NUKL at the NTCIR-15 QA Lab-PoliInfo-2 Task

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ABSTRACT

Our nukl team, which participated in NTCIR-15 QA Lab-PoliInfo-2, has submitted its result on three tasks: dialog summarization, entity linking, and topic detection. This paper describes our three systems and their results.

In dialog summarization, we used the Progressive Ensemble Random Forest (PERF), which we developed at NTCIR-14 QA Lab-PoliInfo. We applied PERF to sentence extraction at NTCIR-14 and also used it for sentence reduction and achieved good performance. In the entity linking task, we applied a simple matching. In the topic detection task, we used a simple rule-based approach and showed that some topics were not described in *Togikai dayori*, which is the official summary of the assembly minutes. Thus, we proposed that another data resource, the Net Report of the Tokyo Metropolitan Assembly, is suitable as the correct answer data for a topic detection task.

TEAM NAME

nukl

SUBTASKS

Dialog Summarization
Entity Linking
Topic Detection

1 INTRODUCTION

NTCIR-15's QA Lab-PoliInfo-2 [2] (Question Answering Lab for Political Information) deals with political information and set four tasks: stance classification, dialog summarization, entity linking, and topic detection. Our team participated in three tasks: dialog summarization, entity linking, and topic detection.

We participated in NTCIR-14's QA Lab-PoliInfo, and during its summarization task we developed a new summarization system: Progressive Ensemble Random Forest (PERF) [4]. Our system achieved good performance, especially in the ROUGE scores evaluation. We applied it to dialog summarization in NTCIR-15's QA Lab-PoliInfo-2. We applied PERF to sentence extraction in NTCIR-14's QA Lab-PoliInfo and also used for sentence reduction.

We applied dictionary-based simple matching to the entity linking task.

We applied a rule-based approach at the topic detection, where we studied the patterns of questions and answers in the minutes.

This paper is organized as follows. In Section 2 we describe our dialog summarization system and its results. Next we describe our results of the entity linking and topic detection tasks in Sections 3 and 4. Finally, Section 5 provides a conclusion.

2 DIALOG SUMMARIZATION

Dialog summarization in NTCIR-15's QA Lab-PoliInfo-2 is an advanced task of the segmentation and summarization tasks in NTCIR-14's QA Lab-PoliInfo. We participated in NTCIR-14 QA Lab-PoliInfo's summarization task and achieved a good result with our new technique: Progressive Ensemble Random Forest [4].

During the dialog summarization task in NTCIR-15's QA Lab-PoliInfo-2, we had to summarize and detect a summarization target paragraph. Since the latter task resembles the segmentation task in NTCIR-14's QA Lab-PoliInfo, we used the technique proposed by Kanasaki et al. [1] for the segmentation task.

Our summarization system consists of three modules: segmentation, sentence extraction, and sentence reduction.

2.1 Segmentation

In this task, we first analyzed the structure of the minutes of the Tokyo Metropolitan Assembly and estimated the range of questions and answers to be summarized for each subtopic. This task resembles the segmentation task in NTCIR-14 QA Lab-PoliInfo. During the segmentation task in NTCIR-14 QA Lab-PoliInfo, the assembly minutes and their summaries were given to the participants who found corresponding original speech from the minutes and answered questions about the positions of the first and last sentences of the found speech. Kanasaki et al. [1] achieved the best performance in the segmentation task and listed the key phrases that effectively segmented the texts as shown in Table 1.

During the dialog summarization task in NTCIR-15's QA Lab-PoliInfo-2, although we could not use the summarized text to estimate summarization source's range, the subtopics and speaker names in the summarized text were available.

We segmented the texts into paragraphs using the key phrases and chose one that contained a subtopic as a summarization candidate. Note that in the case of such a long subtopic as “築地市場移転問題” (Tsukiji market relocation problem), the entire subtopic sometimes is not found in the minutes, even though part of it is: “築地市場” (Tsukiji market) or “移転” (relocation). To solve this problem, we converted both the sentence and subtopic to vectors with BERT and chose the sentence that most closely resembles the topic. After that, we determined the range of the summarization source using heuristic rules, where we assumed that the appearance orders of the subtopics in the summary and the minutes are identical. We call this a rule-based method.

