Microsoft Malware Classification Challenge

3rd place solution

Mikhail Trofimov, Dmitry Ulyanov, Stanislav Semenov

Our team

Mikhail Trofimov

MASTER

Highest† 72nd

Current† 76th /310,554

40,979.9 points
Joined 2 years ago
†Ranking method changed 13 May 2015 (?)

Dmitry Ulyanov

MASTER

Highest† 160th

Current† 167th /310,554

23,195.7 points
Joined a year ago
†Ranking method changed 13 May 2015 (?)

Stanislav Semenov

MASTER

Highest† 12th

Current† 20th /310,554

70,359.3 points
Joined a year ago
†Ranking method changed 13 May 2015 (?)

Team Name * in the money	Score	Entries
say NOOOOO to overfitttttting *	0.002833228	268
Marios & Gert *	0.003240502	80
Mikhail & Dmitry & Stanislav *	**0.003969846**	**71**
Ivica Jovic	0.004470816	11
Octo Guys	0.005191324	37
Oleksandr Lysenko	0.005335339	51
Silogram	0.006328459	98
SSIR	0.006705905	157
gphilippis	0.006810522	86
Gilberto Titericz Junior	0.006849661	47
clustifier	0.006965226	86
David Shinn	0.007070557	24

Further plan

- Problem description
- Feature extraction
- Feature processing and selection
- Models
- Tricks

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The data

~ 20000 program executables, each given in two forms:

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1. HEX dump *"bytes file"*

```
 1  10001000 6A FF 68 A3 16 00 10 64 A1 00 00 00 00 50 64 89
 2  10001010 25 00 00 00 00 83 EC 20 8B 44 24 34 56 50 8D 4C
 3  10001020 24 0C C7 44 24 08 00 00 00 00 FF 15 34 20 00 10
 4  10001030 8B 4C 24 3C 51 8B C8 C7 44 24 30 01 00 00 00 FF
 5  10001040 15 3C 20 00 10 8B 74 24 34 50 8B CE FF 15 34 20
 6  10001050 00 10 8D 4C 24 08 C7 44 24 04 01 00 00 00 C6 44
 7  10001060 24 2C 00 FF 15 30 20 00 10 8B 4C 24 24 8B C6 5E
 8  10001070 64 89 0D 00 00 00 00 83 C4 2C C3 CC CC CC CC CC
 9  10001080 55 8B EC 83 E4 F8 81 EC 0C 03 00 00 8B 55 08 85
10  10001090 D2 A1 20 30 00 10 53 56 89 84 24 10 03 00 00 57
11  100010A0 0F 84 1B 02 00 00 8B 5D 0C 85 DB 0F 84 10 02 00
12  100010B0 00 B9 10 00 00 00 BE B0 20 00 10 8D BC 24 08 01
```

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10001000 6A FF 68 A3 16 00 10 64 A1 00 00 00 00 50 64 89
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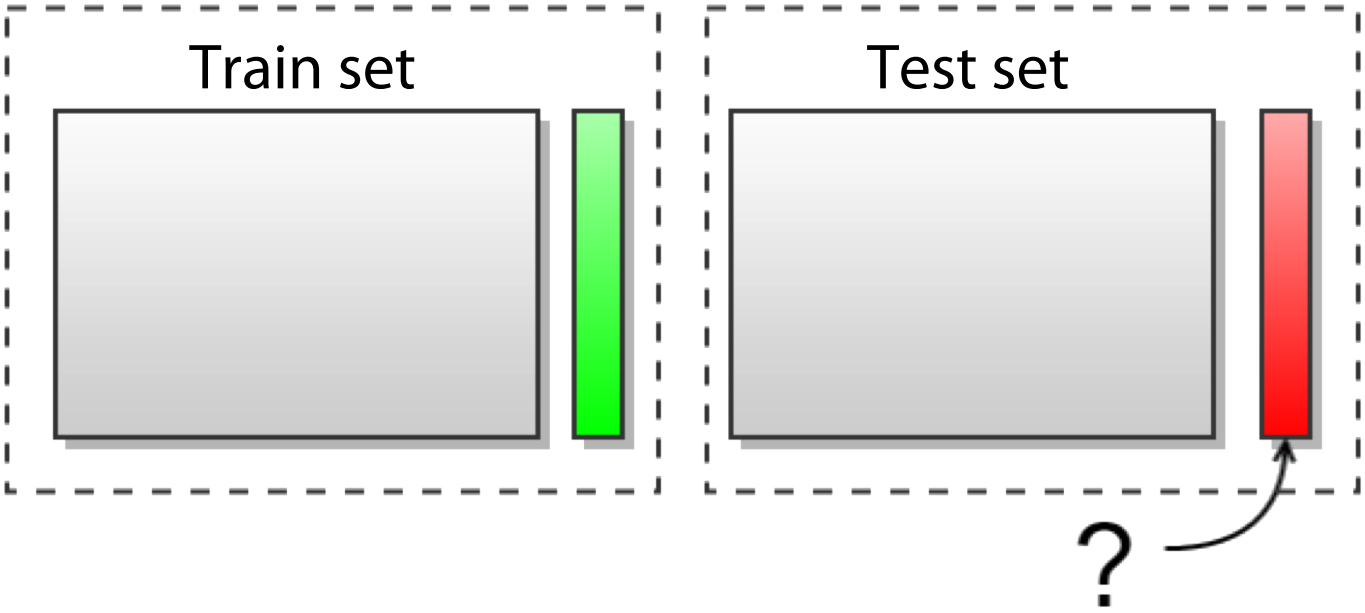
10001030 8B 4C 24 3C 51 8B C8 C7 44 24 30 01 00 00 00 FF
10001040 15 3C 20 00 10 8B 74 24 34 50 8B CE FF 15 34 20
10001050 00 10 8D 4C 24 08 C7 44 24 04 01 00 00 00 C6 44
10001060 24 2C 00 FF 15 30 20 00 10 8B 4C 24 24 8B C6 5E
10001070 64 89 0D 00 00 00 00 83 C4 2C C3 CC CC CC CC CC
10001080 55 8B EC 83 E4 F8 81 EC 0C 03 00 00 8B 55 08 85
10001090 D2 A1 20 30 00 10 53 56 89 84 24 10 03 00 00 57
100010A0 0F 84 1B 02 00 00 8B 5D 0C 85 DB 0F 84 10 02 00
100010B0 00 B9 10 00 00 00 BE B0 20 00 10 8D BC 24 08 01
```

2. IDA disassembly

