paper

by YYE Starry

General metrics

28,588	4,314	643	17 min 15 sec	33 min 11 sec
characters	words	sentences	reading time	speaking time

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Issues left	Critical	Advanced

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1 %

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12	Incorrect noun number	
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Unique Words

Measures vocabulary diversity by calculating the percentage of words used only once in your document

24%
unique words

Rare Words

Measures depth of vocabulary by identifying words that are not among the 5,000 most common English words.

34%
rare words

Word Length

Measures average word length

4.8
characters per word

Sentence Length

Measures average sentence length

6.7
words per sentence

paper

G1 - 1

2011 International Conference on Electrical Engineering and Informatics
17-19 July 2011, Bandung, Indonesia

Multi-Inductive Learning Approach for Information Extraction

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Abstract— The vast amount of information in[2,3] the Internet is not easy to find and use. Information Extraction technology is one of alternatives[4] that can solve this problem. Conventional[5] Natural Language Processing approach is hampered by its portability, scalability and[6] adaptability[7]. Introduction of Machine Learning into Information Extraction is one of solutions[8]. Inductive Learning only needs annotated training examples. The problem is there[9] is no performance consistency of algorithms on various information domains. Automatic and smart classifier selection from various machine learning algorithms is one of the best way[10] to handle this problem. The goal of this paper is to propose a method for Information Extraction System based on Inductive Learning and Meta Learning[11] that have good[12] performance. In this paper[13] Multi-Inductive Learning is developed to answer that question. Multi- Inductive Learning is consist of several Inductive Learning algorithms that have significant[14] difference in their mechanism. This[15] is to ensure there is bias variance[16] in this method. Through k-fold cross validation[17] on training document[18], Multi-Inductive[19] Learning algorithm can choose the best classifier for each slot on a certain[20] domain. These best classifiers then employ to do full extraction on testing[21] document. The conducted experiment shows that Multi-Inductive Learning has better performance than that of single Inductive Learning algorithm-based Information Extraction systems. On Reuters Corporate Acquisition, Multi -Inductive Learning gives a score of 46.3 % and has the best performance among other state[22] of the art information systems. Out of nine slots that should be extracted[23], six of them give the best performance. Multi-

Inductive Learning also gives better performance on Job[24] Posting dataset. Average[25] performance of it gives 82.1 % and is the best among other state[26] of the art of Information Extraction. Out of 17 slots that should be tested[27], nine of them are extracted[28] with the best performance.

Keywords— Information Extraction, inductive learning, meta learning[29], multi inductive learning.

INTRODUCTION

The very fast[30] internet growth causes textual information become[31] abundance. Until now Information Retrieval[32]

technology[33] is not enough to fulfill the specific information need because this technology only provides information in[34,35] the level of document[36] collection. Tools and smart methods development that can access document content are crucial issues on Knowledge Management.

Information Extraction is the process to get information about pre-specified events, entity or[37] relationships in the text like newswire and web pages. Many information extraction researches[38] focus on entity recognition which[39] is a basic[40] task. In general, Information[41] Extraction task can be regarded[42] as information[43] entity recognition task in the text. Information Extraction is very useful[44] for many applications such as business intelligence, automatic annotation on web pages, text mining, and knowledge management.

Information Extraction can be approached [45] as classification [46] problem where text [4] is divided into tokens and classified into related classes. Generally, classification methods need a lot of [48] training examples in order [49] the method to be able to generate extraction rules. The problem is there [50] is no single classifier performs constantly [51,52] among domains.

In this paper [53] we will discuss how multi classifier approach can perform better than single classifier one on Information Extraction.

RELATED WORK

State of The Art of Information Extraction

LP2 [3] learning by using symbolic rules for identifying start tag and end tag class of slot. LP2 identifies start [54] tag and end tag separately. Besides using token features and orthographic, it uses linguistic information such as morphology and POS, and user-defined dictionary or gazetteer. This learning algorithm is covering algorithm which start [55] from specific rules and tries to generalize in order to cover as much as positive examples. This process is strengthened [56] by correcting error [57] that show [58] up. This process is done [59] in two [60]

978-1-4577-0751-3/11/$26.00 ©2011 IEEE

steps.[61] First, simple bottom-up generalization is done[62,63] for learning tagging rules. Second, learning correction rules for diminishing the error made by tagging rules.

In the first step, learning tagging rules set, each rule is used for identifying either start or end tag of information fragment. LP2 approach is token classification where start[64] and end fragment[65] are positive[66] example[67] where the rest are negative examples. For each positive example is treated in the following steps. First, create initial[68] rule; second, generalize rule; third, take k-best generalization of rules and throws the rest.

377 The next step is to choose the best generalization. K-best generalizations have (a) better accuracy, (b) cover more positive examples, (c) cover other part[69] of input,[70] and (d) have error rate less than a given treshold.[71] Rules that are not included[72] in this step then added into best[73] rules pool. Instances that already covered by this pool are then removed[74] from positive examples. Once an instance have[75] been covered by the rule,[76] this instance will never be included[77] in the rule induction process. Initial[78] rule set tends to have high precision but low recall. In this phase, recall is improve[79] through learning using contextual rules.

SNoW-IE [12] is Information[80] Extraction System that based[81] on relational[82] learning algorithm. This system identifiyies[83] text fragment completely without separating start[84] tag and end tag. SNoW-IE have[85] token[86], orthographic, POS and[87] semantic features. This algorithm consist[88] of two steps. First, all posible[89] text fragments are filtered. This[90] is for the purpose of separating[91] non relavant[92] [93,94] negative instance[95]. Two criterias[96] are used[97], (a) if there is[98] no general features on positive examples, and (b) the confidence value of the fragment is less then the given treshold[99]. The first step results in high[100] recall, while the second one results in high precision. SNoW-IE is based[101] on relational learning in form[102] of Inductive Logic Programming (ILP). Every fragment candidate is represented[103] by using pre-defined features. Features are extracted[104] from three parts; the fragment itself, preceeding[105] part of the fragment, and after fragment part. On the second step, correct fragments are collected[106] from the rest of fragments[107].

Rapier [2] uses Inductive Logic Programming to discover extraction rules. Rapier does not separating[108] start tag and end tag, but learn to identify complete relevant string. Bottom-up[109] search is done through the most specific for each example and repeatedly trying to generalize to cover more positive examples. Rapier uses token, POS and[110] semantic features. Rapier uses different[111] representation[112] from other systems. It uses template filling, so it does not use tagging in the text. Each template is filled[113] by slot[114] that asscociated[115] to[116] relevan[1 text. This approach does not accomodate[118] slot apearance[119] in the text and[120] it does not tolerate ambigue[121] text. As an example on job advertisement corpus can have template ‘platforms: windows'. This approach prevents the word of[122] ‘windows' in the text for other[123] context other than ‘platforms'[124]. Rapier's algorithm tries to fill the template and[125] it searchs[126] from specific to general.