We tried another segmentation scheme, which we called a DP-based method. Instead of using the vector model calculated by BERT, we used a character bigram match. In the case of “築地市場移転問題” (Tsukiji market relocation problem), we searched for sentences that include not only “築地市場移転問題” but also “築地,” “地市,” . . . , and “問題.” Instead of the heuristic rule, we calculated each segmentation score by dynamic programming (DP) and scored each paragraph by considering the bigram matching ratio and the number of sentences in the paragraphs and so on by hand.

2.2 Training Data

In this task, the task organizer provided two types of documents: the assembly minutes that consisted of each assembly member’s speeches and their summaries *Togikai dayori*[1]. These summaries were abstractive; a sentence in the summary might not literally appear in the original minutes. In spite of this, our method is based on sentence extraction methods. Thus, we need training data that consist of positive and negative sentences, where *positive* or *negative* denotes whether the sentence was/wasn’t used for making the summary. We determined which sentences are used for making the summaries as follows.

When given a pair consisting of an assembly member’s speech and its summary, we found the speech sentence that contains the most words in the summary. We label this sentence as positive and the others as negative. Since this summarization task has a length limit, if the positive sentence’s length is shorter than the length limit, we selected the sentence with the second-most summary words. To make the training data more correct, redundancy should be considered; we should account for the overlap of the first positive sentence and the second, but we simply choose the second without considering the degree of overlap.

In this task, we used two kinds of training data: one is identical as in NTCIR-14 QA Lab-PoliInfo made from the data in 2011, and the other is made from the data of both 2011 and 2012 provided in NTCIR-15 QA Lab-PoliInfo-2. The former contains 9,979 sentences, 825 (8.3%) of which are positive, although it includes duplicated sentences and 6,337 unique sentences. The latter contains 10,107 unique sentences, 1,290 (12.7%) of which are positive.

We used the following features: sentence position, sentence length, and the presence of a word. We selected nouns that occur more than once in the summary and are not within the top 20 of the number of occurrences in all the source documents. Thus the numbers of features are different between the two kinds of training data; the former is 926, and the latter is 1,231.

[1] https://www.gikai.metro.tokyo.jp/newsletter/ (in Japanese)

2.3 Sentence Extraction

This task suffers from an imbalanced problem because a summary’s length is excessively shorter than the original assembly member’s speech; that is, the ratio of the positive data is low.

To solve this problem, we developed a new approach called the Progressive Ensemble Random Forest (PERF) at NTCIR-14 QA Lab-PoliInfo [4]. Below we describe PERF, which uses multiple random forest classifiers trained on different-sized data sets step by step.

We prepared the following five random forest classifiers trained on the same positive data with different-sized negative data:

(1) classifiers trained equally on positive and negative data,
(2) classifiers trained on negative data twice the size of the positive data,
(3) classifiers trained on negative data three times the size of the positive data,
(4) classifiers trained on negative data four times the size of the positive data,
(5) classifiers trained on negative data five times the size of the positive data.

Table 2 shows how many sentences each random forest classifier extracted from the source documents of the test data. “ID” indicates the identification number of the target documents, and “$\times$ n” indicates the result of the n-th random forest classifier. ID 111 consists of 45 sentences. The first classifier extracted just one sentence, but the others extracted no sentences. ID 106 consists of 11 sentences, and the first classifier extracted nine sentences, which is too many. In this case, the third classifier, which extracted two sentences, seems better. As can be seen from these results, the most suitable classifier varies from document to document.

Our solution to choosing the classifier is to use all the classifiers step by step, which we call *progressive ensemble*.

