Introduction to Machine Learning NPFL 054

http://ufal.mff.cuni.cz/course/npf1054

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Purpose of the demo task

= to show several things related to gold standard data for a supervised machine learning task, especially

- Manual annotation and basic data analysis
- Gold Standard data distribution
- Inter-annotator agreement
- Confusion matrices
- Error analysis

- **Verb Patterns Classification** is a kind of *lexical disambiguation* of verbs. The task is similar to the traditional *word sense disambiguation* (WSD). The two tasks differ in how the semantic categories are defined (word senses vs. patterns of typical verb usage).
- Let's focus on two English verbs, namely *cry* and *enlarge*.

CRY -- dictionary definitions

```
cry ④ ★★★★♦
   1
      crv: cries: crving: cried
      When you cry, tears come from your eyes, usually because you are
      unhappy or hurt.
          I hung up the phone and started to cry.
          Please don't cry.
          He cried with anger and frustration.
          ...a crying baby.
      VB
  2
     cry; cries; crying; cried
      If you cry something, you shout it or say it loudly.
          'Nancy Drew,' she cried, 'you're under arrest!'.
          I cried: 'It's wonderful news!'
      VB
   5
     crv: cries
      You can refer to a public protest about something or appeal for
      something as a cry of some kind. (JOURNALISM)
          There have been cries of outrage about this expenditure.
          Many other countries have turned a deaf ear to their cries for help.
      N-COUNT: usu N of/for n
```

ENLARGE -- dictionary definitions

enlarge 🏾 •••••• enlarge; enlarges; enlarging; enlarged

- When you enlarge something or when it enlarges, it becomes bigger. ...the plan to enlarge Ewood Park into a 30,000 all-seater stadium... The glands in the neck may enlarge. V-ERG
- **enlarged**

The UN secretary-general yesterday recommended an enlarged peacekeeping force.

ADJ-GRADED

2 To enlarge a photograph means to develop a bigger print of it. ...newly-weds wishing to enlarge snaps of their big day.

VB

3 If you enlarge on something that has been mentioned, you give more details about it. (FORMAL)

He didn't enlarge on the form that the interim government and assembly would take.

I wish to enlarge upon a statement made by Gary Docking.

= expand

Pattern 1	[Human] cry [no object]
Explanation	[[Human]] weeps usually because [[Human]] is unhappy or in pain
Example	His advice to stressful women was: ` If you cry , do n't cry alone.
Pattern 4	[Human] cry [THAT-CL WH-CL QUOTE] ({out})
Explanation	[[Human]] shouts ([QUOTE]) loudly typically, in order to attract attention
Example	You can hear them screaming and banging their heads, crying that they want to go home.
Pattern 7	[Entity State] cry [{out}] [{for} Action] [no object]
Explanation	[[Entity State]] requires [[Action]] to be taken urgently

Example Identifying areas which **cry** out for improvement or even simply areas of muddle and misunderstanding, is by no means negative -- rather a spur to action.

ENLARGE -- Pattern definitions

Pattern 1	[[Human]^[Eventuality]] enlarge [Entity]
Explanation	[[Human Eventuality]] causes [[Entity]] to grow or become larger
Example	These were not large powers, but later changes were to enlarge them.
Pattern 2	[Entity] enlarge [no object]
Explanation	[[Entity]] grows or becomes larger
Example	As infants grow, their bodies not only enlarge but change both in shape and colour.
Pattern 3	[[Human]^[Document]] enlarge [{on upon} Anything = Topic] [no object]
Explanation	[[Human]] speaks or writes at length on [[Anything = Topic]] or [[Document]] contains long-winsed comments on [[Topic]]}
Example	Let me enlarge on this a little.
Pattern 4	enlarged

Explanation now larger than before, without any deliberate causer or causer irrelevant

Example The fluid filled spaces or ventricles appear to be **enlarged**, and the blood flow to the front of the brain is reduced.

You will classify *cry* and *enlarge* manually.