Rapier learns rules of pre-filler, post-filler and[127] filler. Pre-filler tries to match text before target[128] slot and[129] post-filler tries to macth[130] text after target[131] slot. Every pattern is sequence[132] element that can be matched[133]. Rapier then proceeds to generalize these rules by selecting pairs of rules and generalizing them by getting the least general generalization of each pair of rules. To consider all possible pre- and

postfiller[134] patterns would be prohibitive so[135] Rapier starts generating pre- and post-fillers[136] from the filler outwards. It maintains a list of the k best rules and repeatedly adds generalizations of the pre- and post-filler seed rules, working outward from the filler. The rules are ordered by Information Gain[137] and weighted by the size of the rule, with small rules being preferred[138]. When a rule gives no bad[139] predictions on the training examples[140] it is added to the final rule-base replacing any less general rules that it performs worst.

SRV [6] uses simple features combination (such as world length, kind of character, POS) and relational features (mapping a token to another token, e.g.[14 next-token, subject-verb). Feature values can be sets, e.g.[142] all synonyms and hypernyms (super ordinate[143] concepts) listed by WordNet are combined in a set for each token. Different rule sets are learned[144] for classifying each text fragment as an instance or non-instance of a single attribute value; there is no component for template unification or other post processing[145]. SRV learns top-down, greedily adding predicates of some predefined types: the number of tokens in the fragment (length), whether a condition is matched by one or several (some) or by all (every) tokens in the fragment; position specifies the position of a token in a some[146] predicate, relpos[147] constrains the ordering and distance between two tokens.[148] Rules are validated and[149] their accuracy estimated by three-fold cross validation[150]; the three resulting rule sets are merged[151]. The accuracy estimations are available for each prediction. An advantage of relational learners is their being able to acquire powerful relational rules that cover a larger[152] and more flexible context than most other rule-learning and statistical approaches. The downside is that the large[153] space of possible rules can lead to high training times and[154] there is no guarantee of finding optimal rules (local maxima problem).

The ELIE system [5] uses Support Vector Machines (SVMs) for Begin/End tagging. Highly improved results are reached by augmenting this setup with a second level (L2) of begin/end classifiers. The L2 end classifier focuses on finding suitable end tags for matching left-over begin tags from the first-level (L1) begin classifier, and the L2 begin classifier matches left-over end tags. While the L1 classifiers are trained[155] on a very high number of tokens, almost all of which are negative instances (O), the L2 classifiers only consider the near context of left-over L1 begin/end tags which[156] allows a more focused classification. Hence the L1 classifiers must be tuned to favor precision over recall to avoid producing lots of false positives (spurious extractions) from all over text[157], but the[158] L2 classifiers can be tuned to favor recall over precision since they only classify a very small[159] subset of all the tokens. In this way, by adding the second level[160] the recall of the overall system can be increased[161] without overly hurting the precision.

B. Meta-Learning

Meta-learning learn[162] how learning[163] system can improve its efficiency through experience. The purpose is how to make learning[164] process can be flexible to domain or task that is handled [16]. All learning systems work through adaptation to the specific environment that have implication to partial ordering or bias to the set of all posible hypotheses explaining concept [9].

Meta-learning is different from base-learning in the scope of its adaptation level: Meta-learning studies how to choose

bias dinamically contrast to base learner where bias is a priori or user parameterized [16]. For example on inductive learning scenario (e.g decision tree, SVM, etc) over some data produces a hypothesis that depends on the fixed bias embbeded in the learner. Learning takes place at the base-level and the quality of hypothesis normally improves with an increasing number of examples. Nonetheless, successive applications of the learner over the same data always produces the same hypothesis, independently of performance; no knowledge is extracted across domains or tasks [11]. Meta-learning in this case, aims to discover ways to dynamically search for the best learning strategy as the number of tasks increases [13]. A computer program qualifies as a learning machine if its performance improve with experience [10]. According to [16] experience is knowledge gained from the analysis of several tasks. Meta-learning is focused on the need of learner to adapt continually on several level abstractions. Learning in this case is not on the base level but also across task (meta) level. Several areas of study related to meta-learning are building meta-learner of base-learners [17], selecting inductive bias dynamically [4] building meta-rules matching task properties with algorithm performance [1], inductive transfer [11] and learning to learn [13].

On Building meta learner from base learner, a set of q base learners are applied[190] to a

training

set

:

,

to

produce

q hypotheses,

, also called level-0

generalizers.[191]Meta-learning

takes place when training[192] set

is

redefined into a

new set

. The

redefinition

replaces each vector X with the class predicted by each of the q hypothesis on

X :

X , X , X , ... , X ,[193] ,[194,195]

The new training set serves as input to a set of meta-

learners, which produce a new set of hypotheses.[196]

379 Dynamic selection of bias enables a learning algorithm to shift region[197] of expertise along[198] the tasks. The goal is to change hypothesis[199] space to have better coverage of the task under analysis. During dynamic bias selection, meta-learning is a required component and is often acting as a guideline in the search over the bias space. [4] develop a framework for the study of dynamic bias as a search in three different tiers. In

the first[200] tier, searching over a hypotesis[201] space where a learning algorithm L looks for the best hypothesis approximating the target concept (most learning algorithms assume this space fixed). For dynamic bias selection to take place, a learning algorithm L must search in a second tier, where the strength and size of[202] can be modified separately. Modification of the meta-spaces defined in the second tier is done[203] in the third tier. The problem can arise here is where to stop building more tiers (i.e.[204] more met-meta-spaces).

One important[205] property of meta-learning is to provide guidelines of[206] how to relate a learning algorithm with those domains in which the algorithm performs well. The general approach is through defining a set of domain characteristics or meta-features that relevant to the performance of a learning algorithm; those meta-features enable us to build a meta-

domain relating domain characteristics with algorithm performance (once a sufficient number of domain[207,208] has been

□

analyzed[209]). A set of rules finally can be induced using meta-learner over to discover the conditions under wich[210] a learning algoritm[211] outperforms others.