First, we use the fifth classifier. If it does not extract any sentences, then we use the fourth classifier. If it also extracts no sentences, then we use the third one. We repeat this process until we obtain a sentence. Note that we use the next classifier if the length of the extracted sentences is ten less than the limit because such extracted sentences are insufficient for summarization. As a result, the length of the extracted sentences may exceed the limit.

2.4 Sentence Reduction

Since the extracted sentences are redundant and sometimes exceed the length limit, we need to reduce them. We analyzed the extracted sentences by CaboCha [3] and selected the important *bunsetsu* segments (hereafter “segments”).

2.4.1 Rule-based Reduction. In NTCIR-14 QA Lab-PoliInfo, we selected important segments by calculating the weights

Table 1: Regular expressions used to find cue phrases [1]

<table>
<tr><th>Pattern</th><th>Regular expressions</th></tr>
<tr><td>Opening</td><td>^まず|^最初に|^初めに|^次に|^次いで|^最後に|^終わりに
|^[一二三四五六七八九十]+点目
|^[^、]+についてで (す|あります|ございます)(が|けれど)
|^終わり (ま|で) す。|^以上で|^ありがとうございま
|他の質問に (ついて|つきまして) は</td></tr>
<tr><td>Closing</td><td>伺い [^、]*ます。|お尋ね [^、]*します|お答えください。
|(見解|所見|答弁) を求め [^、]*ます。
|(いかがで|どうで)(しょうか|すか)。
|.+質問を (終わります|終了します)。</td></tr>
</table>

Table 2: Number of sentences extracted by each classifier

ID	Number of sentences	×1	×2	×3	×4	×5
111	45	1	0	0	0	0
106	11	9	5	2	0	0
19	8	7	3	3	1	0
23	34	3	2	1	0	0
92	13	5	3	1	1	1

based on the frequency of words and handcrafted rules. If a segment contains a noun, its frequency in all the summaries of the training data is used as a weight. The weights of other features, such as the dependency depth and the case information, are adjusted by hand. In particular, we adjusted the weights to improve the ROUGE score between the reduced sentence of a positive sentence in the training data and its corresponding sentence in the summary.

When we reduce an extracted sentence, we first take the last segment. Next we choose the segment with the highest importance score, where we also choose the other segments on the path between the segment with the highest importance score and the last segment to avoid creating ungrammatical sentences. We add subsequent segments unless the sentence length exceeds the limit.

2.4.2 PERF Reduction. In NTCIR-15 QA Lab-PoliInfo-2, we applied PERF to select important segments.

In creating a training data set, we aligned a sentence in the summary to its original speech sentence by bigram matching. We calculated the percentage of bigram matching between a summary sentence and a candidate speech sentence and chose the one with the highest percentage. Nevertheless, we did not add a sentence whose highest percentage is less than 50%. We collected 925 sentences from 1,290 summary sentences and created our training data. We analyzed each sentence into segments by CaboCha [3] and determined the features shown in Table 3 for each segment.

For sentence extraction, we made five random forest classifiers trained on different-sized negative data, where the ratio of the positive data was about 10%. On the other hand, the ratio of the positive data for the sentence reduction was about 40%. We constructed only two random forest classifiers for the sentence reduction, where the ratios between the positive and negative data were one to one and one to two.

We chose segments from an input speech sentence by the second classifier, but we used the first classifier if the result was empty. To avoid creating ungrammatical sentences, we also chose the last segment and the segment on the path between the chosen segment and the last segment. If the length of the created sentence exceeds the length limit, we removed the first segment from the candidates until the limit is met.

2.4.3 Last Segment Reduction. Although both our sentence reduction methods always select the last segment, this last segment is sometimes redundant. Thus, we introduced a replacement process for preprocessing that simply replaces the end of the sentence, as shown in Table 4.

2.5 Evaluation

The task organizer (TO) team submitted the baseline of this task. Our methods are extensions of those of the TO team. Table 5 shows each approach and the results, where the first row ID 148 is the TO team's results.