```
.text:100013DD                          ; ---------------------------------------------------------
.text:100013DD
.text:100013DD                          ; BOOL __stdcall DllEntryPoint(HINSTANCE hinstDLL, DWORD fd
.text:100013DD                                  public DllEntryPoint
.text:100013DD                          DllEntryPoint:
.text:100013DD 83 EC 04                             sub     esp, 4
.text:100013E0 60                               pusha
.text:100013E1 BB 10 00 00 00                           mov     ebx, 10h
.text:100013E6 8D 4C 5B 10                          lea     ecx, [ebx+ebx*2+10h]
.text:100013EA 51                               push    ecx
.text:100013EB B9 01 00 00 00                           mov     ecx, 1
.text:100013F0 C1 E1 0C                             shl     ecx, 0Ch
.text:100013F3 51                               push    ecx
.text:100013F4 BF 00 04 00 00                           mov     edi, 400h
.text:100013F9 81 C7 00 04 00 00                        add     edi, 400h
.text:100013FF 57                               push    edi
.text:10001400 6A 00                                push    0
.text:10001402 FF 15 0C 20 00 10                        call    ds:VirtualAlloc
```

The task

Classify malware into 9 families



- Train: 10k examples
- Test: 10k examples

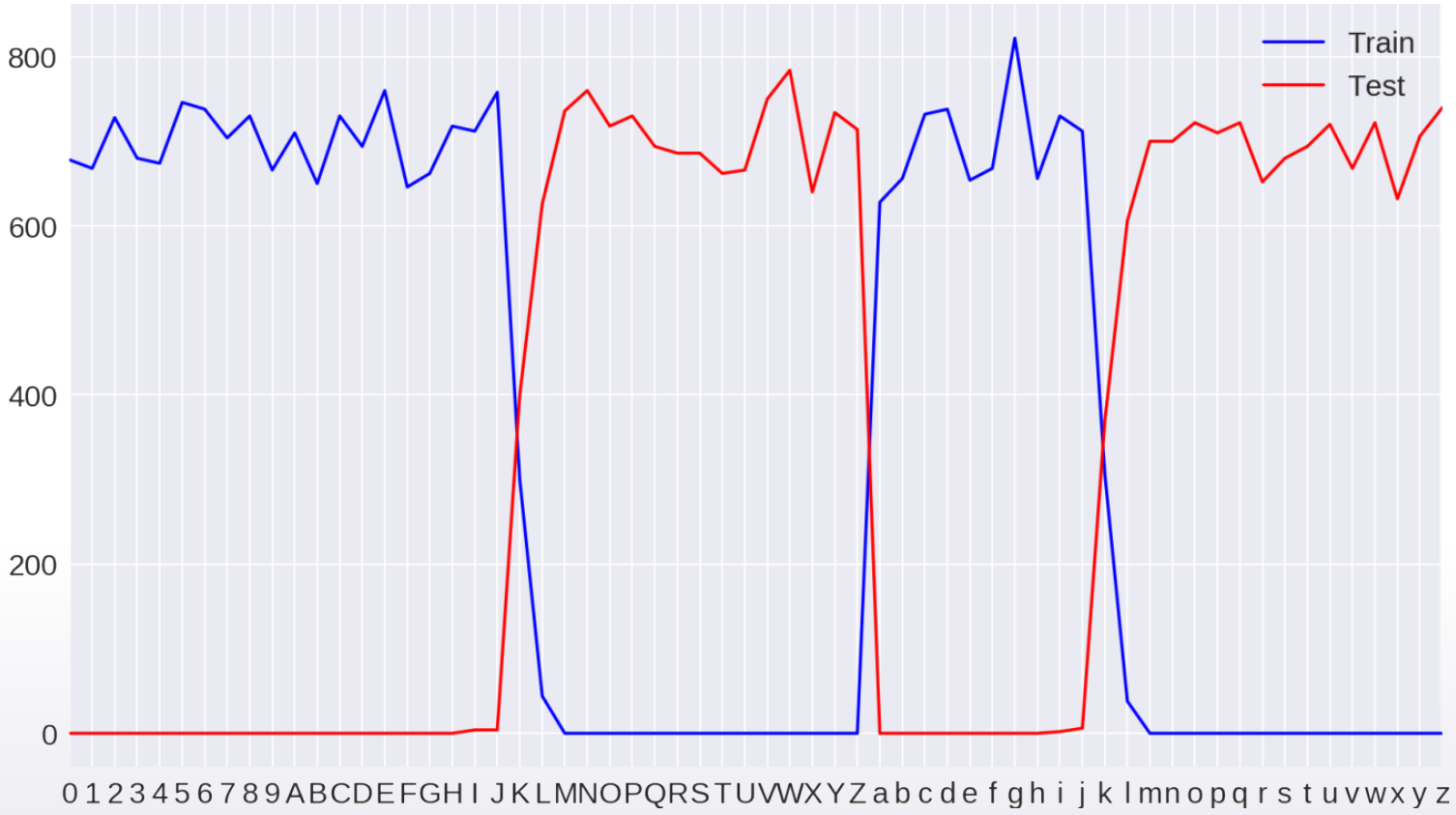
Evaluation metric

$$\text{LogLoss} = -\frac{1}{N}\sum_{i=1}^{L}\sum_{j=1}^{N} y_{ij}\log(\hat{y}_{ij})$$

- **Final LogLoss ~ 0.003**
  - Extremely low for 9-class task
  - Accuracy > 99.7 %

Quick check for leaks

- **Example file names:**
  - `2v8l9FWbJZg4G7MCNB6r`
  - `lyRMjuo5028fa7OEsNBP`



Further plan

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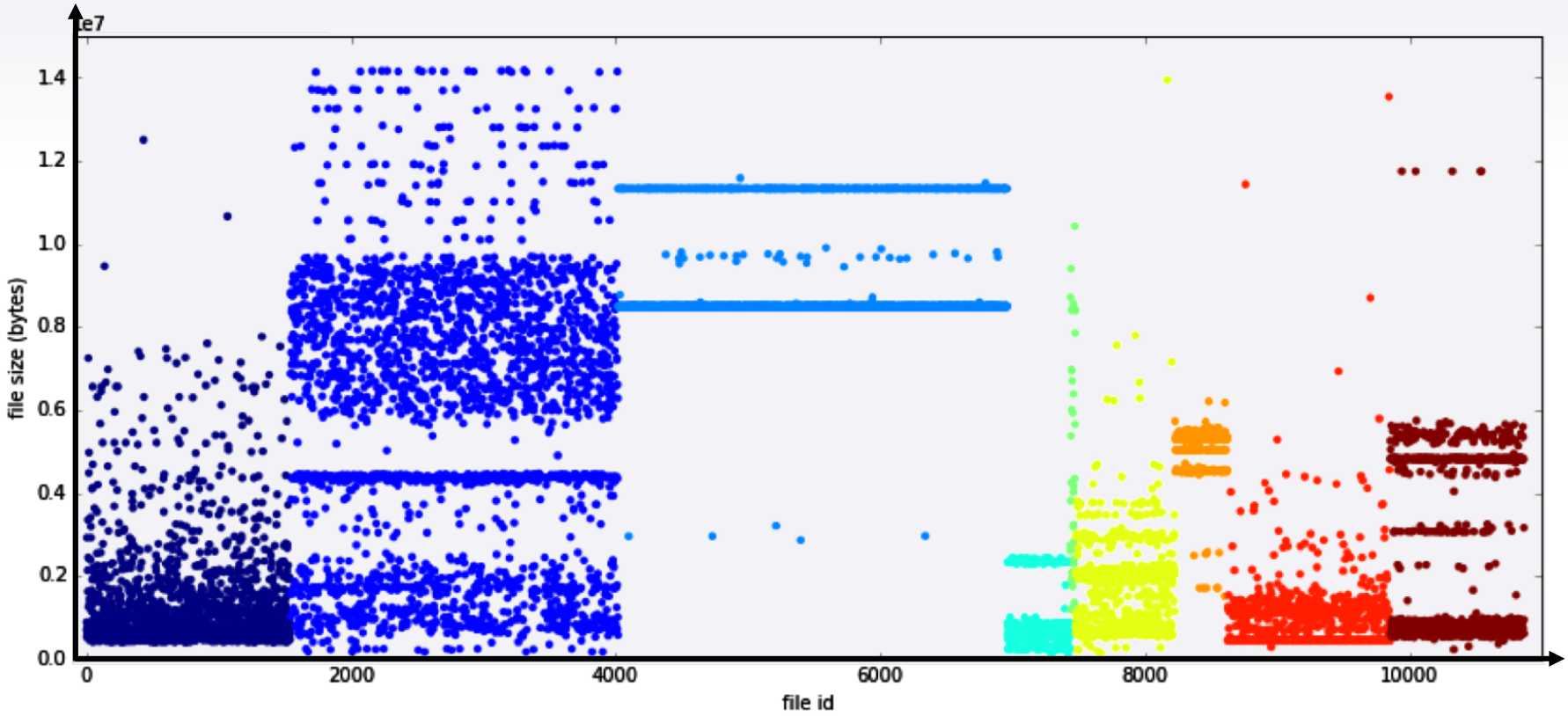
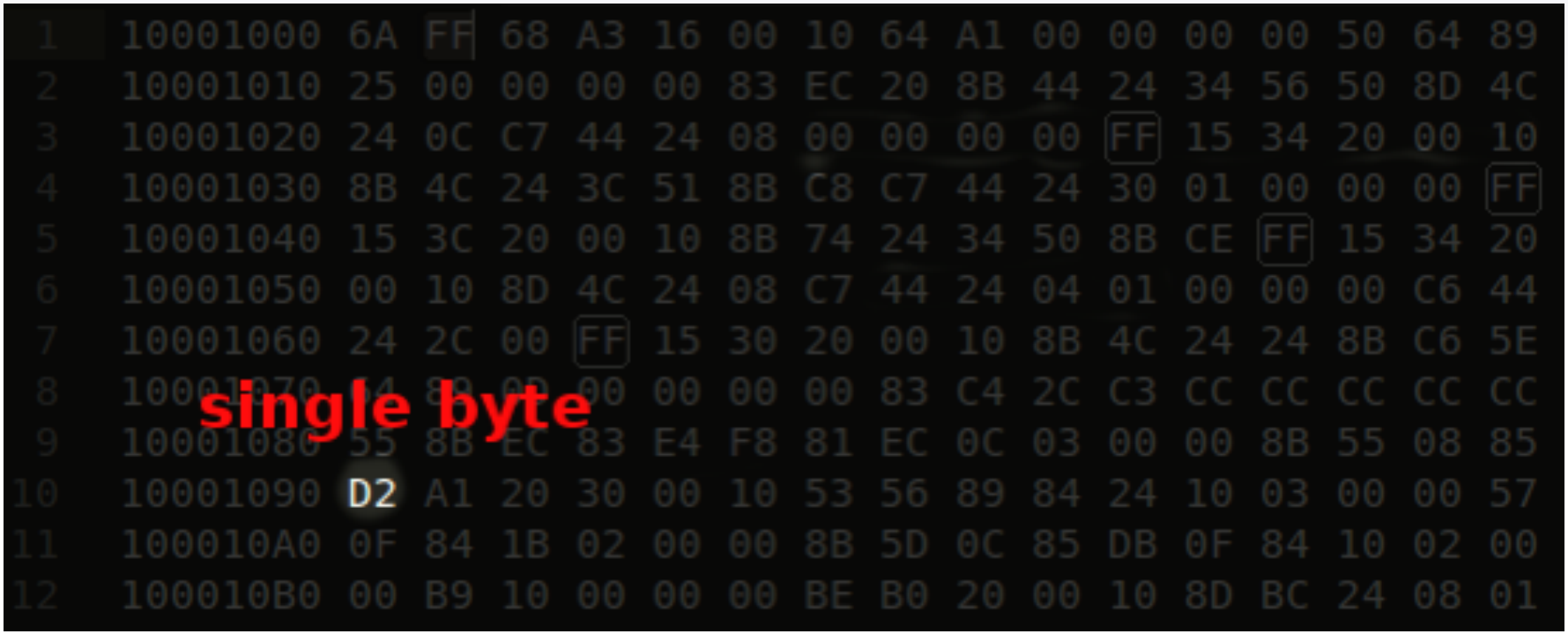
Data exploration: file sizes



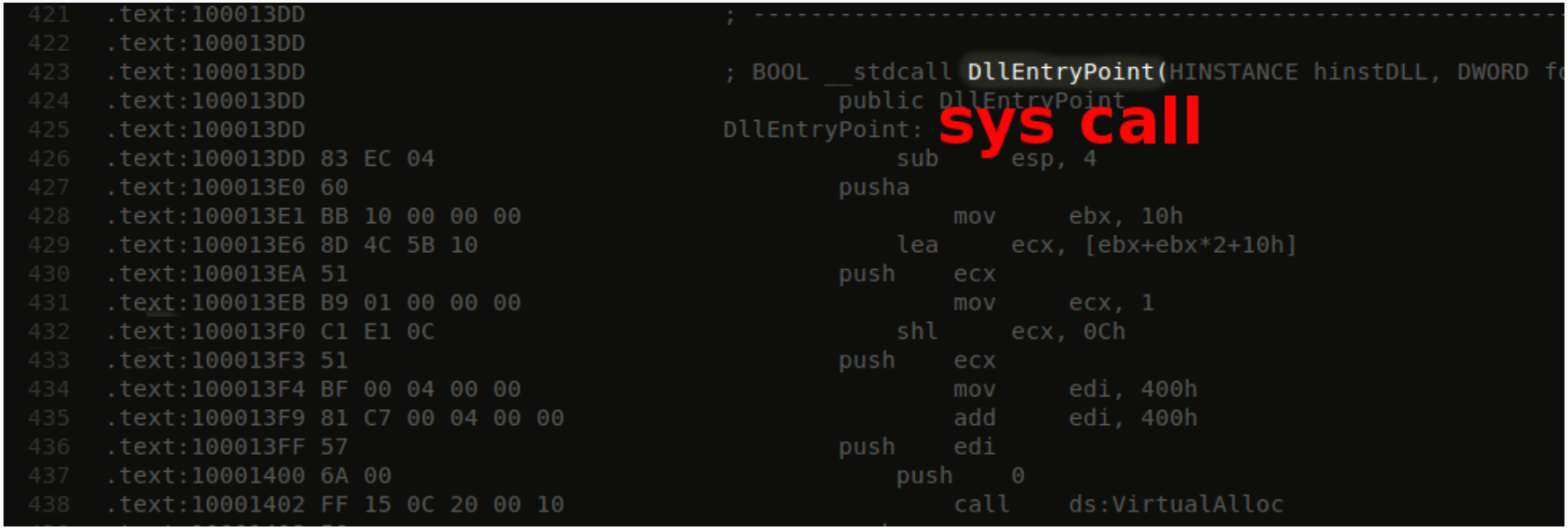
Feature set	Error rate, %	Logloss (10-fold CV)
File sizes	12	0.391

Data exploration: bytes counts



Feature set	Error rate, %	Logloss (10-fold CV)
Single bytes counts	1.3	0.044

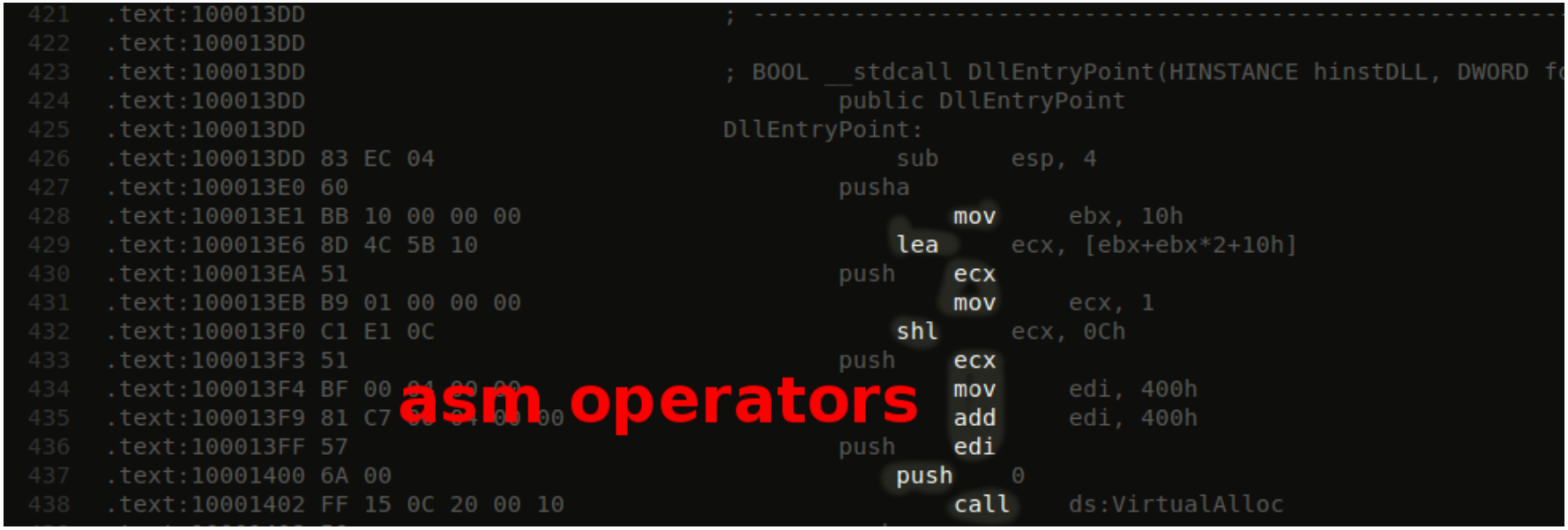
Data exploration: sys calls




