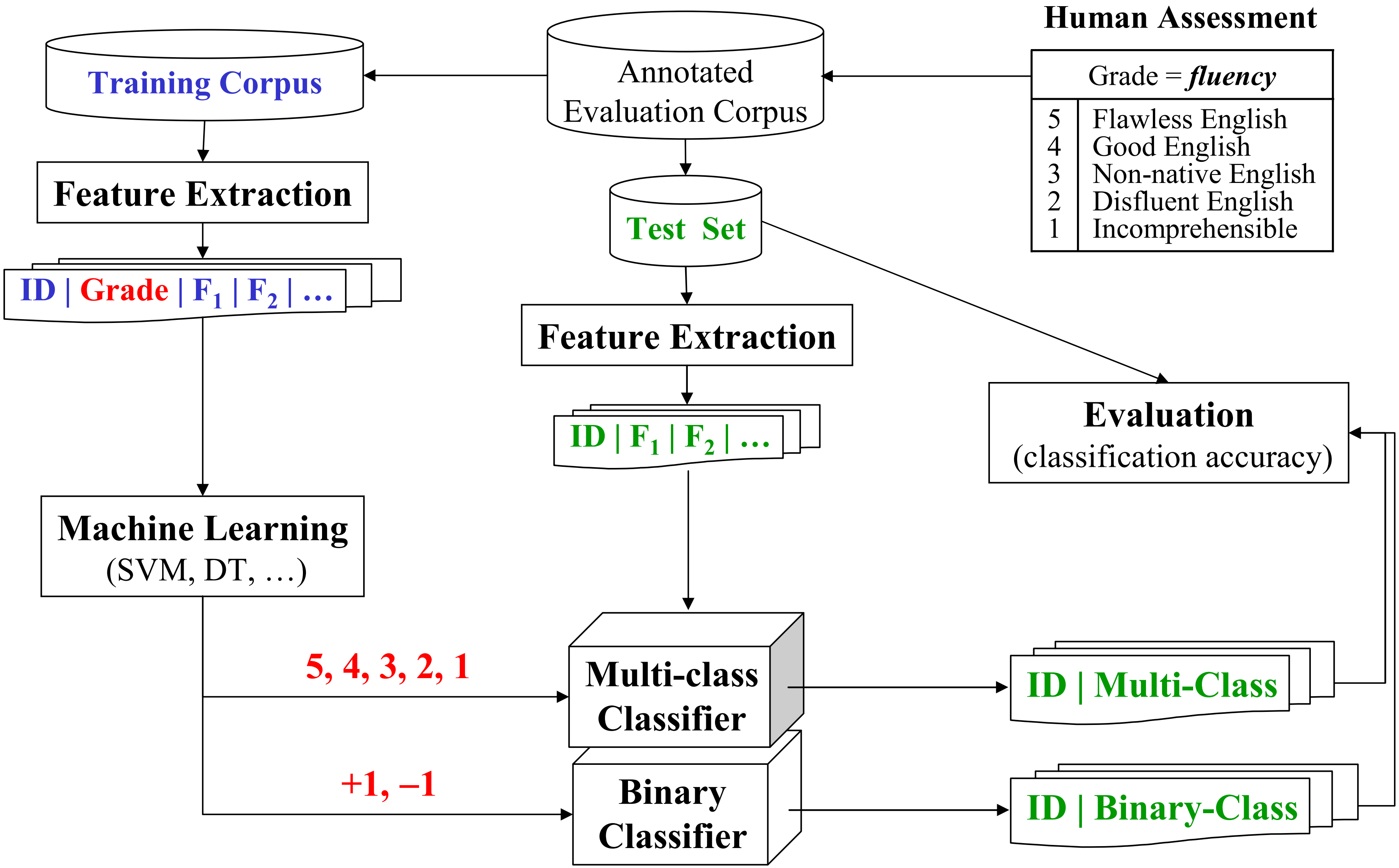
- decompose multi-class to binary classification
  - a *coding matrix*
- learn set of binary classifiers
  - feature selection, standard machine learning techniques
- predict multi-class label
  - compare binary classification results to *coding matrix*

## 2. Experimental Results:

- large-scale human-annotated evaluation corpus
- coding matrix optimization
- classification accuracy
- correlation to human assessments

# Prediction of Sentence-Level Translation Quality



# Classification Task



**Goal:** predict human evaluation grade (*fluency*, *adequacy*, …) for a given translation

→ **multi-class label**

**Multi-Class Classification:**

☺ direct prediction of multi-class label

☹ classification accuracy is low

**Binary-Class Classification:**

☺ classification accuracy is high

☹ multi-class label cannot be derived reliably

# Proposed Solution



## Reduction of Classification Complexity:

- decompose multi-class task into a set of binary classification problems
- apply standard learning algorithm to train binary classifiers
- combine results of binary classifiers using a "***coding matrix***" to predict multi-class label

→ **increase in classification accuracy**

→ **independent from learning algorithm**

# Proposed Solution



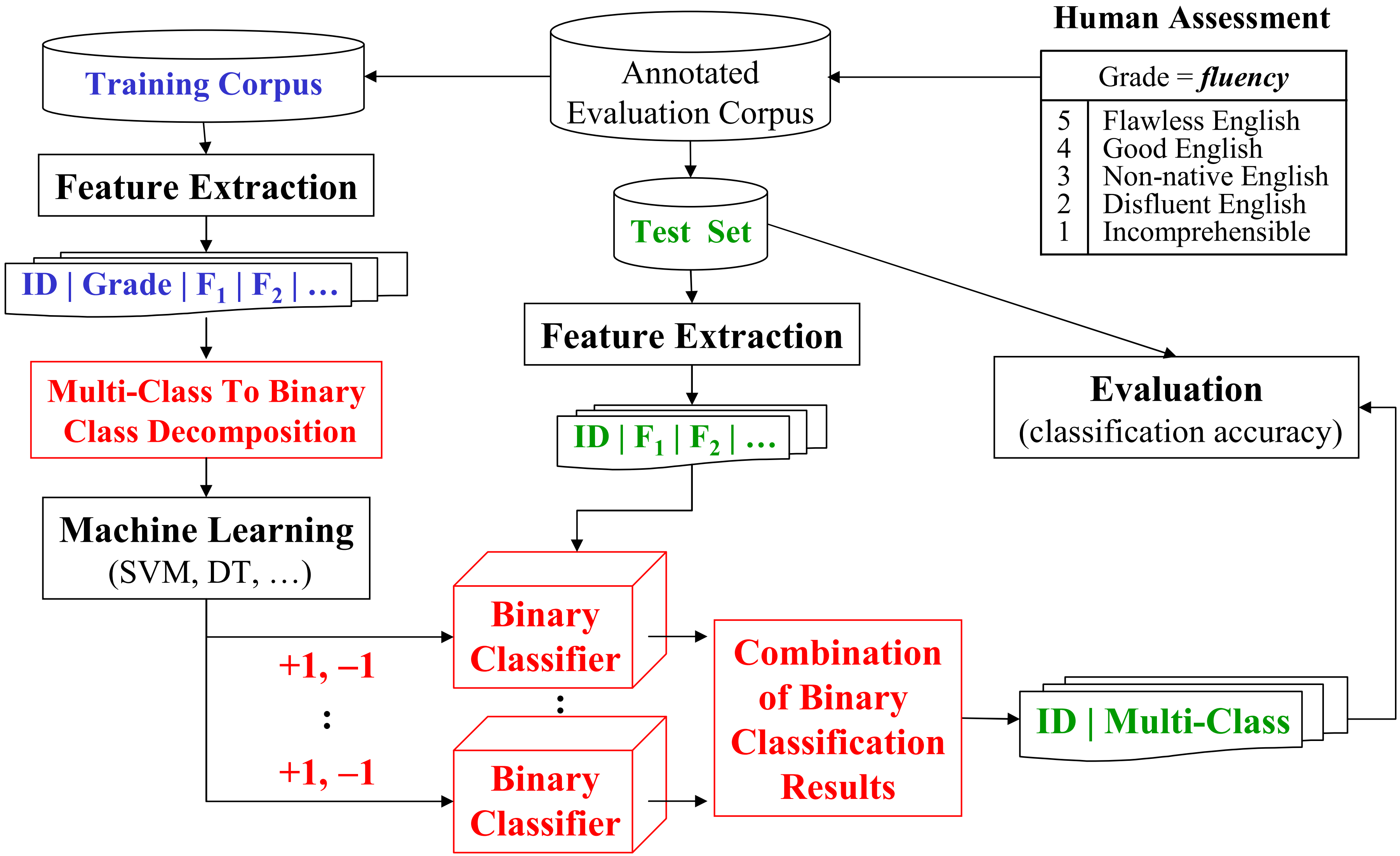
**Feature Selection for Translation Quality Prediction:**