Learning is not an isolated task that starts from zero every time a new problem domain appears. With experience accumulation, a learning mechanism is expected to perform increasingly better. For learning to improve through time, meta-knowledge must be transferred[212] across domains or tasks. The process is known as inductive tansfer[213] [11]. [14] propose a learning algorithm where domains are clustered[214] when mutually related. A new domain is assigned[215] to the most related cluster; inductive transfer takes place when generalization exploits information about the selected cluster. Further [15] propose a learning algorithm where domains are clustered[216] when mutually related. A new domain is assigned[217] to the most related cluster; inductive transfer takes place when generalization exploits information about the selected cluster.

propose[218] general[219] framework to differenciate[220] between learning at base-level and meta-level. In the base-level simply[221] tries to find the correct hypothesis h on a fixed hypothesis space {H}.

propose[222] Learning Classifier System which[223] is a parallel, message-passing, rule-based system. Each message or rule is a condition-action pair; if a message matches the condition part, the rule is candidate[224] to activate and execute the action part. The system assumes an input interface or set of detectors that translates signal[225] from an external environment into messages.

Meta-Learning and Information Extraction

Meta-learning implementation in Information Extraction is done by [7] This system scheme is depict[226] in Figure 1. In this system, learners are considered[227] as black boxes and[228] only its reliability as a function of modeled confidence is considered[229]. Linear regression and calculated probabilities are used to order all predictions. For each prediction made, a datapoint[230] (x,y) is created[231], where x is the prediction confidence and[232] y is 1[233] if the prediction is correct else 0. The result is a line equation that map[234] from learner confidence to probability of success. Prediction with the highest estimate is chosen[235] as the top prediction. MIL is different[236] form [7] since there is no combiner in it.

Combiner

Regression

Model

Learner A

Learner B

Learner C

Fig 1. Multi-strategy learning scheme for Information Extraction by [7]

METHOD

MIL concept is inspired[237] by the idea[238] how to use document training to look for best[239] classifier for each slot in certain[240,241] domain. The best classifier for each slot is chosen to extract information in testing documents. Process[242] is started by evaluating each classifier through k-fold cross validation[243] on training documents D l[244]. The result of this process is a map connecting each slot to classifier performance rank. The

classifier with best[245] performance for each slot is choosen[246] to extract information[247] form[248] testing[249] document[250] Dt.

Given

Extraction Scenario S where

,

, ... ,

, Base

learner

, ,[251] ... ,

, Performance

Index

PIslot,[252]Learner[253] =

F(slot, Learner, Dl) is performance each learner of L for each slot= on Training Document Dl, (where Dataset D = Dl + Dt ,[254] Dt = Testing Document). Base[255] learner consist[256] of several learners that have significant different[257] in their learning mechanism. To characterize each learner,[258] Performance[259] Index of each learner on each slot is measured. This[260] is done[261] by doing 10-fold cross validation on Training Document Dl. MIL then asociating[263] base -learner with each slot. In

380 this situation, meta -learning[264] is area[265] of expertise search for each learner. The next step is to choose the best learner that will be used to extract information from Testing Document Dt. Multi-Inductive[266] Learning algorithm is shown[267] in Figure 2.

____

/* Multi-Inductive Learning Algorithm

Input : Base Learner L = {L1, L2, ..., Ln}, Extraction

Schenario S where , , ... , ,, Training Documents Dl, Testing Documents D t

where D = Dl + Dt

/* generate Meta-info by k-fold validation test for every learner & slot on

Training Document

Performance Pslot,Learner = P(learner,slot,Dl)

where

/*k-fold cross validation[268] on Dl

/* select best learner for each slot for each slot[269] in S do:

arg max , [270]

/*retrain each learner on each slot on full Learning Document

Extraction Rule Rslot = train (slot, Mslot, Dl)

end for

____

Fig 2. Multi-Inductive Learning Algorithm

Figure 3 shows extraction [271] process algorithm on Testing Document.

/* extraction slot filler on Testing Document Result Å {}

for each slot in E do:

for each document in Dt do :

Extract slot filler (slot, document, Rslot)

/*using best learner to extract doc

Result Å Result + {document,(slot1, filler of slot1), ..., (slotm, filler of slotm)}

end for

end for

return Result

Fig 3. Extraction process algorithm

IV. RESULT AND DISCUSSION

Experiment[272] is conduct using two dataset[273] (dataset Reuters Corporate and dataset Job Posting). Base classifier are[274] PAUM (IND1), SVM (IND2), AODE (IND3), and KNN (IND4). These base classifiers are chosen[275] as they are varied[276] in their approaches. This[277] is to guarantee a variation[278] of bias in MIL. Performance[279] measure in this experiment is F-Measure. As comparison[280,281] several results of other methods that are using the same datasets are displayed.

MIL performance on Dataset Reuters Corporate

Area[282] of expertise test on this dataset is shown[283] in Table 1. It is shown[284] for[285] example, on acqabr[286] slot[287] IND2 learner perform[288] better than the rest. On the contrary, IND1 learner perform[289] better than the rest on slot dlramnt[290].

TABLE I

AREA OF EXPERTISE TEST (10-FOLD CROSS VALIDATION TEST) OF LEARNERS ON DATASET REUTERS CORPORATE ACQUITITION[291]

Slot

,

IND1

IND2

IND3

IND4

acqabr[292]

45,8

51,9

18,9

23,5

acqloc[293]

40,1

44,0

16,2

2,9

acquired

46,9

48,9

26,2

0,0

dlramt[294]

63,4

60,1

28,0

6,3

purchabr[295]

42,4

45,0

35,0

21,8

purchaser

48,9

48,6

37,6

0,2

seller

18,9

21,4

21,3

0,2

sellerabr[296]

16,0

18,0

19,8

8,3

status

52,4

52,2

21,2

10,4

According to this analysis, the best learner that is chosen by MIL to extract information on testing[297] document[298] for slot acqabr[299], acqloc[300], acquired, purchabr[301] and[302] seller is IND2, while for extracting slot dlramt[303], purchaser, and status is IND1 and[304] for extracting slot[305] sellerabr[306] is IND3.

Table 2 shows performance[307] of MIL on testing[308] document[309] for dataset Corporate Acquition[310]. It shows MIL performance is better than other methods on slot acqabr[311], acqloc,acquired[312],[313]

dlramt[314], purchabr[315], purchaser, and status. Average[316] performance of MIL is 46.3% which[317] is higher than Rapier (27.8%), SRV (41.2 %) and[318] ELIE (39.4%). This result is supported[319] by the chosen best learner from IND1 and IND2. IND1 performs best on slot: dlramt[320], purchabr[321], purchaser and[322] status. While IND2 is best on slot acqabr[323], acqloc[324], and acquired.

On slot: seller and sellerabr[325], MIL performance is a little bit lower than SRV but better than RAPIER and ELIE. Generally[326] all methods do not get good[327] result[328] in these slots.