```
421  .text:100013DD                          ; ---------------------------------------------------------
422  .text:100013DD
423  .text:100013DD                          ; BOOL __stdcall DllEntryPoint(HINSTANCE hinstDLL, DWORD fd
424  .text:100013DD                                  public DllEntryPoint
425  .text:100013DD                          DllEntryPoint:
426  .text:100013DD 83 EC 04                         sub     esp, 4
427  .text:100013E0 60                               pusha
428  .text:100013E1 BB 10 00 00 00                   mov     ebx, 10h
429  .text:100013E6 8D 4C 5B 10                      lea     ecx, [ebx+ebx*2+10h]
430  .text:100013EA 51                               push    ecx
431  .text:100013EB B9 01 00 00 00                   mov     ecx, 1
432  .text:100013F0 C1 E1 0C                         shl     ecx, 0Ch
433  .text:100013F3 51                               push    ecx
434  .text:100013F4 BF 00 04 00 00                   mov     edi, 400h
435  .text:100013F9 81 C7 00 04 00 00                add     edi, 400h
436  .text:100013FF 57                               push    edi
437  .text:10001400 6A 00                            push    0
438  .text:10001402 FF 15 0C 20 00 10                call    ds:VirtualAlloc
```

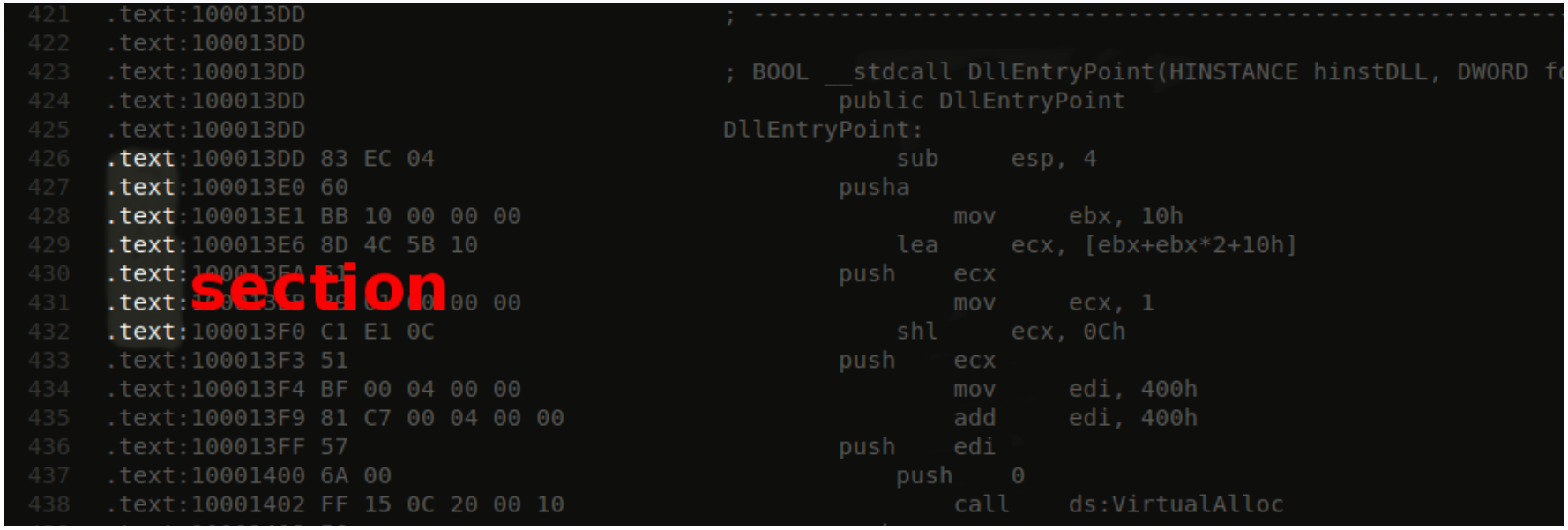
Feature set	Error rate, %	Logloss (10-fold CV)
System calls	2.3	0.078

Data exploration: asm operators



Feature set	Error rate, %	Logloss (10-fold CV)
Asm operators	1.5	0.055

Data exploration: asm operators

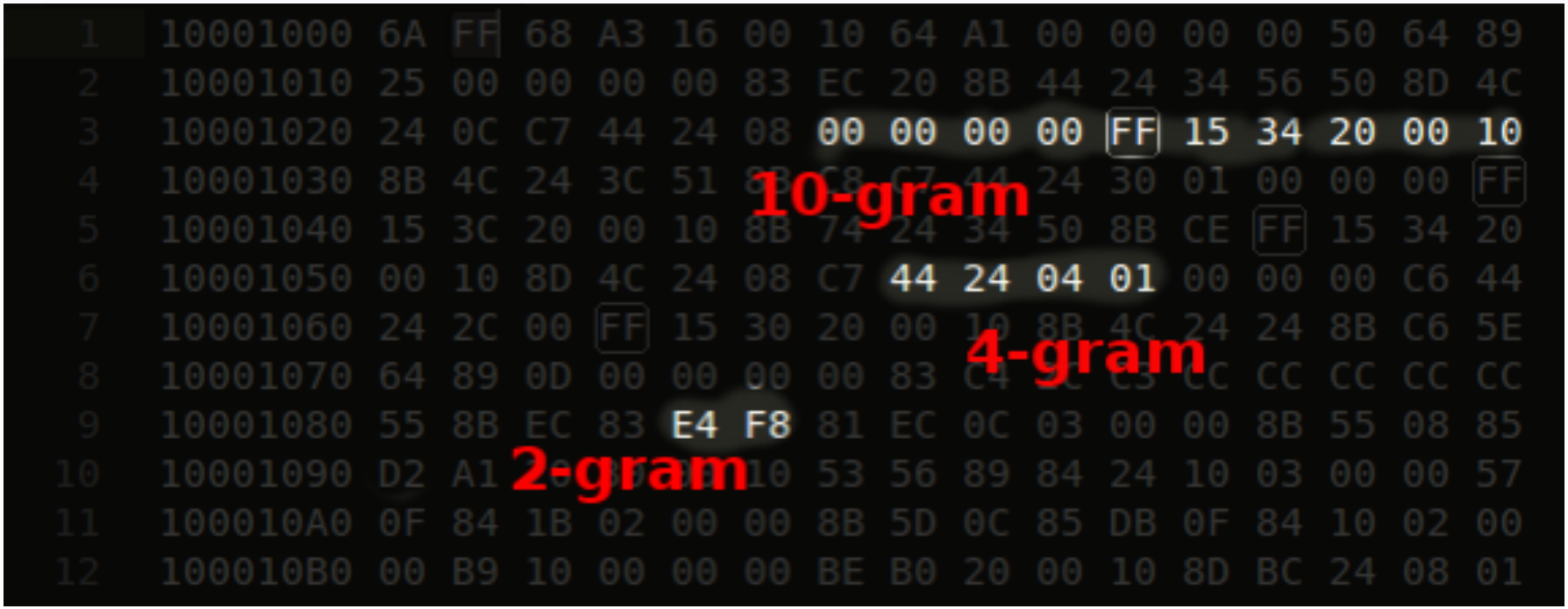


Feature set	Error rate, %	Logloss (10-fold CV)
Sections distribution	0.8	0.027

First results

Feature set	Error rate, %	Logloss (10-fold CV)
File sizes	12	0.391
System calls	2.3	0.078
Asm operators	1.5	0.055
Single bytes counts	1.3	0.044
Sections distribution	0.8	0.027
All together	**0.46**	**0.014**

Features: n-grams

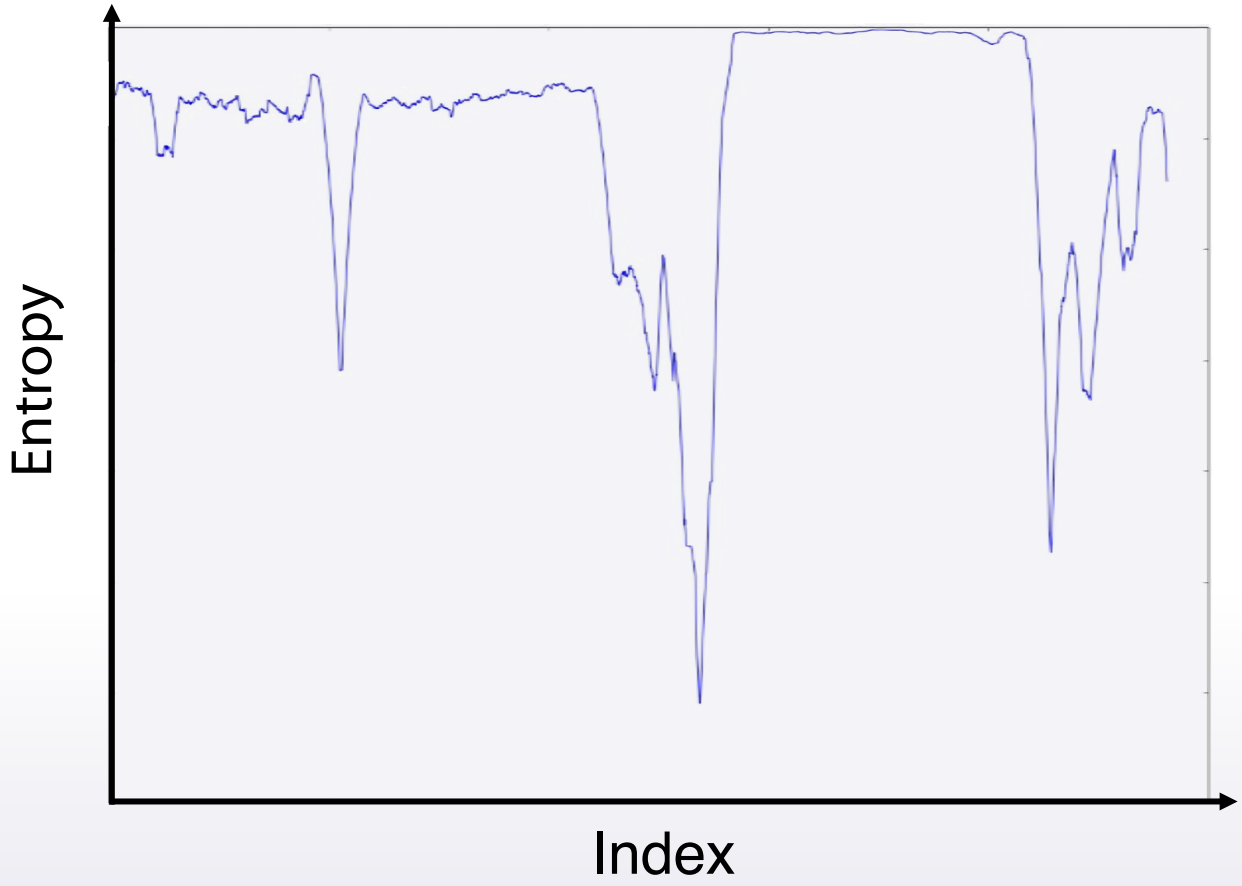


Features: n-grams

n	Possible #features	Selected #features	mlogloss	error rate, %
1	256+1	–	0.044	1.3
2	$(256+1)^2 \sim 65k$	–	0.019	0.6
4	$(256+1)^4 \sim 4.3*10^9$	**131**	0.016	0.48
10	$(256+1)^{10} \sim 1.2*10^{24}$ **hashed into $2^{28} = 2.6*10^8$**	831	**0.011**	**0.32**

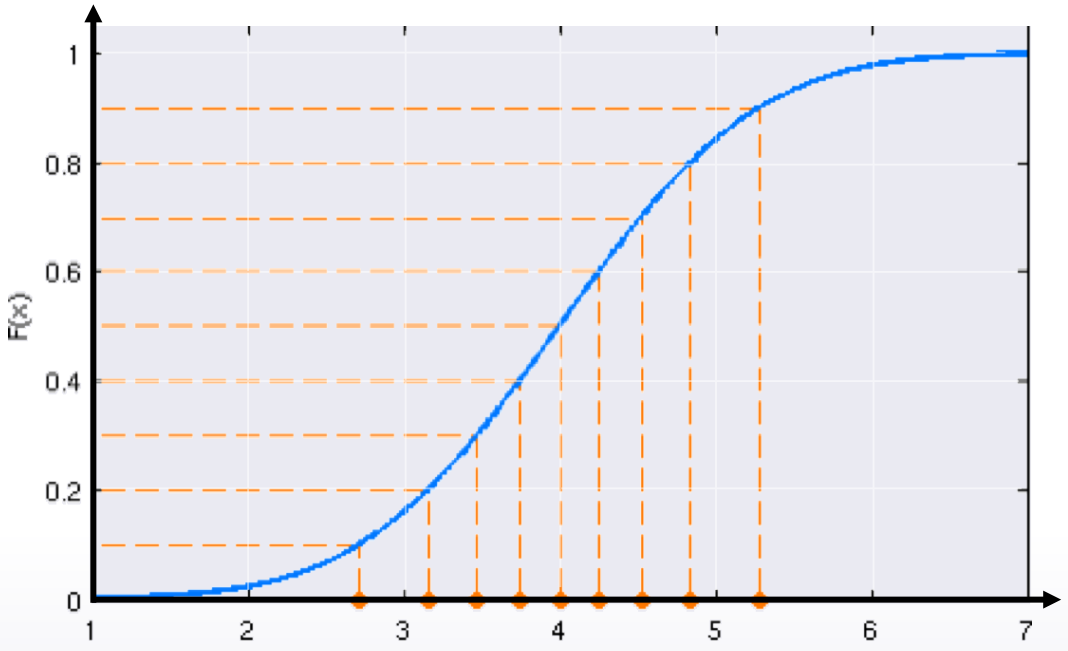
Entropy

- **Entropy extraction**
  - Compute entropy for a sliding window over byte sequence



Entropy