- multiple automatic evaluation metric scores
  - BLEU
  - NIST
  - METEOR
  - WER
  - PER
  - TER
  - GTM
- metric-internal features
  - ngram-prec
  - length ratio
  - …

→ **takes into account different aspects of MT quality**

→ **independent from target language and MT system**

# Prediction of Sentence-Level Translation Quality



# Proposed Method



## 1. Decomposition Phase:

- **decompose multi-class** into set of binary classification tasks:

  ◦ ***one-against-all*** (**5**, **4**, **3**, **2**, **1**):

  *Example*:

  **5** : +1 → all training examples tagged with grade *5*

  –1 → all training examples tagged with grade *4* or *3* or *2* or *1*)

  ◦ ***boundary*** (54_321 , 543_21):

  *Example*:

  **54_321** : +1 → all training examples tagged with grade *5* or *4*

  –1 → all training examples tagged with grade 3 or 2 or 1

  ◦ ***all-pairs*** (**5_4** , **5_3** , **5_2** , **5_1** , **4_3** , **4_2** , **4_1** , **3_2** , **3_1** , **2_1**):

  *Example*:

  **5_4** : +1 → all training examples tagged with grade *5*

  –1 → all training examples tagged with grade *4*

# Proposed Method



## 2. Learning Phase:

- **learn binary classifier** for each decomposition task
  - ***feature set selection/extraction***

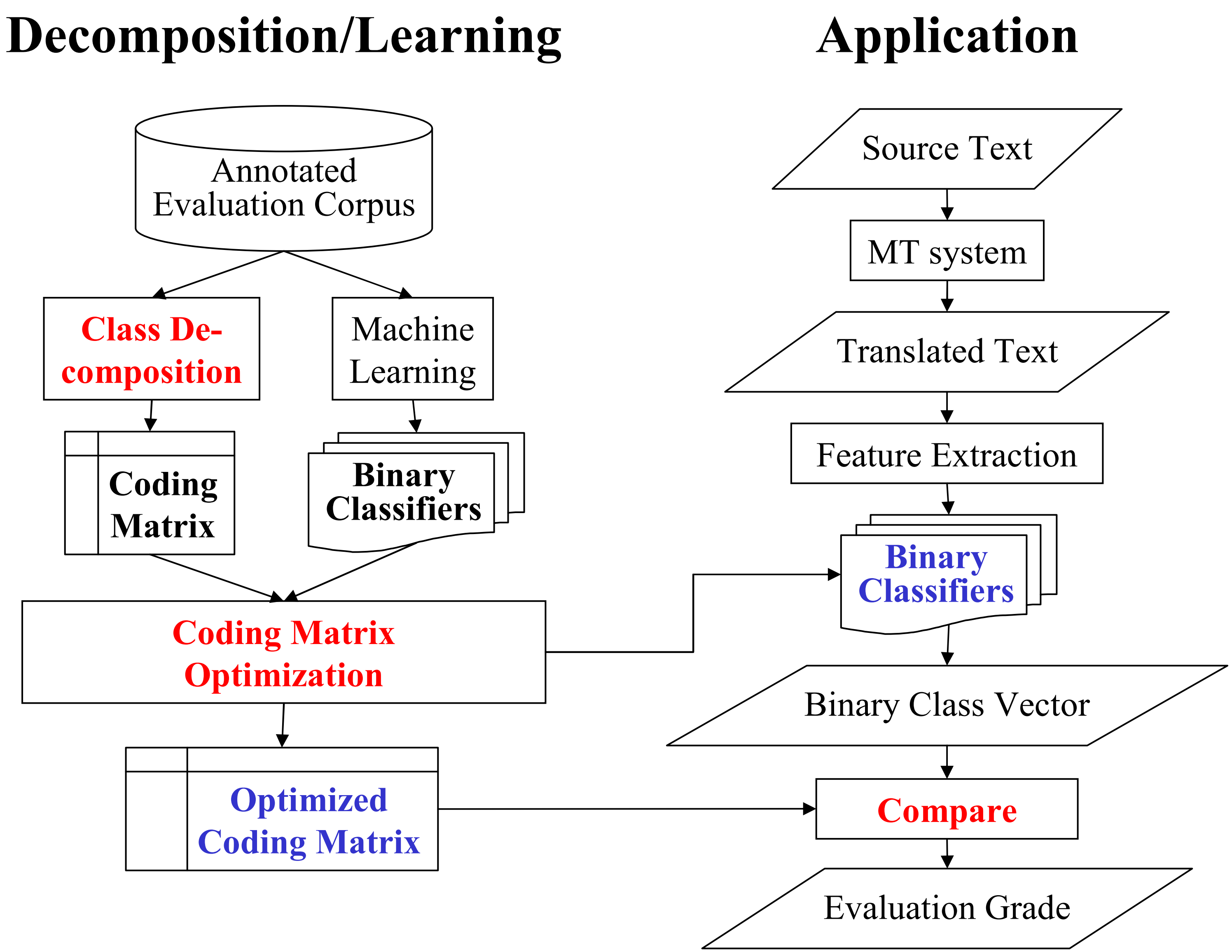
    *(exp)*: + 54 features (7 autom. eval. scores + metric-internal features)
  - ***classifier training***

    *(exp)*: + *fluency/adequacy*, DT classifier (+ SVM classifier)
- **identify optimal subset of binary classifiers**
- create ***coding matrix***
  - ***column***: class of pos./neg. training examples (for given binary classifier)
  - ***row***: correct binary classification result (for a given multi-class label)

## 3. Application Phase:

- apply all binary classifiers to given input → ***classification vector v***
- match *v* against *coding matrix* rows to identify ***multi-class label***

# Outline of Proposed Method



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# Coding Matrix

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$$M = (m_{i,j})_{i=1,\dots,k\,;\,j=1,\dots,l}$$

$$m_{i,j} \in \{+1, -1, 0\}$$

( k=3 , l=3 )

***one-against-all***

| | $c_1 \bullet c_2\, c_3$ | $c_2 \bullet c_1\, c_3$ | $c_3 \bullet c_1\, c_2$ |
|---|---|---|---|
| $c_1$ | $+1$ | $-1$ | $-1$ |
| $c_2$ | $-1$ | $+1$ | $-1$ |
| $c_3$ | $-1$ | $-1$ | $+1$ |

***all-pairs***

| | $c_1 \bullet c_2$ | $c_1 \bullet c_3$ | $c_2 \bullet c_3$ |
|---|---|---|---|
| $c_1$ | $+1$ | $+1$ | $0$ |
| $c_2$ | $-1$ | $0$ | $+1$ |
| $c_3$ | $0$ | $-1$ | $-1$ |

# Combination of Binary Classifiers using a Coding Matrix

input

| | $c_1 \bullet c_2$ | $c_1 \bullet c_3$ | $c_2 \bullet c_3$ |
|---|---|---|---|
| ***v*** | +1 | +1 | –1 |