TABLE 2

MULTI-INDUCTIVE LEARNING (MIL) PERFORMANCE ON DATASET REUTERS CORPORATE ACQUITITION

ELIE/L2

Method

Rapier

SRV

(SMO-

MIL

SVM)

Slot

Ref [2]

Ref [6]

Ref [5]

acqabr [329]

26.0

38.1

39.7

57,0

acqloc [330]

24.2

22.3

34.4

46,8

acquired

28.8

38.5

43.5

50,6

dlramt[331]

39.3

61.8

59.0

65,0

purchabr[332]

24.0

48.5

28.7

48,7

purchaser

27.7

45.1

46.2

52,0

seller

15.3

23.4

15.6

22,4

sellerabr [333]

8.6

25.1

13.4

21,0

status

41.3

47.0

49.7

53,4

Average

27.8

41.2

39.4

46,3

MIL performance on Dataset Job Posting

Area[334] of expertise test on this dataset is shown[335] in Table 3. It is shown[336] that IND1 learner is expert[337] on slot application, area, company, country, desired_degree, language, paltform[338], recruiter, req_degree, and salary. While[339] IND2 learner is expert[340] on slot city, desired _years_experience, id, post_date, req_years_experience, state and[341] title.

TABLE 3

AREA OF EXPERTISE TEST (10-FOLD CROSS VALIDATION TEST) OF LEARNERS ON DATASET JOB POSTING

Slot

,

IND1

IND2

IND3

IND4

application

66,7

57,4

19,1

19.7

area

48,6

42,9

7,8

18.5

city

71,1

74,0

49,8

50.0

company

72,5

66,9

30,7

39.3

country

56,4

46,4

51,9

21.4

desired_degree

46,4

45,6

7,6

5.8

desired_years_experience

72,3

80,7

75,9

59.5

id

96,3

96,8

52,0

96.6

language

84,4

75,9

35,9

39.4

platform

74,9

67,5

23,2

22.3

post_date

97,5

97,8

96,9

97.5

recruiter

81,8

80,4

52,6

51.6

req_degree

78,5

70,1

19,0

19.4

req_years_experience

70,7

74,0

56,9

69.8

salary

80,0

78,8

25,6

55.3

state

60,7

61,7

38,3

42.3

title

54,2

56,7

13,6

30.9

Table 4 shows performance[342] of MIL on testing[343] document[344] for dataset Job Posting. It shows MIL performance is better than other methods on slot city, company, desired_degree, platform, recruiter, req_degree, salary, state, and title. This performance is contributed[345] by IND1 which[346] is best on slot application, area, company, country, desired_degree, language, platform, recruiter, req_degree, and salary. While the best learner for slot city, desired_years_experience, id, post_date, req_years_ experience, state and[347] title is IND2. If we compare MIL to other state[348] of the art methods in Information Extraction, the average performance of MIL is 82.1% which[349] is better than RAPIER (75.1 %) ,[350] LP2 (77.2%), and SNOW (78.7%).

TABLE 4

MULTI-INDUCTIVE LEARNING (MIL) PERFORMANCE ON DATASET JOB POSTING

Method

Rapier

LP2

SNOW

MIL

Slot

[2]

[3]

[12]

application

69,3

78,4

60,9

73,9

area

42,4

66,9

51,6

57,3

city

90,4

93,0

89,0

95,5

company

70,0

71,9

75,4

82,0

country

93,2

81,0

95,5

58,8

desired_degree

72,2

65,1

60,9

74,5

desired_years

87,5

60,4

79,0

86,0

_experience

id

97,5

100,0

99,7

99,0

language

80,6

91,0

82,5

88,2

platform

72,5

80,5

74,1

81,9

post_date

99,5

99,5

99,2

99,0

recruiter

68,4

80,6

85,3

87,2

req_degree

81,5

84,7

83,5

85,8

req_years

67,1

68,8

83,9

81,0

_experience

salary

67,4

62,8

72,9

84,1

state

90,2

84,7

91,7

92,5

title

40,5

43,9

52,7

69,0

average

75,1

77,2

78,7

82,1

CONCLUSIONS

Through classification[351] approach, Information extraction can be solved[352] through inductive learning. Nevertheless[353] single[354] classifier approach is not always consistent in performance across domains and slots. Multi-inductive learning is proposed to cope with this problem. By carefully choosing base classifiers, meta-learner in Multi-Inductive Learning can perform better than single[355] classifier approach and other state[356] of the art in Information Extraction.

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1.	~~Ganeca~~ → Geneva	Misspelled Words	Correctness
2.	~~in~~ → on	Confused Words	Correctness
3.	~~in~~ → on	Wrong or Missing Prepositions	Correctness
4.	the alternatives	Determiner Use (a/an/the/this, etc.)	Correctness
5.	~~Conventional~~ → The conventional	Determiner Use (a/an/the/this, etc.)	Correctness
6.	, and	Comma Misuse within Clauses	Correctness
7.	Its portability, scalability and adaptability hamper conventional Natural Language Processing approach	Passive Voice Misuse	Clarity
8.	the solutions	Determiner Use (a/an/the/this, etc.)	Correctness
9.	that there	Inappropriate Colloquialisms	Delivery
10.	~~way~~ → ways	Incorrect Noun Number	Correctness
11.	~~Meta Learning~~ → Meta-Learning	Misspelled Words	Correctness
12.	~~good~~ → excellent	Word Choice	Engagement
13.	paper,	Comma Misuse within Clauses	Correctness
14.	a significant	Determiner Use (a/an/the/this, etc.)	Correctness
15.	*This*	Intricate Text	Clarity
16.	~~bias variance~~ → bias-variance	Misspelled Words	Correctness
17.	cross-validation	Misspelled Words	Correctness
18.	~~document~~ → documents	Incorrect Noun Number	Correctness

19.	the Multi-Inductive	Determiner Use (a/an/the/this, etc.)	Correctness
20.	~~certain~~ → specific, particular	Word Choice	Engagement
21.	the testing, or a testing	Determiner Use (a/an/the/this, etc.)	Correctness
22.	~~other state~~ → another state, other states	Determiner Use (a/an/the/this, etc.)	Correctness
23.	*be extracted*	Passive Voice Misuse	Clarity
24.	the Job	Determiner Use (a/an/the/this, etc.)	Correctness
25.	The average	Determiner Use (a/an/the/this, etc.)	Correctness
26.	~~other state~~ → another state, other states	Determiner Use (a/an/the/this, etc.)	Correctness
27.	*be tested*	Passive Voice Misuse	Clarity
28.	*are extracted*	Passive Voice Misuse	Clarity
29.	~~meta learning~~ → meta-learning	Misspelled Words	Correctness
30.	~~very fast~~ → speedy, swift, breakneck, high-speed	Word Choice	Engagement
31.	to become	Incorrect Verb Forms	Correctness
32.	Retrieval.	Closing Punctuation	Correctness
33.	~~technology~~ → Technology	Improper Formatting	Correctness
34.	~~in~~ → on	Confused Words	Correctness
35.	~~in~~ → on	Wrong or Missing Prepositions	Correctness
36.	the document, or a document	Determiner Use (a/an/the/this,	Correctness