- **Features generation**
  - Mean, median, max, min, etc.
  - *Percentiles, inverse percentiles*



  - The same with ***diff(entropy sequence)***

Strings

- **Strings extraction**
  - Find printable sequences with “\0” at the end
- **Feature generation**
  - Discard string content
  - Compute strings length distribution in files
  - Quantiles, percentiles, inverse percentiles...

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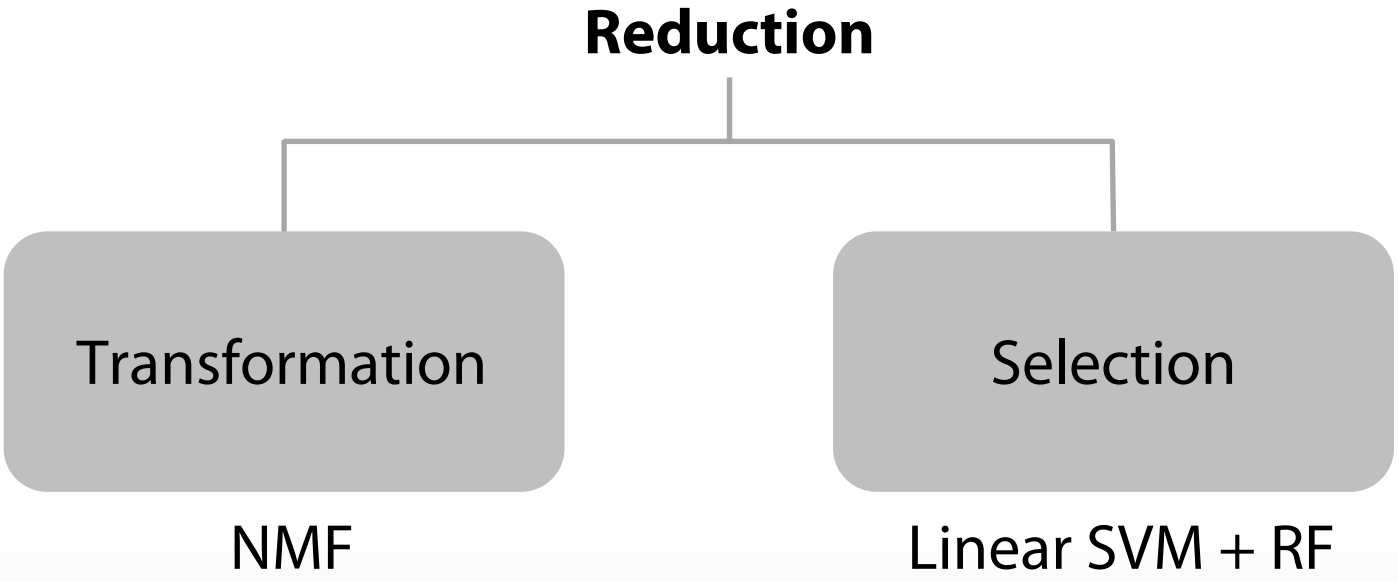
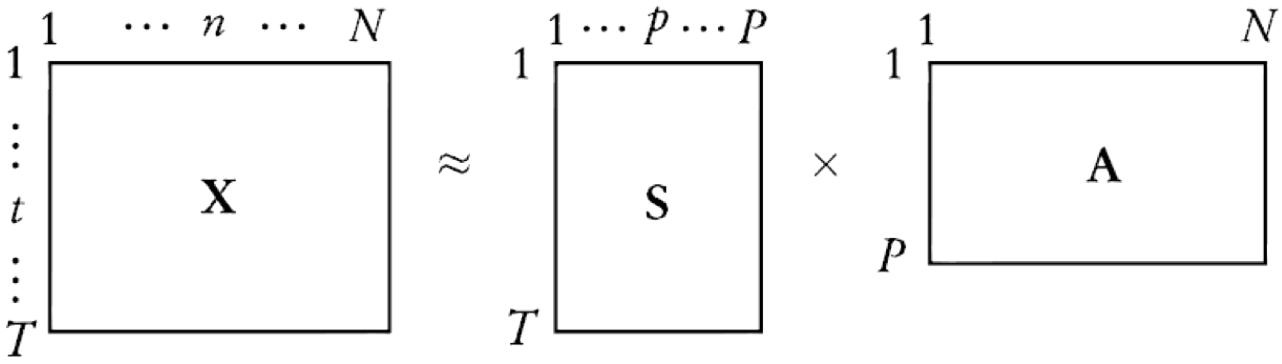
Dimensionality reduction

A lot of noisy features → Need processing



Feature transformations: NMF vs PCA

- **Matrix factorizations:**
  - Non-negative matrix factorization (NMF)
  - Principal component analysis (PCA)



PCA

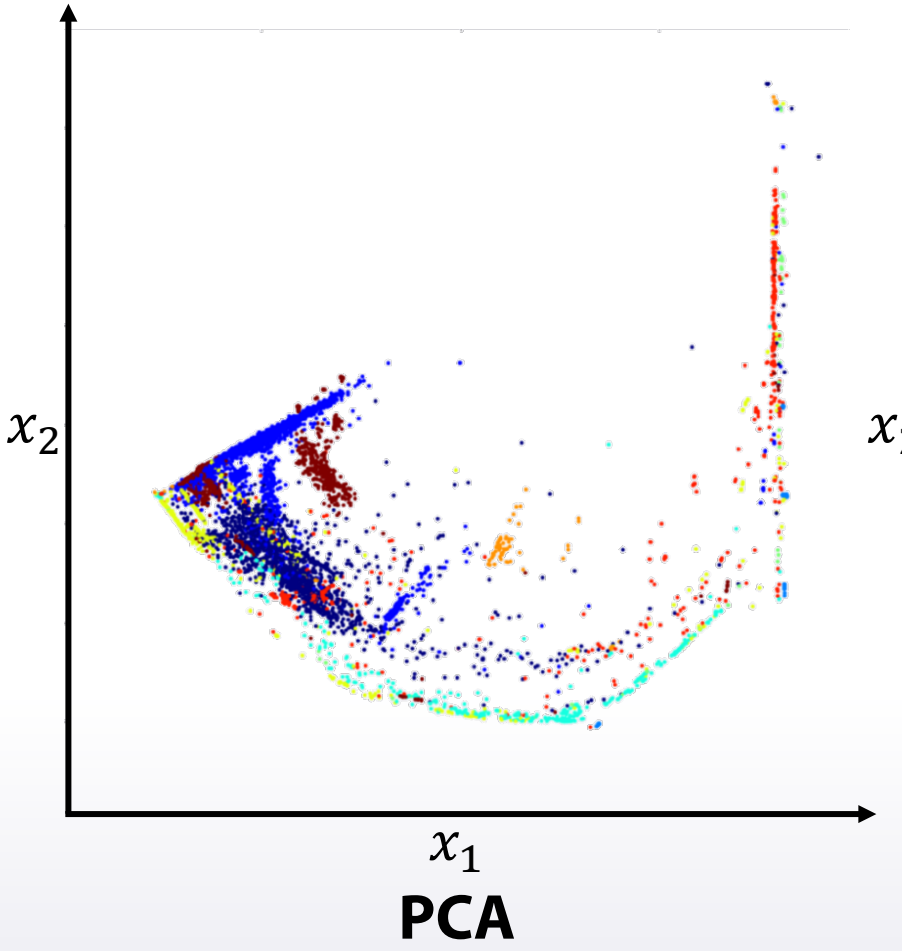
$$\min_{S,A} ||X - SA||_2$$

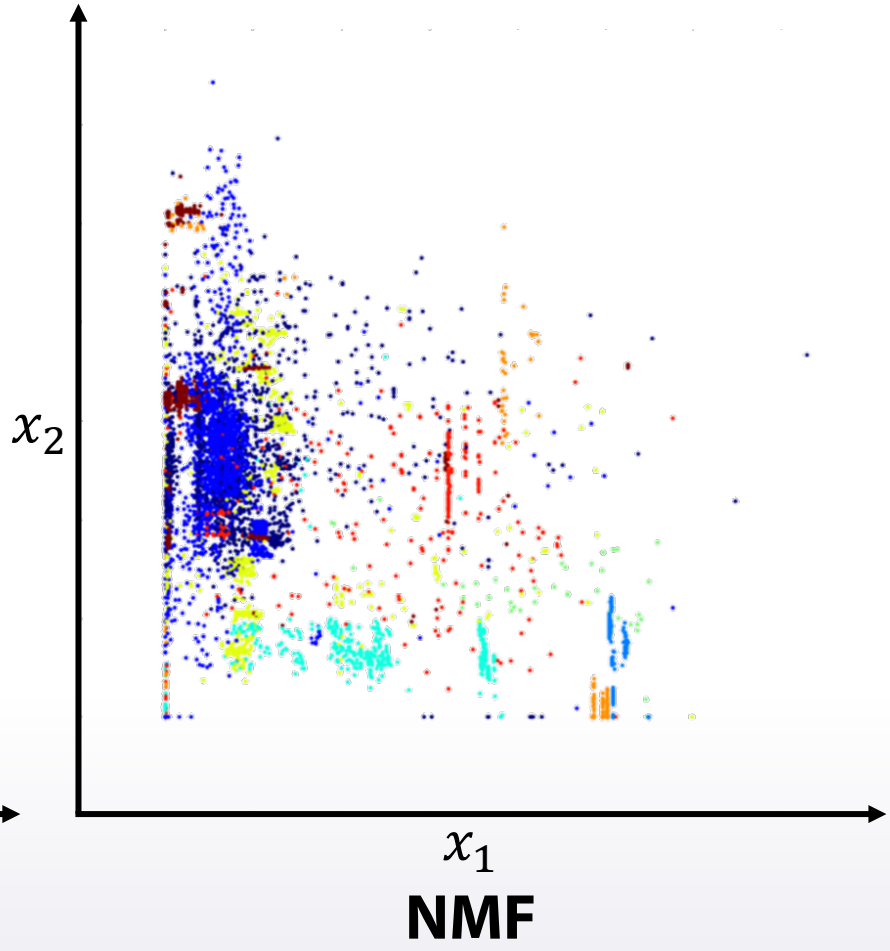
NMF

$$\begin{cases} \min_{S,A} ||X - SA||_2 \\ S_{ij} \geq 0 \\ A_{ij} \geq 0 \end{cases}$$

NMF vs PCA

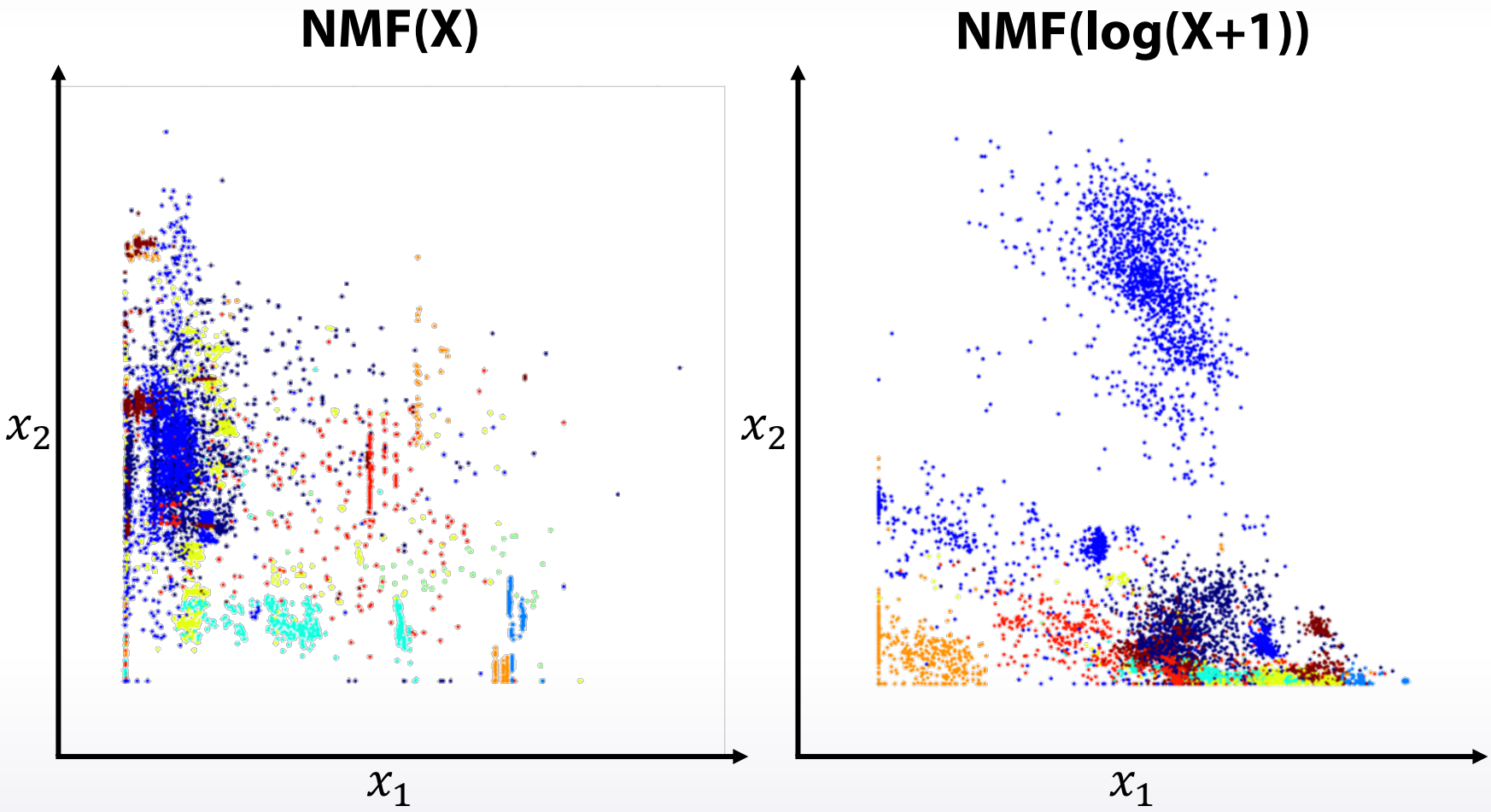
- NMF is better for using in Random Forest





A simple way to get different features

- Apply transform to data and run NMF



- Log transform changes objective from MSE to RMSLE