***all-pairs***

| | $c_1 \bullet c_2$ | $c_1 \bullet c_3$ | $c_2 \bullet c_3$ |
|---|---|---|---|
| $c_1$ | +1 | +1 | 0 |
| $c_2$ | –1 | 0 | +1 |
| $c_3$ | 0 | –1 | –1 |

**Hamming Distance**
(number of positions that differ)

**= 3**

# Combination of Binary Classifiers using a Coding Matrix

**input**

| | $c_1 \bullet c_2$ | $c_1 \bullet c_3$ | $c_2 \bullet c_3$ |
|---|---|---|---|
| ***v*** | +1 | +1 | −1 |

***all-pairs***

| | $c_1 \bullet c_2$ | $c_1 \bullet c_3$ | $c_2 \bullet c_3$ |
|---|---|---|---|
| $c_1$ | +1 | +1 | 0 |
| $c_2$ | −1 | 0 | +1 |
| $c_3$ | 0 | −1 | −1 |

| distance | select |
|---|---|
| 1 | |
| 3 | $c_1$ |
| 2 | |

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# Evaluation Corpus

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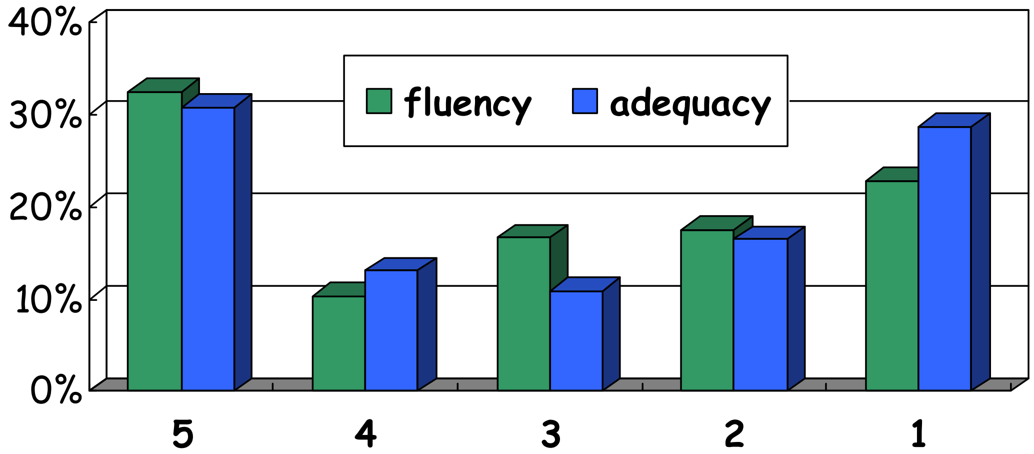
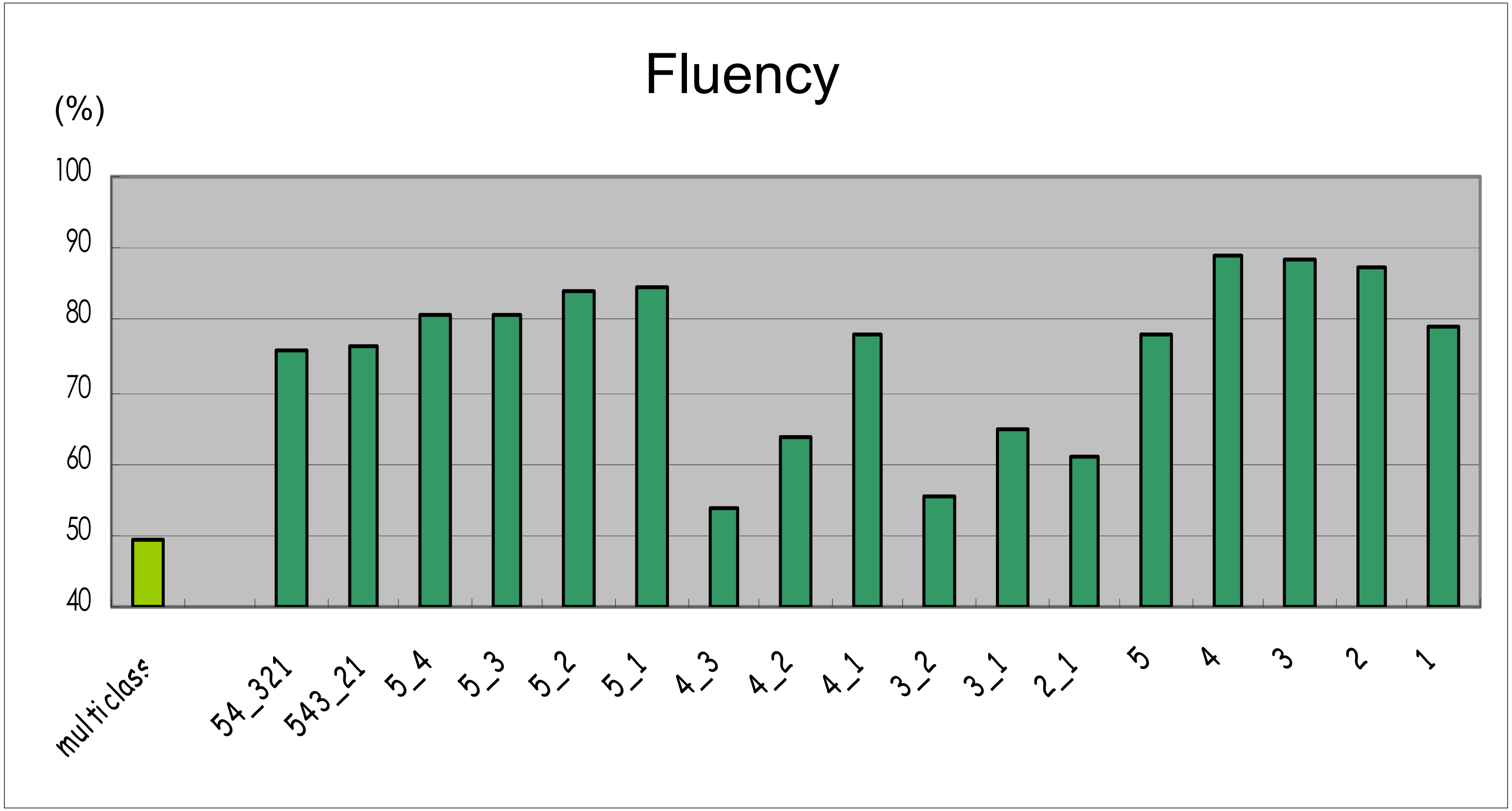
## Basic Travel Expression Corpus (BTEC):

- 36K English translations of 4K Japanese/Chinese inputs
- human assessments and automatic evaluation scores




| sentence count | fluency/ adequacy |
|---|---|
| *training* | 25,988 |
| *develop* | 2,024 ( 4 MT x 506) |
| *test* | 7,590 (15 MT x 506) |