		etc.)	
37.	, or	Punctuation in Compound/Complex Sentences	Correctness
38.	~~researches~~ → types of research, pieces of research, kinds of research	Incorrect Noun Number	Correctness
39.	, which	Punctuation in Compound/Complex Sentences	Correctness
40.	~~a basic~~ → an essential, a primary, a necessary, a fundamental	Word Choice	Engagement
41.	the Information	Determiner Use (a/an/the/this, etc.)	Correctness
42.	*be regarded*	Passive Voice Misuse	Clarity
43.	an information	Determiner Use (a/an/the/this, etc.)	Correctness
44.	~~very useful~~ → beneficial	Word Choice	Engagement
45.	*be approached*	Passive Voice Misuse	Clarity
46.	a classification	Determiner Use (a/an/the/this, etc.)	Correctness
47.	the text	Determiner Use (a/an/the/this, etc.)	Correctness
48.	~~a lot of~~ → many	Inappropriate Colloquialisms	Delivery
49.	order for	Wrong or Missing Prepositions	Correctness
50.	that there	Inappropriate Colloquialisms	Delivery
51.	constantly performs	Misplaced Words or Phrases	Correctness
52.	~~constantly~~ → regularly, consistently,	Word Choice	Engagement

	always		
53.	paper,	Comma Misuse within Clauses	Correctness
54.	the start	Determiner Use (a/an/the/this, etc.)	Correctness
55.	~~start~~ → starts	Faulty Subject-Verb Agreement	Correctness
56.	*is strengthened*	Passive Voice Misuse	Clarity
57.	an error, or the error	Determiner Use (a/an/the/this, etc.)	Correctness
58.	~~show~~ → shows	Faulty Subject-Verb Agreement	Correctness
59.	*is done*	Passive Voice Misuse	Clarity
60.	two.	Closing Punctuation	Correctness
61.	~~steps~~ → Steps	Improper Formatting	Correctness
62.	*is done*	Passive Voice Misuse	Clarity
63.	~~done~~ → made	Incorrect Phrasing	Correctness
64.	the start	Determiner Use (a/an/the/this, etc.)	Correctness
65.	~~fragment~~ → fragments	Incorrect Noun Number	Correctness
66.	a positive	Determiner Use (a/an/the/this, etc.)	Correctness
67.	~~example~~ → examples	Incorrect Noun Number	Correctness
68.	~~initial~~ → fundamental, first	Word Choice	Engagement
69.	~~other part~~ → another part, other parts	Determiner Use (a/an/the/this, etc.)	Correctness
70.	the input	Determiner Use (a/an/the/this,	Correctness

		etc.)	
71.	~~treshold~~ → threshold	Misspelled Words	Correctness
72.	*are not included*	Passive Voice Misuse	Clarity
73.	the best	Determiner Use (a/an/the/this, etc.)	Correctness
74.	*are then removed*	Passive Voice Misuse	Clarity
75.	~~have~~ → has	Faulty Subject-Verb Agreement	Correctness
76.	the rule has covered an instance	Passive Voice Misuse	Clarity
77.	*be included*	Passive Voice Misuse	Clarity
78.	~~Initial~~ → The initial	Determiner Use (a/an/the/this, etc.)	Correctness
79.	~~is improve~~ → is improved, is improving	Incorrect Verb Forms	Correctness
80.	an Information	Determiner Use (a/an/the/this, etc.)	Correctness
81.	~~that~~ based	Determiner Use (a/an/the/this, etc.)	Correctness
82.	a relational	Determiner Use (a/an/the/this, etc.)	Correctness
83.	~~identifiyies~~ → identifies	Misspelled Words	Correctness
84.	the start	Determiner Use (a/an/the/this, etc.)	Correctness
85.	~~have~~ → has	Faulty Subject-Verb Agreement	Correctness
86.	a token, or the token	Determiner Use (a/an/the/this, etc.)	Correctness
87.	, and	Punctuation in	Correctness

		Compound/Complex Sentences	
88.	~~consist~~ → consists	Faulty Subject-Verb Agreement	Correctness
89.	~~posible~~ → possible	Misspelled Words	Correctness
90.	*This*	Intricate Text	Clarity
91.	to separate	Wordy Sentences	Clarity
92.	*non*	Unknown Words	Correctness
93.	~~non relavant~~ → nonrelavant, non-relavant	Misspelled Words	Correctness
94.	~~relavant~~ → relevant	Misspelled Words	Correctness
95.	~~instance~~ → instances	Incorrect Noun Number	Correctness
96.	~~criterias~~ → criteria	Misspelled Words	Correctness
97.	*are used*	Passive Voice Misuse	Clarity
98.	~~is~~ → are	Faulty Subject-Verb Agreement	Correctness
99.	~~treshold~~ → threshold	Misspelled Words	Correctness
100.	the high, or a high	Determiner Use (a/an/the/this, etc.)	Correctness
101.	*is based*	Passive Voice Misuse	Clarity
102.	the form	Determiner Use (a/an/the/this, etc.)	Correctness
103.	*is represented*	Passive Voice Misuse	Clarity
104.	*are extracted*	Passive Voice Misuse	Clarity
105.	~~preceeding~~ → preceding	Misspelled Words	Correctness
106.	*are collected*	Passive Voice Misuse	Clarity

107.	the fragments	Determiner Use (a/an/the/this, etc.)	Correctness
108.	~~separating~~ → separate	Incorrect Verb Forms	Correctness
109.	~~Bottom-up~~ → The bottom-up	Determiner Use (a/an/the/this, etc.)	Correctness
110.	, and	Punctuation in Compound/Complex Sentences	Correctness
111.	a different	Determiner Use (a/an/the/this, etc.)	Correctness
112.	~~representation~~ → representations	Incorrect Noun Number	Correctness
113.	*is filled*	Passive Voice Misuse	Clarity
114.	a slot	Determiner Use (a/an/the/this, etc.)	Correctness
115.	~~asscociated~~ → associated	Misspelled Words	Correctness
116.	~~to~~ → with	Wrong or Missing Prepositions	Correctness
117.	~~relevan~~ → relevant	Misspelled Words	Correctness
118.	~~accomodate~~ → accommodate	Misspelled Words	Correctness
119.	~~apearance~~ → appearance	Misspelled Words	Correctness
120.	, and	Punctuation in Compound/Complex Sentences	Correctness
121.	~~ambigue~~ → ambiguity, ambiguous	Misspelled Words	Correctness
122.	~~of~~	Wrong or Missing Prepositions	Correctness
123.	~~other~~ → another	Determiner Use (a/an/the/this, etc.)	Correctness