2.5.1 Evaluation of Dialog Summarization. First, we increased the training data (Section 2.2), and its result is indicated at ID 161. Unfortunately, its ROUGE score decreased, probably due to the randomness of learning. Thus we trained the model again and fixed some bugs, and its result is indicated at ID 187. Although the score outperformed ID 161, it is worse than the baseline. Even though the score is worse than the baseline, we used the new training data in other experiments.

Next we changed the segmentation method into the DP-based model (Section 2.1), and its result is indicated at ID 172. Since our method using dynamic programming did not achieve good results, we used the rule-based method in other experiments.

Finally, we changed the sentence reduction method into the PERF reduction method (Section 2.4.2), which exceeded the baseline.

Table 3: Features used for sentence reduction by PERF

segment position from beginning of sentence
segment position from end of sentence
segment relative position
dependency depth
case information
number of occurrences of first content word in all summaries
number of occurrences of first content word in all speeches
ratio of above two values
number of occurrences of second content word in all summaries
number of occurrences of second content word in all speeches
ratio of above two values

Table 4: String replacement as preprocessing

Target string	Replaced string
(伺い)?(、)?(私の)?質問を終わります。	。
てまいります。	ていく。
でまいります。	でいく。
ております。	ている。
でおります。	でいる。
でございます。	です。
であります。	です。
いたします。	する。
お伺いする。	。
伺います。	。
と思 (います |っている)。	。

2.5.2 Evaluation of Sentence Reduction. Since we exceeded the baseline score by applying PERF to the sentence reduction, we compared the reduced sentences by PERF with those by the rule-based method as shown in Table 6.

The rule-based reduction method sometimes drops the object. For example, the object "役割" was lost in ID 17 since adjusting the weight of case information by hand is complicated. By contrast, the PERF reduction method retained the object.

The rule-based reduction method gives lower scores as the dependency deepens, and when CaboCha analyzes a series of nouns, each noun generally depends on the next one. Thus the listed nouns are sometimes lost, as shown in the case of ID 33. By contrast, the PERF reduction method kept the nouns.

3 ENTITY LINKING

At NTCIR-15 QA Lab-PoliInfo-2, we were required by the entity linking task to assign a unique identity of a "law name" and make a link to a Wikipedia entry.

Table 7 shows our results. We constructed a list of the names of Japanese statutes from the Japanese Law Index[2]. We extracted names from the assembly minutes by the longest match using the list. We also extracted the law name followed by "案" (draft). Our first submitted result, ID 190, did not make a link to a Wikipedia entry. After the formal run, we made a link to a Wikipedia entry by an exact match by deleting "案" (draft) from the extracted law name, when such matches were found. This is shown in Table 7 as ID 225. Since our method is too simple, we did not achieve a high score in this task.

[2] http://hourei.ndl.go.jp/

4 TOPIC DETECTION

For the topic detection task, a list of argument topics is made from the newsflashes of assembly minutes. We used a rule-based approach for this task.

4.1 Topic Definition

Since no correct answer data or topic definition are provided in this task, each participant defines a topic. One idea is to consider the subtopics to be correct in the summary of the assembly minutes, which we used in the dialog summarization task (Section 2). However, such a summary does not include several topics. Thus, since we did not strictly define a topic, we selected topic candidates for discussion.

4.2 Extraction Rules

Our main idea is that questioners and answerers can use boilerplate to refer to topics. Thus, we can extract topics from questions and answers by rule-based pattern matching.

Table 8 shows our extraction rules for questions and answers. The important keyword is "について" (about), which follows the topic in the speeches. However, since this word sometimes follows other phrases, we added additional words for question patterns after it, including "伺う" (ask), "質問" (question), "見解" (opinion), "答弁" (response), "いかが" (how), and "知事" (governor).

The other problem is how to identify the start of a topic. Since we believe that a topic begins from the start of the sentence or after a comma, our extracted topics do not include commas.

In the case of answers, there are many variations for referring to topics. We only used three particles in the extraction rules: "で," "は," "の," and one verb, "お答え" (answer).