# Coding Matrix Optimization
## (classification accuracy on DEV set)



# Coding Matrix Optimization (classification accuracy on DEV set)

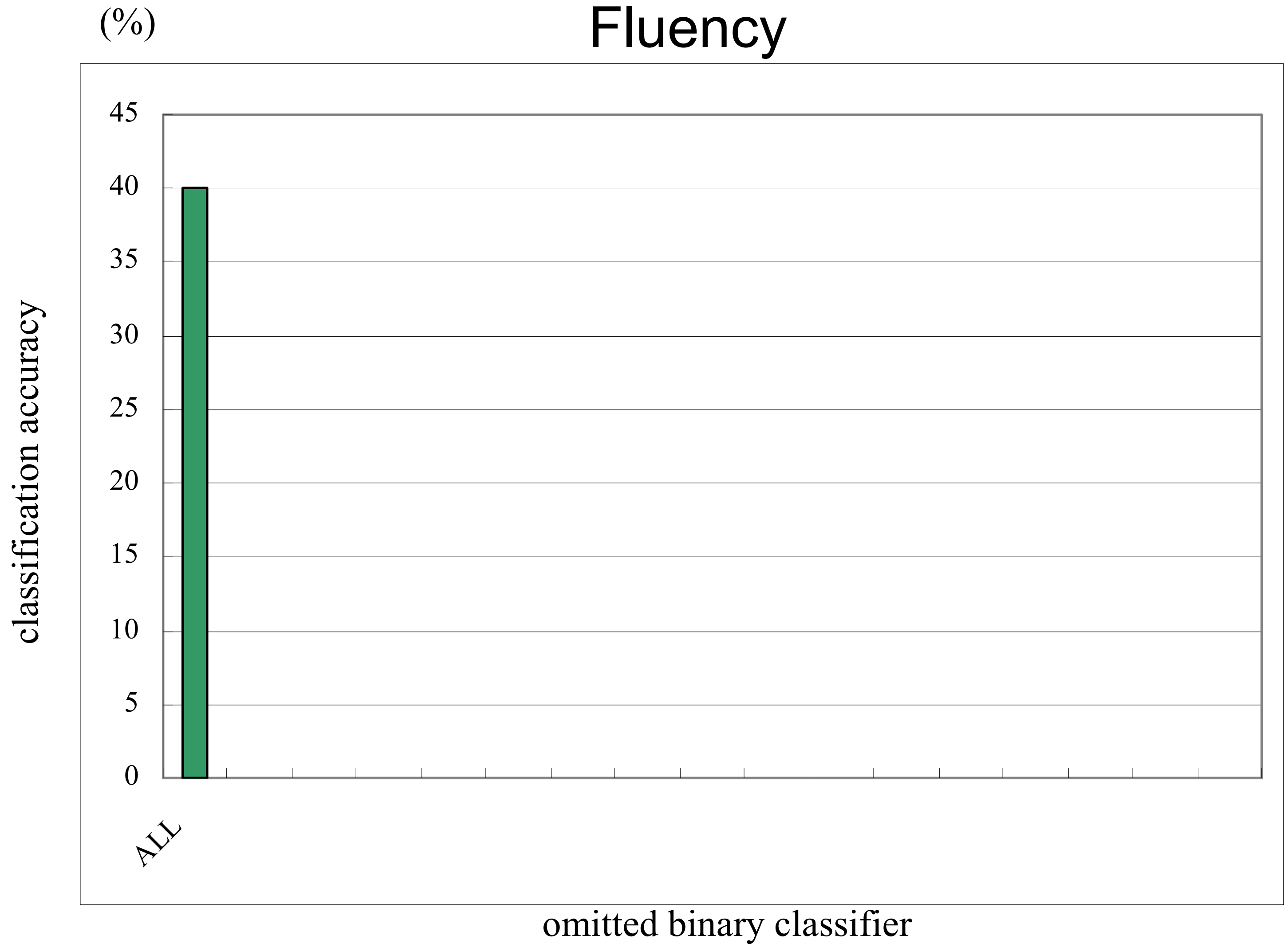
Coding Matrix

| | 54_ 321 | 543 _21 | 5_4 | 5_3 | 5_2 | 5_1 | 4_3 | 4_2 | 4_1 | 3_2 | 3_1 | 2_1 | 5 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **5** | +1 | +1 | +1 | +1 | +1 | +1 | 0 | 0 | 0 | 0 | 0 | 0 | +1 | –1 | –1 | –1 | –1 |
| **4** | +1 | +1 | –1 | 0 | 0 | 0 | +1 | +1 | +1 | 0 | 0 | 0 | –1 | +1 | –1 | –1 | –1 |
| **3** | –1 | +1 | 0 | –1 | 0 | 0 | –1 | 0 | 0 | +1 | +1 | 0 | –1 | –1 | +1 | –1 | –1 |
| **2** | –1 | –1 | 0 | 0 | –1 | 0 | 0 | –1 | 0 | –1 | 0 | +1 | –1 | –1 | –1 | +1 | –1 |
| **1** | –1 | –1 | 0 | 0 | 0 | –1 | 0 | 0 | –1 | 0 | –1 | –1 | –1 | –1 | –1 | –1 | +1 |