- You will be given 10+10 sentences with the given verbs
- For each sentence you will assign a pattern that fits best the given sentence
 - there are 3 predefined patterns for the verb cry
 - there are 4 predefined patterns for the verb enlarge
 - if you think that no pattern matches the sentence, choose "u"
 - if you think that the given word is not a verb, choose "x"
- Use the forms posted at https://ufal.mff.cuni.cz/courses/npf1054/demo

Gold standard data sets are posted on the course web page (DEMO).

CRY – 250 instances in the GS set

class	1	4	7	u	х	
frequency	131	59	13	33	14	-

ENLARGE - 300 instances in the GS set

Automatic classifier is a function that assigns certain output class to each input instance.

Output class is a discrete (possibly categorical) value.

In the demo task: Pattern tags are categorical output values, sentences containing the verbs in question are input instances.

Classifier accuracy is often *estimated* using a test data sample as a percentage of correctly classified instances in the sample. This estimate is called *sample accuracy*.

Automatic predictions made by automatic classifier (our best model F1) are posted on the course web page (DEMO).

- NOTE that it is the same GS set, and it was also used as training data (!).
- Thus, you can compute only the training error, not the test error.

Manual annotation

Annotated data – a subset of the GS

- the same data set annotated by each group

- 2014 2 groups
 - A (5 Czech)
 - B (2 Czech, 3 foreign)

2015 - 4 groups

- A (6 Czech)
- B (6 Czech)
- C (6 Czech)
- D (6 Czech)

Now we can analyse/compare

- which group is closer to the Gold Standard
- inter-annotator agreement between groups
- error types
 - made by people
 - made by automatic classifier

A, B and GS distributions - CRY (2014)

Cry GS histogram





Cry B histogram



A, B, C, D distributions - CRY (2015)













A vs GS - confusion matrix - CRY (2014)



		GS				
		1	4	7	u	х
	1	27	2	0	2	0
	4	1	6	0	0	1
А	7	0	1	2	3	1
	u	1	0	0	0	0
	х	2	0	0	1	0

Number of agreements: 35 (70%) Number of disagreements: 15 (30%)

A, B, C, D vs GS - confusion matrix - CRY (2015)



Agreement: 41 (68%) **Disagreement:** 19 (32%)



Agreement: 40 (67%) **Disagreement:** 20 (33%) GS C u x 1 4 7 u 3 0 5 2 0 x 1 1 2 2 0 1 1 0 28 0 0 4 1 0 3 6 0 7 0 1 0 2 2

Agreement: 40 (67 %) **Disagreement:** 20 (33 %)



Agreement: 45 (75%) **Disagreement:** 15 (25%)

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A, B, C, D vs GS - confusion m. - ENLARGE (2015)



Agreement: 38 (63 %) **Disagreement:** 22 (37 %)



Agreement: 28 (47%) **Disagreement:** 32 (53%)

NPFL054, 2017

Agreement: 28 (47 %) **Disagreement:** 32 (53 %)

GS

1 2 3



u 1 2 3 4 0 5 2 0 1 1 18 0 0 0 0 6 6 0 2 0 4 0 0 0

0 11 0 0

4

Agreement: 36 (60 %) **Disagreement:** 24 (40 %)

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Inter-annotator agreement (IAA) (2014)

CRY – confusion matrix (50 instances, 33 agreements = 66%)

				В		
		1	4	7	u	х
	1	24	3	1	3	0
	4	3	3	0	1	1
A	7	0	2	4	0	1
	u	1	0	0	0	0
	х	0	1	0	0	2

ENLARGE – confusion matrix (50 instances, 31 agreements = 62%)



Example 1

Assume two annotators (A_1, A_2) , two classes (t_1, t_2) , and the following distribution:

	t_1	t ₂
A_1	50 %	50 %
A_2	50 %	50 %

Then

- the best possible agreement is $100\,\%$
- the worst possible agreement is 0 %
- the "agreement-by-chance" would be 50 %

Example 2

Assume two annotators (A_1, A_2) , two classes (t_1, t_2) , and the following distribution:

	t_1	t ₂
A_1	90 %	10%
A_2	90 %	10%

Then

- the best possible agreement is $100\,\%$
- the worst possible agreement is $80\,\%$
- the "agreement-by-chance" would be 82 %