Table 5: Results of our dialog summarization

ID*	Team name	Segmentation	Training data	Sentence reduction	ROUGE
148	TO	rule-based	PoliInfo	Rule	0.2436
161	nukl	rule-based	PoliInfo-2	Rule	0.2274
172	nukl	DP-based	PoliInfo-2	Rule	0.2198
187	nukl	rule-based	PoliInfo-2	Rule	0.2387
216	nukl	rule-based	PoliInfo-2	PERF	**0.2581**

*ID is identical as the leader board on the PoliInfo-2 web site (https://poliinfo2.net/).

Table 6: Comparison of sentence reduction methods

ID	Method	Shortened sentences
17	Rule	果たすとともに、こうした施策展開を支え得る堅実な財政運営を行っていくべきと考えますが、知事に所見を。
	PERF	役割を確実に果たすとともに、施策展開を支え得る堅実な財政運営を行っていくべきと考えますが、所見を。
33	Rule	ことを提案するものですが、いかがですか、職員などの増員を実施することを求めるものです。
	PERF	教員や消防士、救急隊員の採用、環境、福祉、介護分野の職員などの増員を実施することを求めるものです。

Table 7: Results of entity linking

ID	Team name	F-score
190	nukl	0.2375
225	nukl	0.3813

4.3 Experimental Result

Tables 9 and 10 show the extracted topics from the questions and answers of two assembly members. The *Togikai dayori* column indicates the topics in the summary. We discuss the Net report column in Section 4.4. For Nakamura in Table 9, there were three topics in the summary. Our method detected one from the questions and two from the answers. However, he also discussed "ロスジェネ対策" (measures for 'lost generation'), although it was ignored in the summary.

For Izumi in Table 10, our method only detected one topic from her questions because her speeches did not fit our extraction rules. Our method detected topics in the summary from answers and other topics since our extraction rules for answers are less restricted than those for questions. We should unify some of them, for example, "羽田新飛行経路における着陸時の進入角度の引き上げ" (Raising the landing approach angle of Haneda's new flight routes), "羽田新飛行経路の運航" (Operation of Haneda's new flight routes), and "羽田新飛行経路の実施" (Implementation of Haneda's new flight routes) should be combined into "羽田の新飛行経路" (Haneda's new flight routes).

4.4 Discussion

Although we did not define topics, we extracted some topic candidates. Other teams, which have different definitions for topics, extracted other types of topics.

Now we address exactly what a topic is. Topics may form a hierarchy, for example, "羽田の新飛行経路" (Haneda's new flight route). Since a topic might have subtopics, as shown above, defining a topic is complicated.

Answerers often start their speech with a boilerplate utterance: "n 点のご質問にお答えいたします" (I will answer n questions). We focus on it. This utterance indicates that the answerer recognizes the number of questions to which he/she should respond. When we assume that one question has one topic, we can define the number of basic topics as the number of questions. We can create a higher-level topic by applying a clustering method to the basic topics. One purpose of topic detection is to identify all the topics being discussed in the assembly. Thus, all the basic topics must be collected, and capturing the number of questions is useful.

The Tokyo Metropolitan Assembly publishes a website called the "Net Report of the Assembly"[3]. These reports have a one-to-one correspondence between questions and answers, and some question and answer pairs are divided by higher-level topics. Thus, we can use such net reports as correct data for topic detection.

The Net report column in Tables 9 and 10 indicates the higher-level topics from the Net Report. The number in parentheses is the number of question/answer pairs on the topic. *Togikai dayori* and Net Report have different numbers of topics; the latter has more topics. Since the number of topics extracted by our method is almost the same as that of the sentences in each topic of the Net Report, our method extracted the basic topics from the assembly minutes.

Notice that we arranged the topics in Tables 9 and 10 by hand, suggesting that the first step of topic detection is to align a question to its answer since they are separated in the assembly minutes.