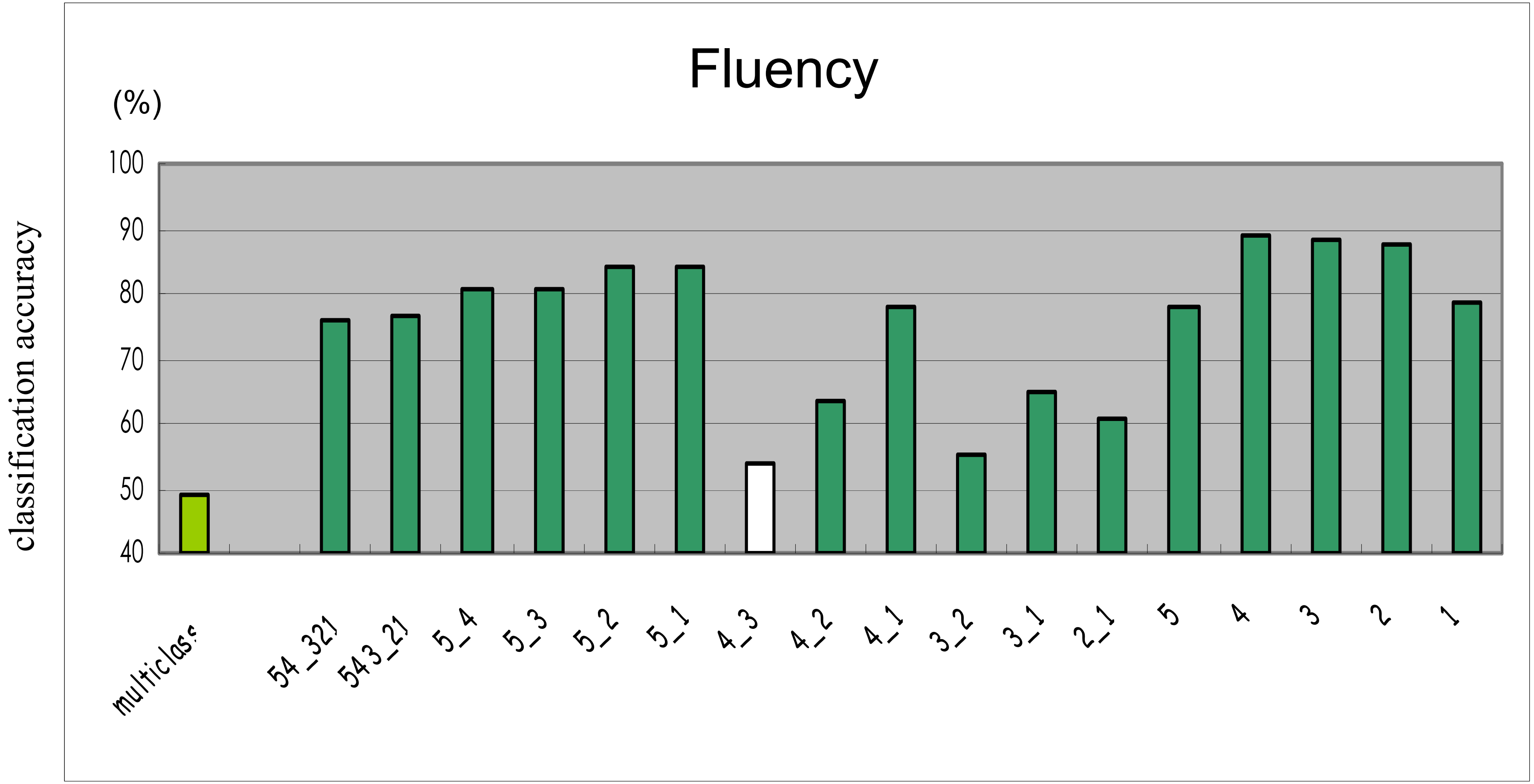
# Coding Matrix Optimization

## (omission of worst-performing classifier)





# Coding Matrix Optimization
## (classification accuracy on DEV set)



# Coding Matrix Optimization
## (classification accuracy on DEV set)

Coding Matrix

| | 54_321 | 543_21 | 5_4 | 5_3 | 5_2 | 5_1 | 4_3 | 4_2 | 4_1 | 3_2 | 3_1 | 2_1 | 5 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **5** | +1 | +1 | +1 | +1 | +1 | +1 | 0 | 0 | 0 | 0 | 0 | 0 | +1 | –1 | –1 | –1 | –1 |
| **4** | +1 | +1 | –1 | –1 | 0 | 0 | +1 | +1 | +1 | 0 | 0 | 0 | –1 | +1 | –1 | –1 | –1 |
| **3** | –1 | +1 | 0 | –1 | 0 | 0 | –1 | 0 | 0 | +1 | +1 | 0 | –1 | –1 | +1 | –1 | –1 |
| **2** | –1 | –1 | 0 | 0 | –1 | 0 | 0 | –1 | 0 | –1 | –1 | +1 | –1 | –1 | –1 | +1 | –1 |
| **1** | –1 | –1 | 0 | 0 | 0 | –1 | 0 | 0 | –1 | 0 | 0 | –1 | –1 | –1 | –1 | –1 | +1 |

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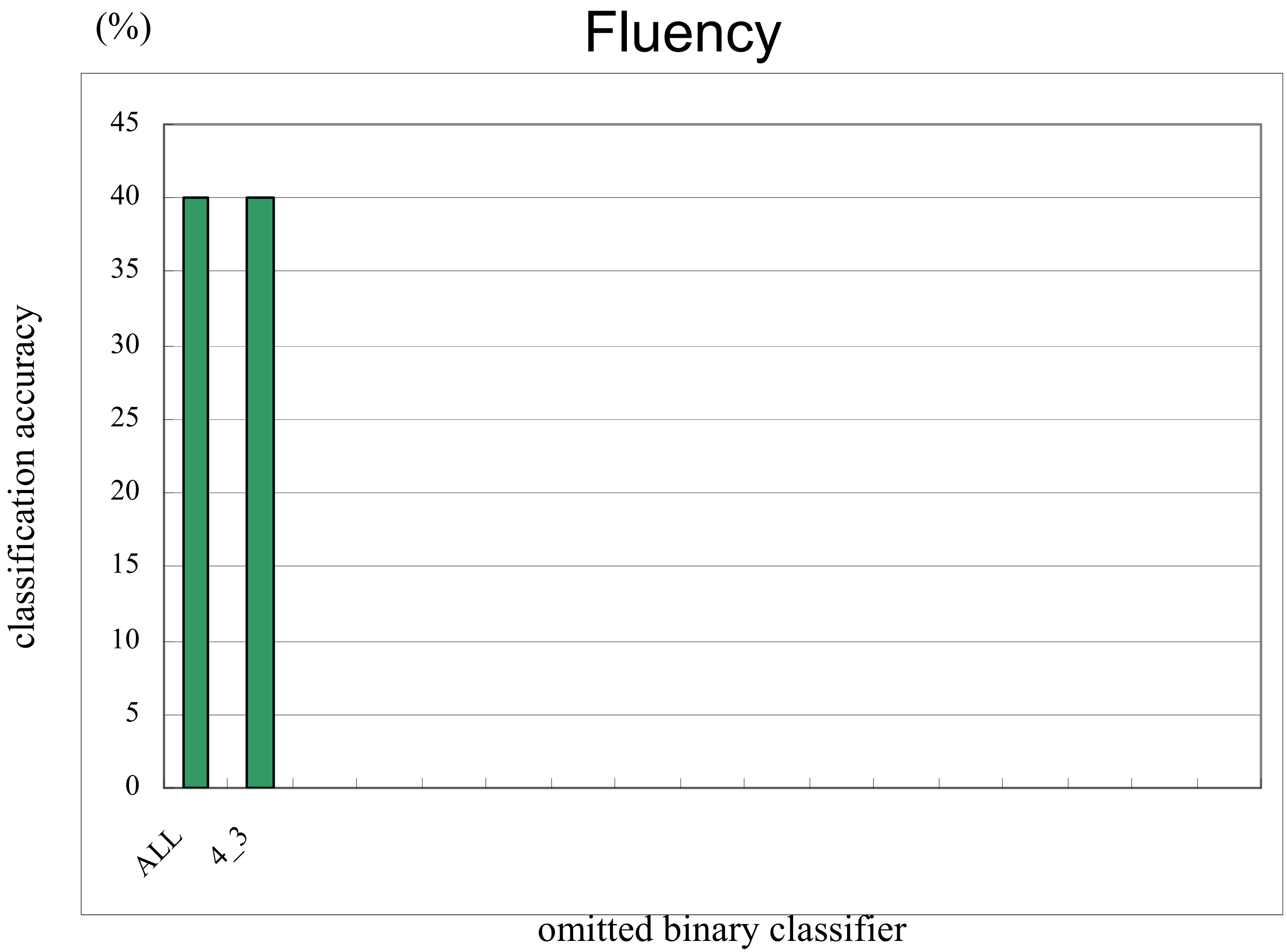
# Coding Matrix Optimization

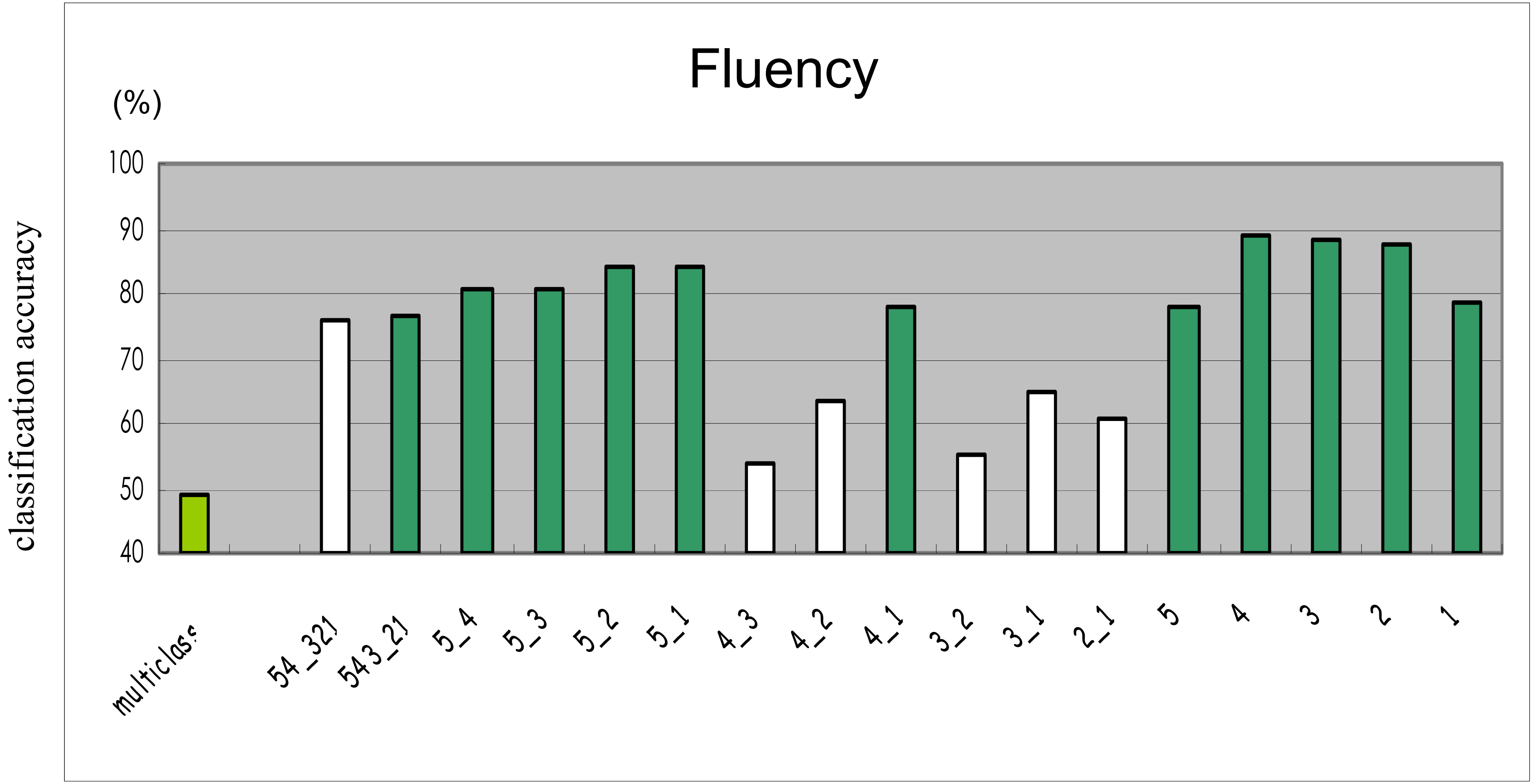
## (omission of worst-performing classifier)