124.	~~'.~~ → .'	Misuse of Semicolons, Quotation Marks, etc.	Correctness
125.	, and	Punctuation in Compound/Complex Sentences	Correctness
126.	~~searchs~~ → searches, search	Misspelled Words	Correctness
127.	, and	Punctuation in Compound/Complex Sentences	Correctness
128.	the target	Determiner Use (a/an/the/this, etc.)	Correctness
129.	, and	Punctuation in Compound/Complex Sentences	Correctness
130.	~~macth~~ → match	Misspelled Words	Correctness
131.	the target	Determiner Use (a/an/the/this, etc.)	Correctness
132.	a sequence	Determiner Use (a/an/the/this, etc.)	Correctness
133.	*be matched*	Passive Voice Misuse	Clarity
134.	~~postfiller~~ → postfilter	Misspelled Words	Correctness
135.	, so	Punctuation in Compound/Complex Sentences	Correctness
136.	~~post-fillers~~ → post-filters	Confused Words	Correctness
137.	Information Gain orders the rules	Passive Voice Misuse	Clarity
138.	*being preferred*	Passive Voice Misuse	Clarity
139.	~~bad~~ → wrong	Word Choice	Engagement
140.	examples,	Punctuation in Compound/Complex Sentences	Correctness

141.	e.g.,	Comma Misuse within Clauses	Correctness
142.	e.g.,	Comma Misuse within Clauses	Correctness
143.	~~super ordinate~~ → superordinate	Confused Words	Correctness
144.	*are learned*	Passive Voice Misuse	Clarity
145.	~~post processing~~ → post-processing	Misspelled Words	Correctness
146.	~~a~~ some	Determiner Use (a/an/the/this, etc.)	Correctness
147.	~~relpos~~ → response	Misspelled Words	Correctness
148.	*SRV learns top-down, greedily adding predicates of some predefined types: the number of tokens in the fragment (length), whether a condition is matched by one or several (some) or by all (every) tokens in the fragment; position specifies the position of a token in a some predicate, relpos constrain...*	Hard-to-read text	Clarity
149.	, and	Punctuation in Compound/Complex Sentences	Correctness
150.	cross-validation	Misspelled Words	Correctness
151.	*are merged*	Passive Voice Misuse	Clarity
152.	~~larger~~ → broader	Word Choice	Engagement
153.	~~large~~ → vast, ample	Word Choice	Engagement
154.	, and	Punctuation in Compound/Complex Sentences	Correctness
155.	*are trained*	Passive Voice Misuse	Clarity
156.	, which	Punctuation in Compound/Complex Sentences	Correctness

157.	the text	Determiner Use (a/an/the/this, etc.)	Correctness
158.	~~, but the~~ → . However, the	Hard-to-read text	Clarity
159.	~~a very small~~ → a tiny, a minimal	Word Choice	Engagement
160.	level,	Punctuation in Compound/Complex Sentences	Correctness
161.	*be increased*	Passive Voice Misuse	Clarity
162.	~~learn~~ → learns	Faulty Subject-Verb Agreement	Correctness
163.	the learning	Determiner Use (a/an/the/this, etc.)	Correctness
164.	the learning	Determiner Use (a/an/the/this, etc.)	Correctness
165.	~~have~~ → has	Faulty Subject-Verb Agreement	Correctness
166.	~~have implication to~~ → imply	Wordy Sentences	Clarity
167.	~~posible~~ → possible	Misspelled Words	Correctness
168.	~~bias~~ → Bias	Improper Formatting	Correctness
169.	~~dinamically~~ → dynamically	Misspelled Words	Correctness
170.	the base	Determiner Use (a/an/the/this, etc.)	Correctness
171.	, or	Punctuation in Compound/Complex Sentences	Correctness
172.	*bias dinamically contrast to base learner where bias is a priori or user parameterized [16].*	Incomplete Sentences	Correctness
173.	example,	Punctuation in Compound/Complex Sentences	Correctness

174.	~~e.g~~ → e.g.	Comma Misuse within Clauses	Correctness
175.	etc.	Comma Misuse within Clauses	Correctness
176.	*etc*	Inappropriate Colloquialisms	Delivery
177.	~~embbeded~~ → embedded	Misspelled Words	Correctness
178.	, and	Punctuation in Compound/Complex Sentences	Correctness
179.	the hypothesis	Determiner Use (a/an/the/this, etc.)	Correctness
180.	improves typically	Word Choice	Engagement
181.	*is extracted*	Passive Voice Misuse	Clarity
182.	, in	Punctuation in Compound/Complex Sentences	Correctness
183.	case,	Comma Misuse within Clauses	Correctness
184.	~~improve~~ → improves	Faulty Subject-Verb Agreement	Correctness
185.	],	Punctuation in Compound/Complex Sentences	Correctness
186.	*is focused*	Passive Voice Misuse	Clarity
187.	~~of~~ → for	Wrong or Missing Prepositions	Correctness
188.	, in this case,	Comma Misuse within Clauses	Correctness
189.	the base, or a base	Determiner Use (a/an/the/this, etc.)	Correctness
190.	*are applied*	Passive Voice Misuse	Clarity
191.	~~generalizers~~ → Generalizers	Improper Formatting	Correctness
192.	the training	Determiner Use (a/an/the/this,	Correctness

		etc.)	
193.	~~X,~~ → X,	Improper Formatting	Correctness
194.	X, ,	Punctuation in Compound/Complex Sentences	Correctness
195.	, ,	Comma Misuse within Clauses	Correctness
196.	*learners, which produce a new set of hypotheses.*	Incomplete Sentences	Correctness
197.	the region	Determiner Use (a/an/the/this, etc.)	Correctness
198.	along with	Wrong or Missing Prepositions	Correctness
199.	the hypothesis	Determiner Use (a/an/the/this, etc.)	Correctness
200.	~~the first~~ → The first	Improper Formatting	Correctness
201.	~~hypotesis~~ → hypothesis	Misspelled Words	Correctness
202.	~~of~~	Wrong or Missing Prepositions	Correctness
203.	*is done*	Passive Voice Misuse	Clarity
204.	i.e.,	Comma Misuse within Clauses	Correctness
205.	~~One important~~ → A critical, One crucial	Word Choice	Engagement
206.	~~of~~ → on	Wrong or Missing Prepositions	Correctness
207.	*a sufficient number of domain*	Misuse of Quantifiers	Correctness
208.	the domain, or a domain	Determiner Use (a/an/the/this, etc.)	Correctness
209.	~~analyzed~~ → Analyzed	Improper Formatting	Correctness