Feature selection: 4-grams

Stage	Number of features
Original	$(256+1)^4$
Omit rare	4 995 597
Linear SVM + L1-penalty	6369
RF features importances	131

logloss	error rate, %
0.016	0.48

Feature selection: 10-grams

Stage	Number of features
Original	$(256+1)^{10}$
Hashing	2^{28}
Omit rare	3 438 702
Linear SVM + L1-penalty	10865
RF feature importance	861

mlogloss	error rate, %
0.011	0.32

Feature selection: 10-grams

- We wanted to find good 10-grams *in addition* to the features X that we had.

Feature selection: 10-grams

- We wanted to find good 10-grams *in addition* to the features X that we had.

Our method:

1. Fit a classifier on the features X and obtain out of fold predictions for the train set.
2. Sort the objects by their loss and create a new dataset:
   - Assign class 1 to top K error-prone objects
   - Assign class 0 to all the others
3. Fit a model on the new dataset and select best-performing features.

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Model

- **At first: Random Forest**
  - Needs manual logloss calibration
- **Moved to GBDT (XGBoost)**
- **Bagging works well with boosting:**
  - Use L train objects
  - + sample αL train objects with replacement
  - We use $\alpha = 7$
- **Use only use half of features for every tree**
- **Average over ~20 runs**

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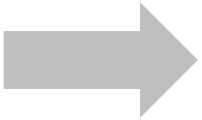
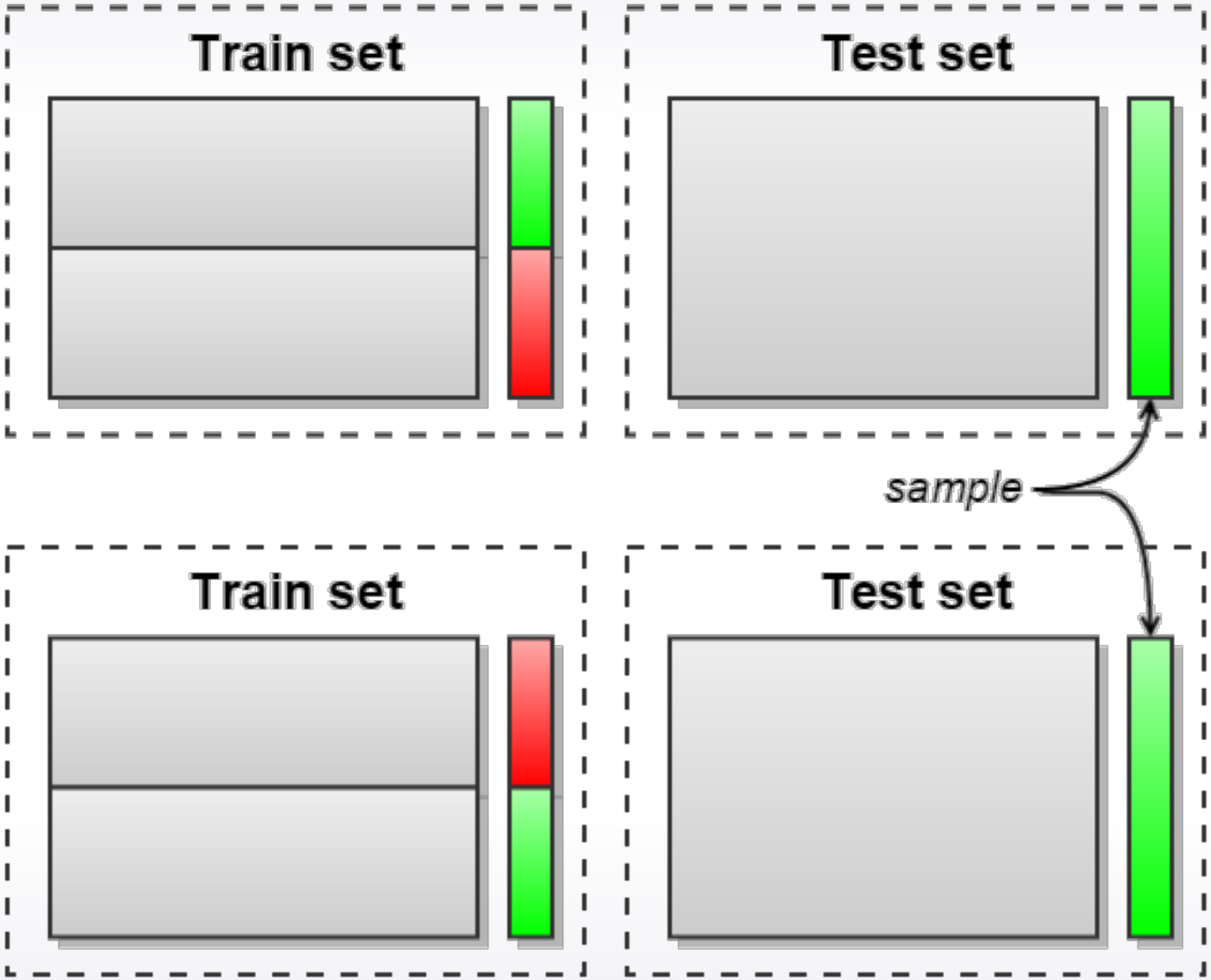
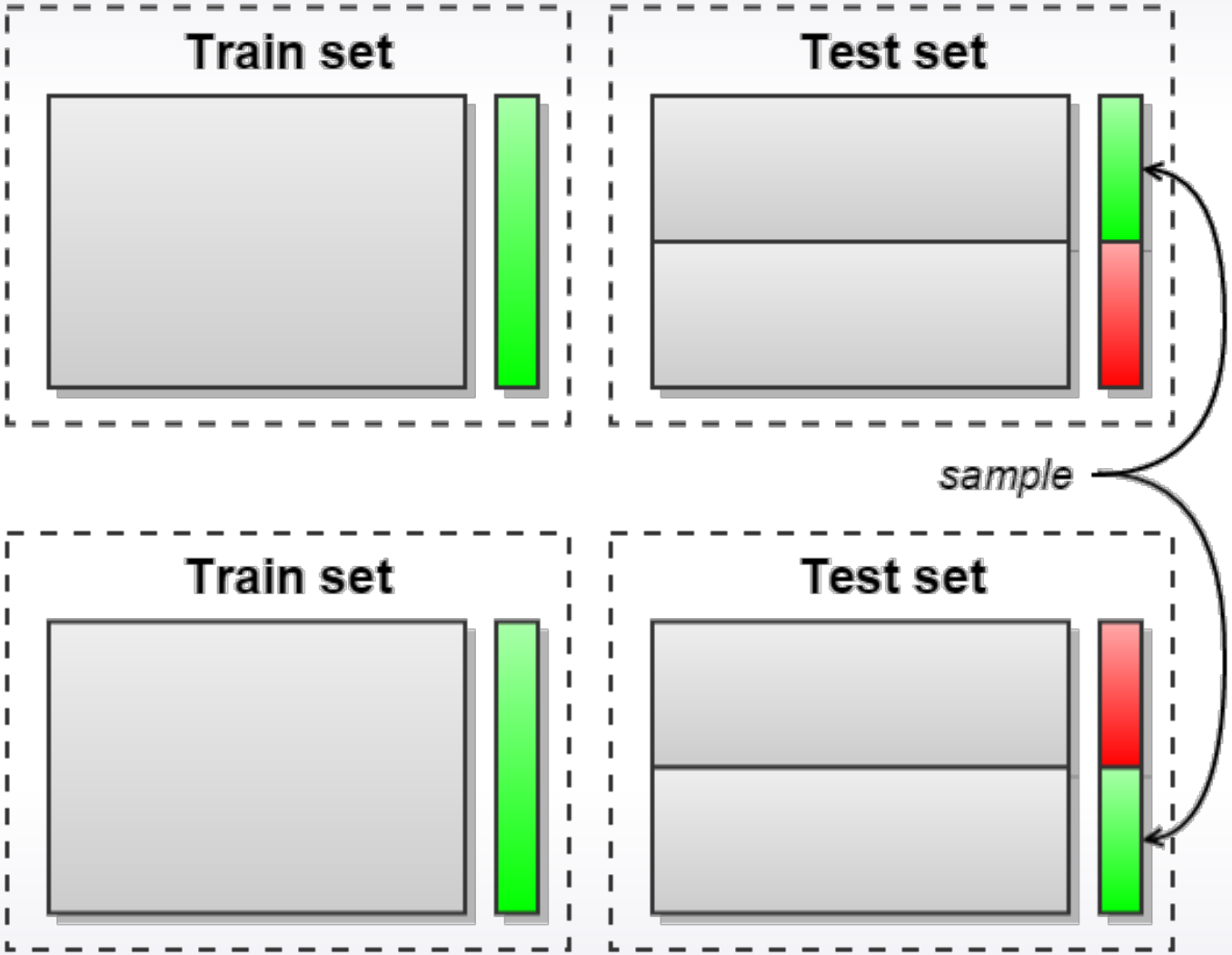
Pseudo labelling

- **CV accuracy is high (>0.997)**
- **The more data**  **the better**
  - Use the test data for training
    - Sample labels according to predicted distribution
    - Or just use predicted class

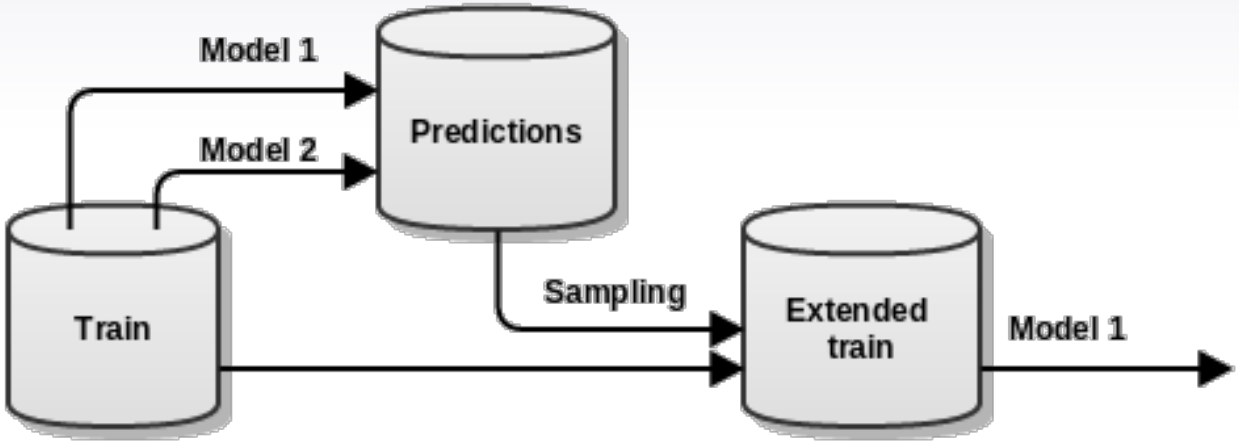
Pseudo labelling: cross validation

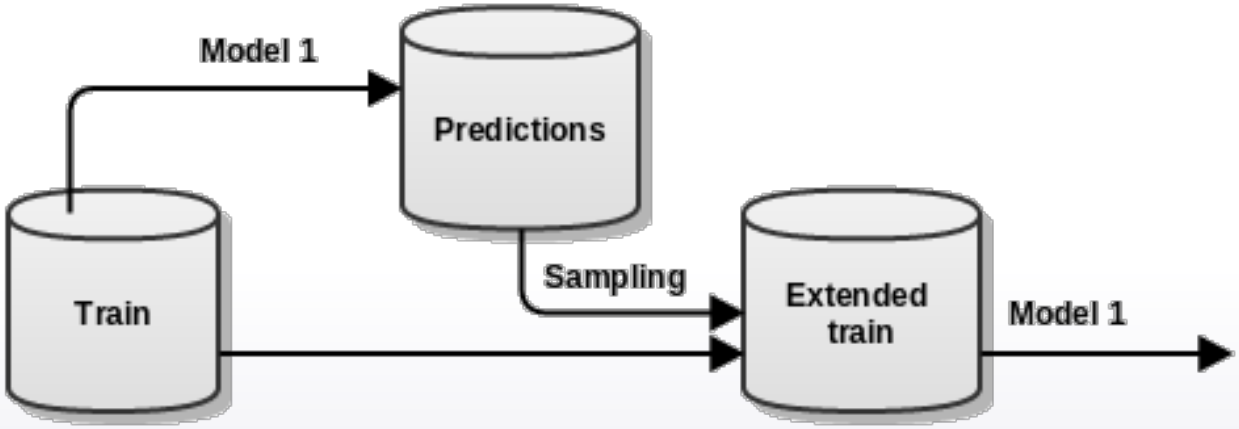


Pseudo labelling: test prediction



Pseudo labeling: how To Use





Tricks: per-class weighting

Linear mixing

$$y_w = \alpha y_1 + (1 - \alpha) y_2$$

Per-class linear mixing

$$y_w^i = \alpha^i y_1^i + (1 - \alpha^i) y_2^i$$

Source code

The code is available at github:

https://github.com/geffy/kaggle-malware

Conclusion

- **Technically challenging competition**
  - ~500 GB of data
- **Competitions with raw data are fun!**
  - A lot of room for feature generation
- **Tricks:**
  - Extreme bagging
  - Pseudo labelling
  - Per-class mixing