# Coding Matrix Optimization

## (classification accuracy on DEV set)



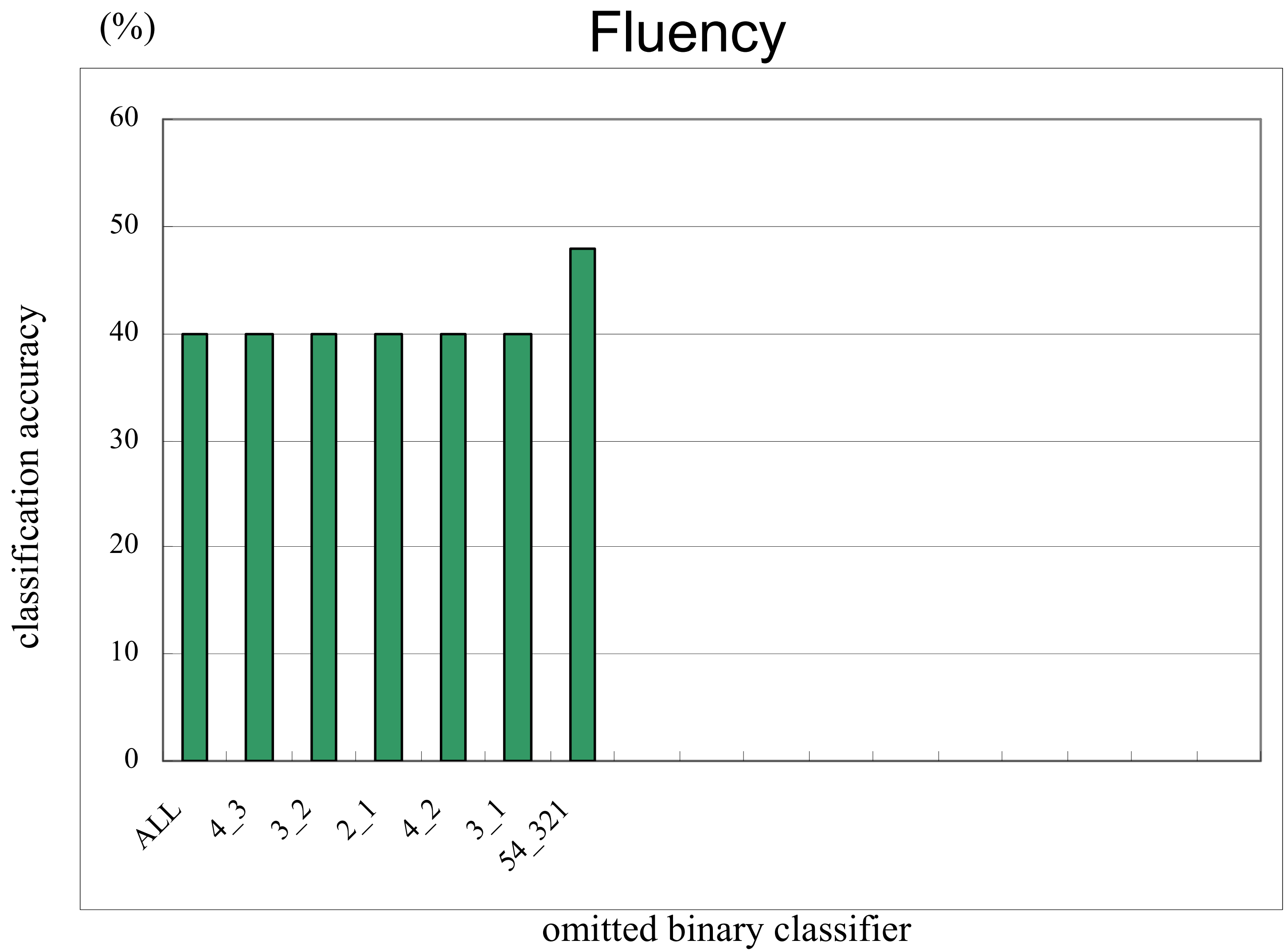


# Coding Matrix Optimization
## (classification accuracy on DEV set)

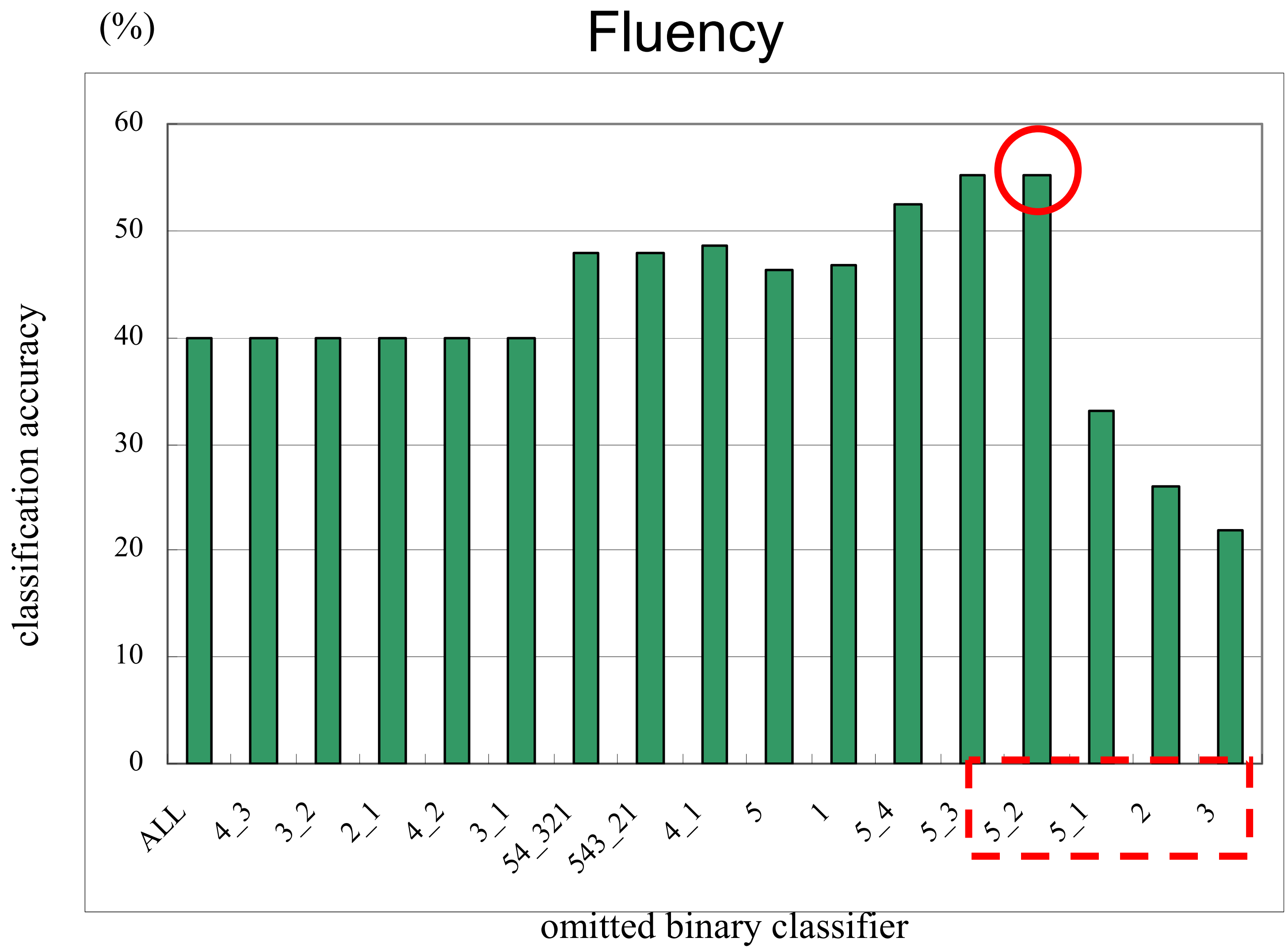
Coding Matrix

| | 54_321 | 543_21 | 5_4 | 5_3 | 5_2 | 5_1 | 4_3 | 4_2 | 4_1 | 3_2 | 3_1 | 2_1 | 5 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **5** | +1 | +1 | +1 | +1 | +1 | +1 | 0 | 0 | 0 | 0 | 0 | 0 | +1 | –1 | –1 | –1 | –1 |
| **4** | +1 | +1 | –1 | –1 | 0 | 0 | +1 | +1 | +1 | 0 | 0 | 0 | –1 | +1 | –1 | –1 | –1 |
| **3** | –1 | +1 | 0 | –1 | 0 | 0 | –1 | 0 | 0 | +1 | +1 | 0 | –1 | –1 | +1 | –1 | –1 |
| **2** | –1 | –1 | 0 | 0 | –1 | 0 | 0 | –1 | 0 | –1 | –1 | +1 | –1 | –1 | –1 | +1 | –1 |
| **1** | –1 | –1 | 0 | 0 | 0 | –1 | 0 | 0 | –1 | 0 | 0 | –1 | –1 | –1 | –1 | –1 | +1 |