210.	~~wich~~ → which	Confused Words	Correctness
211.	~~algoritm~~ → algorithm	Misspelled Words	Correctness
212.	*be transferred*	Passive Voice Misuse	Clarity
213.	~~tansfer~~ → transfer	Misspelled Words	Correctness
214.	*are clustered*	Passive Voice Misuse	Clarity
215.	*is assigned*	Passive Voice Misuse	Clarity
216.	*are clustered*	Passive Voice Misuse	Clarity
217.	*is assigned*	Passive Voice Misuse	Clarity
218.	~~propose~~ → Propose	Improper Formatting	Correctness
219.	a general	Determiner Use (a/an/the/this, etc.)	Correctness
220.	~~differenciate~~ → differentiate	Misspelled Words	Correctness
221.	~~simply~~	Weak or Uncertain Language	Delivery
222.	~~propose~~ → Propose	Improper Formatting	Correctness
223.	, which	Punctuation in Compound/Complex Sentences	Correctness
224.	a candidate	Determiner Use (a/an/the/this, etc.)	Correctness
225.	the signal	Determiner Use (a/an/the/this, etc.)	Correctness
226.	~~is depict~~ → is depicted	Incorrect Verb Forms	Correctness
227.	*are considered*	Passive Voice Misuse	Clarity
228.	, and	Punctuation in	Correctness

		Compound/Complex Sentences	
229.	*is considered*	Passive Voice Misuse	Clarity
230.	~~datapoint~~ → data point	Confused Words	Correctness
231.	*is created*	Passive Voice Misuse	Clarity
232.	, and	Punctuation in Compound/Complex Sentences	Correctness
233.	~~1~~ → one	Improper Formatting	Correctness
234.	~~map~~ → maps	Faulty Subject-Verb Agreement	Correctness
235.	*is chosen*	Passive Voice Misuse	Clarity
236.	a different	Determiner Use (a/an/the/this, etc.)	Correctness
237.	*is inspired*	Passive Voice Misuse	Clarity
238.	idea of	Wrong or Missing Prepositions	Correctness
239.	a best	Determiner Use (a/an/the/this, etc.)	Correctness
240.	a certain	Determiner Use (a/an/the/this, etc.)	Correctness
241.	~~certain~~ → specific, particular, specified	Word Choice	Engagement
242.	The process	Determiner Use (a/an/the/this, etc.)	Correctness
243.	cross-validation	Misspelled Words	Correctness
244.	~~DI~~ → Dl	Confused Words	Correctness
245.	the best	Determiner Use (a/an/the/this, etc.)	Correctness

246.	~~choosen~~ → chosen, choose	Misspelled Words	Correctness
247.	extract information	Improper Formatting	Correctness
248.	information form	Improper Formatting	Correctness
249.	~~form testing~~ → form testing	Improper Formatting	Correctness
250.	testing document	Improper Formatting	Correctness
251.	~~,,~~ → ,,	Improper Formatting	Correctness
252.	~~Plslot~~ → slot, pilot	Misspelled Words	Correctness
253.	, Learner	Improper Formatting	Correctness
254.	~~Dt ,~~ → Dt,	Improper Formatting	Correctness
255.	~~Base~~ → The base	Determiner Use (a/an/the/this, etc.)	Correctness
256.	~~consist~~ → consists	Faulty Subject-Verb Agreement	Correctness
257.	~~different~~ → differences	Confused Words	Correctness
258.	*To characterize each learner*	Misplaced Words or Phrases	Correctness
259.	the Performance	Determiner Use (a/an/the/this, etc.)	Correctness
260.	*This*	Intricate Text	Clarity
261.	*is done*	Passive Voice Misuse	Clarity
262.	cross-validation	Misspelled Words	Correctness
263.	~~ascociating~~ → associating	Misspelled Words	Correctness
264.	~~meta learning~~ → meta-learning	Misspelled Words	Correctness
265.	an area	Determiner Use (a/an/the/this, etc.)	Correctness

266.	The multi-inductive, or A multi-inductive	Determiner Use (a/an/the/this, etc.)	Correctness
267.	*is shown*	Passive Voice Misuse	Clarity
268.	cross-validation	Misspelled Words	Correctness
269.	~~for each slot~~	Misspelled Words	Correctness
270.	~~max ,~~ → max,	Improper Formatting	Correctness
271.	the extraction	Determiner Use (a/an/the/this, etc.)	Correctness
272.	The experiment, or An experiment	Determiner Use (a/an/the/this, etc.)	Correctness
273.	~~dataset~~ → datasets	Incorrect Noun Number	Correctness
274.	~~are~~ → is	Faulty Subject-Verb Agreement	Correctness
275.	*are chosen*	Passive Voice Misuse	Clarity
276.	*are varied*	Passive Voice Misuse	Clarity
277.	*This*	Intricate Text	Clarity
278.	~~variation~~ → variety	Confused Words	Correctness
279.	~~Performance~~ → The performance	Determiner Use (a/an/the/this, etc.)	Correctness
280.	comparison,	Comma Misuse within Clauses	Correctness
281.	a comparison	Determiner Use (a/an/the/this, etc.)	Correctness
282.	~~Area~~ → The area	Determiner Use (a/an/the/this, etc.)	Correctness
283.	*is shown*	Passive Voice Misuse	Clarity

284.	*is shown*	Passive Voice Misuse	Clarity
285.	, for	Comma Misuse within Clauses	Correctness
286.	~~acqabr~~ → Aqaba	Misspelled Words	Correctness
287.	slot,	Comma Misuse within Clauses	Correctness
288.	~~perform~~ → performs	Faulty Subject-Verb Agreement	Correctness
289.	~~perform~~ → performs	Faulty Subject-Verb Agreement	Correctness
290.	~~dlramnt~~ → dormant	Misspelled Words	Correctness
291.	~~ACQUITITION~~ → ACQUISITION	Misspelled Words	Correctness
292.	~~acqabr~~ → Aqaba	Misspelled Words	Correctness
293.	*acqloc*	Unknown Words	Correctness
294.	~~dlramt~~ → dreamt, drama	Misspelled Words	Correctness
295.	~~purchabr~~ → purchase	Misspelled Words	Correctness
296.	*sellerabr*	Unknown Words	Correctness
297.	the testing, or a testing	Determiner Use (a/an/the/this, etc.)	Correctness
298.	~~document~~ → documents	Incorrect Noun Number	Correctness
299.	*acqabr*	Unknown Words	Correctness
300.	*acqloc*	Unknown Words	Correctness
301.	~~purchabr~~ → purchaser, purchase, purchased	Misspelled Words	Correctness
302.	, and	Punctuation in Compound/Complex Sentences	Correctness