Example 3

Assume two annotators (A_1, A_2) , two classes (t_1, t_2) , and the following distribution:

	t_1	t ₂
A_1	90 %	10%
A_2	80 %	20 %

Then

- the best possible agreement is $90\,\%$
- the worst possible agreement is $70\,\%$
- the "agreement-by-chance" would be 74 %

The situation from Example 3 can be simulated in R

```
# N will be the sample size
> N = 10^{6}
# two annotators will annotate randomly
> A1 = sample(c(rep(1, 0.9*N), rep(0, 0.1*N)))
> A2 = sample(c(rep(1, 0.8*N), rep(0, 0.2*N)))
# percentage of their observed agreement
> mean(A1 == A2)
[1] 0.740112
# exact calculation -- just for comparison
> 0.9*0.8 + 0.1*0.2
[1] 0.74
```

Cohen's kappa

Cohen's kappa was introduced by Jacob Cohen in 1960.

$$\kappa = rac{\Pr(a) - \Pr(e)}{1 - \Pr(e)}$$

- Pr(a) is the relative observed agreement among annotators
 - = percentage of agreements in the sample
- Pr(e) is the hypothetical probability of chance agreement
 - = probability of their agreement if they annotated randomly
- $\bullet \ \kappa > 0$ if the observed agreement is better than what would be expected by chance

Limitations

- Cohen's kappa measures agreement between two annotators only
- for more annotators you should use the more general Fleiss' kappa
 - see http://en.wikipedia.org/wiki/Fleiss'_kappa

CRY Number of agreements: 33 (66 %) Number of disagreements: 17 (34 %) Cohen's kappa: 0.437 Fleiss's kappa: 0.434

ENLARGE Number of agreements: 31 (62 %) Number of disagreements: 19 (38 %) Cohen's kappa: 0.438 Fleiss's kappa: 0.433

CRY – Cohen's kappa

	A	В	С	D
А	_	0.36	0.28	0.41
В	-	-	0.37	0.41
С	-	_	_	0.33
D	-	_	_	_

ENLARGE – Cohen's kappa

	A	В	С	D
А	-	0.31	0.41	0.30
В	-	-	0.22	0.32
С	-	-	-	0.37
D	-	-	-	-

CRY – Fleiss's kappa 0.35 ENLARGE – Fleiss's kappa 0.32

Automatic classifier – training error analysis ENLARGE (2014)

		GS						GS				
		1	2	3	4	u		1	2	3	4	u
	1	224	1	1	12	2	1	0.97	0.05	0.05	0.46	0.67
	2	2	17	3	0	0	2	0.01	0.81	0.15	0.00	0.00
С	3	1	2	15	0	0	3	0.00	0.10	0.75	0.00	0.00
	4	3	1	0	14	1	4	0.01	0.05	0.00	0.54	0.33
	u	0	0	1	0	0	u	0.00	0.00	0.05	0.00	0.00

Number of agreements: 270 (90%) Number of disagreements: 30 (10%)



Number of agreements: 72 (72%) Number of disagreements: 28 (28%)

Summary of Lab #1 Examination Requirements

You should be able to practically compute and understand/use

- categorical data distribution
- confusion matrices
- classifier accuracy
- inter-annotator agreement
 - simple percentage
 - Cohen's kappa
- probability (both conditional and unconditional) of errors of different types

- Download two files with annotated data cry-A.csv and cry-C.csv.
 https://ufal.mff.cuni.cz/courses/npf1054/demo
- Run R and read the data using read.csv().
 - Hint: see the posted Tutorial, Part I.
 - ... and create objects cry.A and cry.C.
- Make the confusion matrix between groups A and C.
 Hint: use table(cry.A\$class, cry.C\$class)
- Compute simple agreement (in percentage) between A and C.
 Hint: use diag() and sum()
- compute the Cohen's kappa value between groups A and C.
 For hints see Part III of the Tutorial.

Summary of Lab #1 Homework

- Go through all details in the Tutorial (Parts I, II, and III)
- Get familiar with the data.table package - just to understand Part II
- Do all exercises in Part III