# Coding Matrix Optimization
## (omission of worst-performing classifier)



# Coding Matrix Optimization
## (omission of worst-performing classifier)

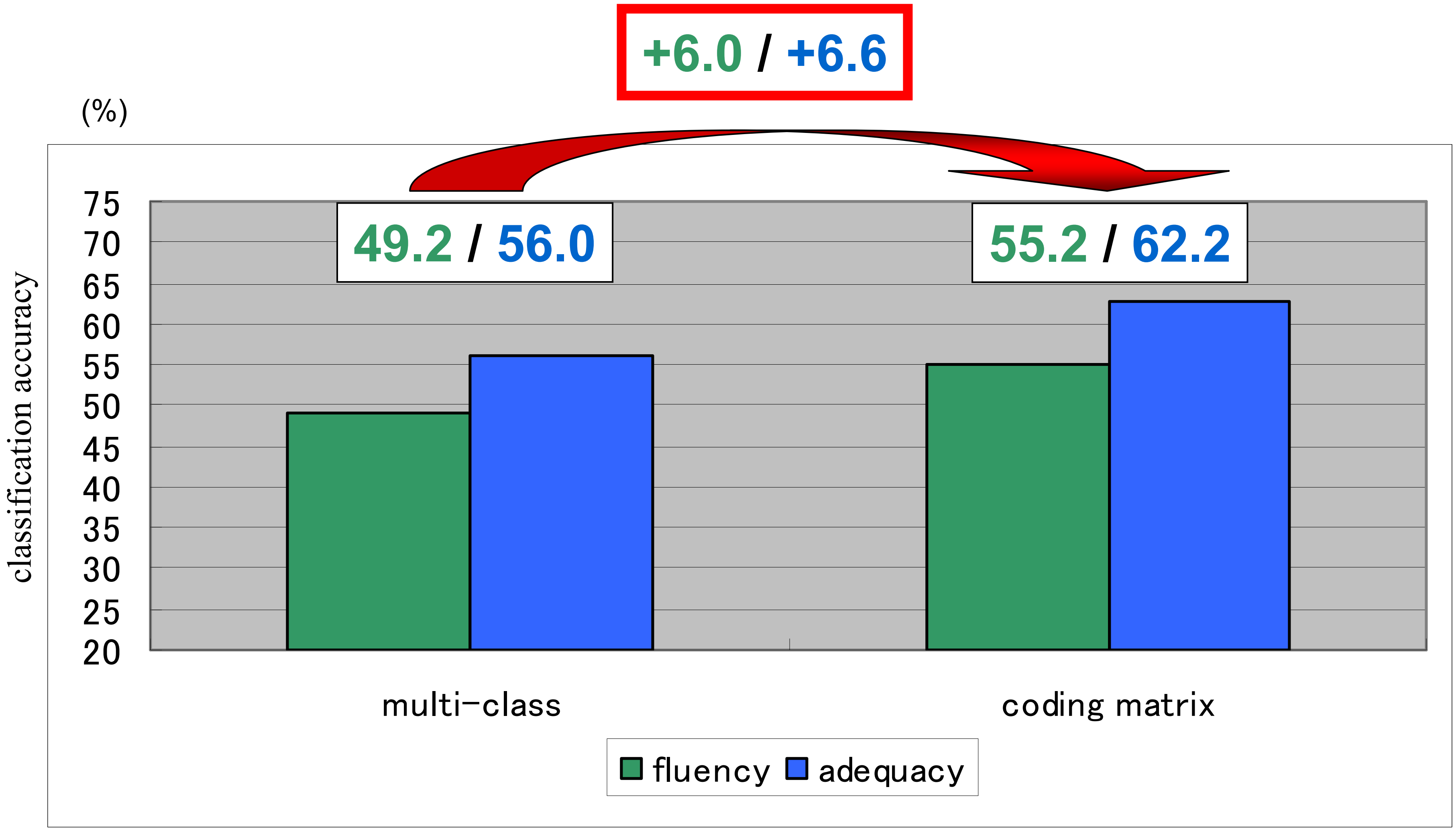


# Coding Matrix Optimization
## (classification accuracy on DEV set)

Optimized Coding Matrix

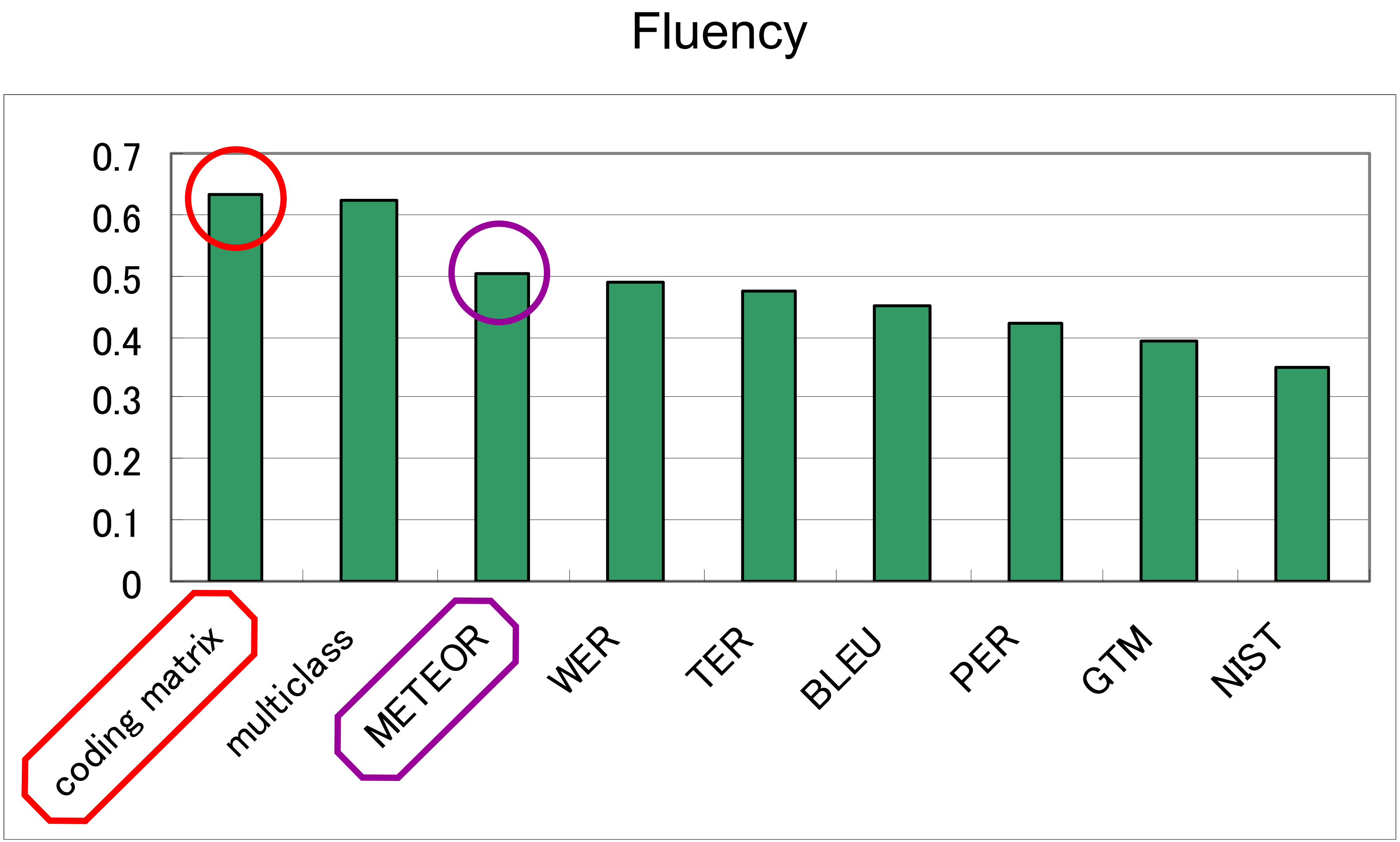
| | 54_321 | 543_21 | 5_4 | 5_3 | 5_2 | 5_1 | 4_3 | 4_2 | 4_1 | 3_2 | 3_1 | 2_1 | 5 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **5** | +1 | +1 | +1 | +1 | +1 | +1 | 0 | 0 | 0 | 0 | 0 | 0 | +1 | –1 | –1 | –1 | –1 |
| **4** | +1 | +1 | –1 | –1 | 0 | 0 | +1 | +1 | +1 | 0 | 0 | 0 | –1 | +1 | –1 | –1 | –1 |
| **3** | –1 | +1 | 0 | –1 | 0 | 0 | –1 | 0 | 0 | +1 | +1 | 0 | –1 | –1 | +1 | –1 | –1 |
| **2** | –1 | –1 | 0 | 0 | –1 | 0 | 0 | –1 | 0 | –1 | –1 | +1 | –1 | –1 | –1 | +1 | –1 |
| **1** | –1 | –1 | 0 | 0 | 0 | –1 | 0 | 0 | –1 | 0 | 0 | –1 | –1 | –1 | –1 | –1 | +1 |