303.	*dlramt*	Unknown Words	Correctness
304.	, and	Punctuation in Compound/Complex Sentences	Correctness
305.	slot,	Punctuation in Compound/Complex Sentences	Correctness
306.	*sellerabr*	Unknown Words	Correctness
307.	the performance	Determiner Use (a/an/the/this, etc.)	Correctness
308.	the testing, or a testing	Determiner Use (a/an/the/this, etc.)	Correctness
309.	~~document~~ → documents	Incorrect Noun Number	Correctness
310.	~~Acquition~~ → Acquisition	Misspelled Words	Correctness
311.	*acqabr*	Unknown Words	Correctness
312.	*acqloc*	Unknown Words	Correctness
313.	, acquired	Improper Formatting	Correctness
314.	~~dlramt~~ → dreamt, drama	Misspelled Words	Correctness
315.	~~purchabr~~ → purchase, purchaser	Misspelled Words	Correctness
316.	The average	Determiner Use (a/an/the/this, etc.)	Correctness
317.	, which	Punctuation in Compound/Complex Sentences	Correctness
318.	, and	Punctuation in Compound/Complex Sentences	Correctness
319.	*is supported*	Passive Voice Misuse	Clarity
320.	~~dlramt~~ → drama	Misspelled Words	Correctness

321.	~~purchabr~~ → purchase, purchaser	Misspelled Words	Correctness
322.	, and	Punctuation in Compound/Complex Sentences	Correctness
323.	*acqabr*	Unknown Words	Correctness
324.	*acqloc*	Unknown Words	Correctness
325.	*sellerabr*	Unknown Words	Correctness
326.	Generally,	Comma Misuse within Clauses	Correctness
327.	a good	Determiner Use (a/an/the/this, etc.)	Correctness
328.	~~result~~ → results	Incorrect Noun Number	Correctness
329.	~~acqabr~~ → Aqaba	Misspelled Words	Correctness
330.	*acqloc*	Unknown Words	Correctness
331.	~~dlramt~~ → dreamt, drama	Misspelled Words	Correctness
332.	~~purchabr~~ → purchase	Misspelled Words	Correctness
333.	*sellerabr*	Unknown Words	Correctness
334.	~~Area~~ → The area	Determiner Use (a/an/the/this, etc.)	Correctness
335.	*is shown*	Passive Voice Misuse	Clarity
336.	*is shown*	Passive Voice Misuse	Clarity
337.	an expert	Determiner Use (a/an/the/this, etc.)	Correctness
338.	~~paltform~~ → platform	Misspelled Words	Correctness
339.	~~. While~~ → while	Incomplete Sentences	Correctness

340.	an expert	Determiner Use (a/an/the/this, etc.)	Correctness
341.	, and	Comma Misuse within Clauses	Correctness
342.	the performance	Determiner Use (a/an/the/this, etc.)	Correctness
343.	the testing, or a testing	Determiner Use (a/an/the/this, etc.)	Correctness
344.	~~document~~ → documents	Incorrect Noun Number	Correctness
345.	*is contributed*	Passive Voice Misuse	Clarity
346.	, which	Punctuation in Compound/Complex Sentences	Correctness
347.	, and	Comma Misuse within Clauses	Correctness
348.	~~other state~~ → another state, other states	Determiner Use (a/an/the/this, etc.)	Correctness
349.	, which	Punctuation in Compound/Complex Sentences	Correctness
350.	~~),~~ →),	Improper Formatting	Correctness
351.	the classification	Determiner Use (a/an/the/this, etc.)	Correctness
352.	*be solved*	Passive Voice Misuse	Clarity
353.	Nevertheless,	Comma Misuse within Clauses	Correctness
354.	a single	Determiner Use (a/an/the/this, etc.)	Correctness
355.	a single	Determiner Use (a/an/the/this, etc.)	Correctness
356.	~~other state~~ → another state, other states	Determiner Use (a/an/the/this, etc.)	Correctness

357.	, 2000	Punctuation in Compound/Complex Sentences	Correctness
358.	~~Meta Learning~~ → Meta-Learning	Misspelled Words	Correctness
359.	, 2001	Punctuation in Compound/Complex Sentences	Correctness
360.	the IJCAI-2001	Determiner Use (a/an/the/this, etc.)	Correctness
361.	~~DesJardins~~ → Desjardins	Misspelled Words	Correctness
362.	, and	Punctuation in Compound/Complex Sentences	Correctness
363.	, 2006	Punctuation in Compound/Complex Sentences	Correctness
364.	~~data sheet~~ → datasheet	Confused Words	Correctness
365.	, 1980	Punctuation in Compound/Complex Sentences	Correctness
366.	~~University ,~~ → University,	Improper Formatting	Correctness
367.	, 1997	Punctuation in Compound/Complex Sentences	Correctness
368.	, Inc	Improper Formatting	Correctness
369.	, and	Comma Misuse within Clauses	Correctness
370.	, 1998	Punctuation in Compound/Complex Sentences	Correctness
371.	, and	Punctuation in Compound/Complex Sentences	Correctness
372.	, 1998	Punctuation in Compound/Complex Sentences	Correctness
373.			

	, and	Punctuation in Compound/Complex Sentences	Correctness
374.	, 1998	Punctuation in Compound/Complex Sentences	Correctness
375.	~~Learniing~~ → Learning	Misspelled Words	Correctness
376.	, 1992	Punctuation in Compound/Complex Sentences	Correctness
377.	*The next step is to choose the best*	Docker storage drivers | Docker Documentation https://docs.docker.com/storage/storagedriver/select-storage-driver/	Originality
378.	*over some data produces a hypothesis that depends on the fixed bias*	How our knowledge of mindfulness can improve machine learning https://medium.com/@steve.strates/how-our-knowledge-of-mindfulness-can-improve-machine-learning-4e4a7cca225e	Originality
379.	*Dynamic selection of bias enables a learning algorithm to shift*	How our knowledge of mindfulness can improve machine learning https://medium.com/@steve.strates/how-our-knowledge-of-mindfulness-can-improve-machine-learning-4e4a7cca225e	Originality
380.	*The next step is to choose the best*	Docker storage drivers | Docker Documentation https://docs.docker.com/storage/storagedriver/select-storage-driver/	Originality
381.	*Relational Learning of Pattern-Match Rules for Information Extraction.*	Relational Learning of Pattern-Match Rules for Information ... http://www.dfki.de/~neumann/esslli04/reader/templatelearning/califf98relationalRapier.pdf	Originality
382.	*In Proceedings of the Sixteenth*	A Retrospective on Mutual	Originality

	National Conference on Artificial Intelligence	Bootstrapping	
383.	*36th Annual Meeting of the Association for Computational Linguistics,*	A Retrospective on Mutual Bootstrapping	Originality