# Evaluation
## (classification accuracy on TEST set)

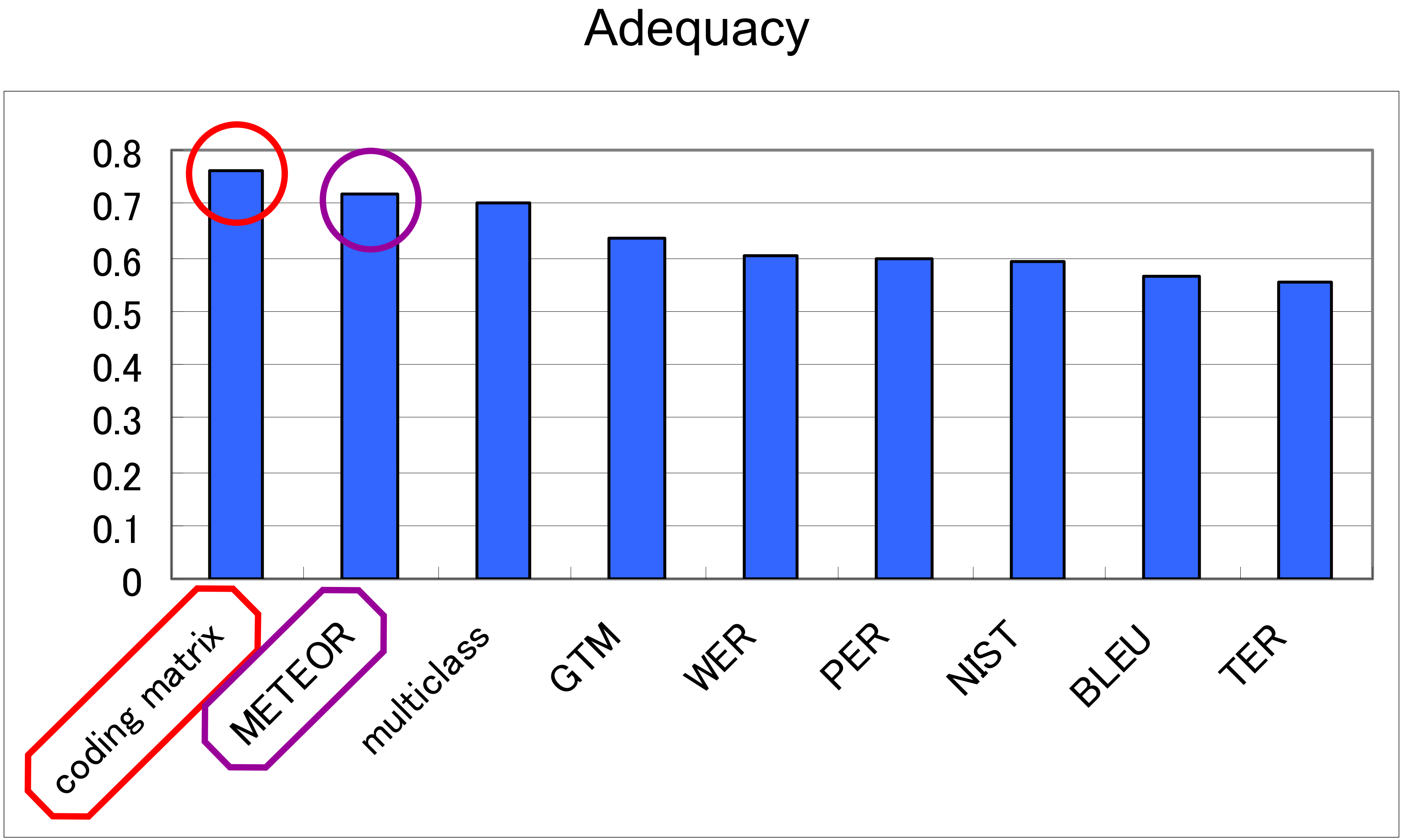


# Correlation to Human Assessment on Sentence-Level



# Correlation to Human Assessment on Sentence-Level



# Summary



## Multiclass reduction to binary:

- **robust and reliable** method to predict human assessments on sentence-level
- **high correlation to human judges** outperforming commonly used automatic evaluation metrics
- **outperforms standard classification methods**
  → gains: **+6.0** (*fluency*) and **+6.6** (*adequacy*) in classification accuracy

## Extension of proposed method:

- apply learning method to **select features used to build the coding matrix**
- investigate in the use of **additional features** that increase binary classification accuracy and thus boost overall multi-class prediction accuracy