5 CONCLUSIONS

This paper described our three tasks in NTCIR-15 QA Lab-PoliInfo-2. For the dialog summarization task, we used a Progressive Ensemble Random Forest, which we proposed in NTCIR-14 QA Lab-PoliInfo, for sentence reduction and

[3]https://www.gikai.metro.tokyo.jp/netreport/ (in Japanese)

Table 8: Extraction rules for questions

<table>
<tr><th>Pattern</th><th>Regular expressions</th></tr>
<tr><td>Question</td><td>(、|^)(?P<topic>[^、]*?) について (です|伺い|お伺い|お尋ね|尋ね|お答|質問|見解|所見|答弁|いかがで|どうで|知事)</td></tr>
<tr><td>Answer</td><td>(、|^)(?P<topic>[^、]*?) について (で|の|は|お答え)</td></tr>
</table>

Table 9: Extracted topics from Nakamura's questions and their answers

中村ひろし（立憲・民主）(Hiroshi Nakamura, DP-CDP)

Togikai dayori	Net report	From questions	From answers
		都政の諸課題	
新型コロナウイルス感染症対策	新型コロナウイルス感染症対策 (6)	**新型コロナウイルス感染症対策**	
		非常時における働く人の安全確保	非常時における働き手の安全確保
		多くの都民が心配しているオリンピックの開催	大会の開催に向けた取り組み
			都内で実施されますイベントの取り扱い
			東京マラソン二〇二〇の対応
	都政運営 (2)	都政運営	
		ロスジェネ対策	就職氷河期世代に対する就労支援
			財政収支の長期推計
介護と仕事の両立	高齢者施策 (3)	高齢者施策	**介護と仕事の両立**
		知事の選挙公約である介護離職ゼロの実現	
		介護人材確保	
		シルバーパス	
	知事の政治姿勢 (5)	知事の政治姿勢	昨年十一月の昼食勉強会
			昼食勉強会の参加団体
IR		いわゆるカジノの誘致	**IR**
		カジノ関連企業との関係の有無など	
			非核都市宣言

improved performance. For the entity linking task, we applied a simple matching technique. For topic detection, we used a rule-based approach and discussed how to define a topic. "Net Report of the Assembly" is a useful resource in a topic detection.

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Table 10: Extracted topics from Izumi's questions and answers

和泉なおみ（共産党）(Naomi Izumi, JCP)

Togikai dayori	Net report	From questions	From answers
新型コロナ肺炎	新型コロナ肺炎への対応 (9)		新型コロナウイルス感染症の現状
			高齢者施設での感染対策
			新型コロナウイルスに児童生徒や教職員が感染した場合における学校の対応
			国への働きかけ
			新型コロナウイルス感染症の検査体制
			検査を行う職員の専門性確保
			医師向けの情報提供
			新型コロナウイルスに関連いたしました肺炎への対応
介護基盤整備	高齢者福祉 (4)		**介護基盤整備**
			特別養護老人ホームの整備
			介護と仕事の両立
			介護職員の処遇改善
国民健康保険	国民健康保険 (1)		国民健康保険におけます子供の均等割保険料
	都民生活への支援 (5)		
			経済情勢
			経済政策
			労働者の処遇に関する調査
公契約条例			公契約条例の必要性
	待機児童対策 (2)		待機児童対策
			保育サービスの拡充
	子ども・子育て支援 (3)		子供食堂
			学校給食における必要な栄養確保や食育
私立高校の授業料負担軽減	私立高校生の保護者負担軽減 (1)		私立高校生の保護者負担軽減
子供の意見表明権	子どもの権利 (2)		**子供の意見表明権**
			子供の権利
	教育施策 (5)		学力テストの目的
			未来の東京戦略ビジョンにおける政策目標
			学力調査に関する政策目標
			小中学校の三十五人学級の状況
			小中学校全学年での三十五人学級の実施
都立・公社病院	都立病院・公社病院の独立行政法人化等 (5)		都立病院への一般会計からの繰り入れ
			地方独立行政法人化の目的
			地方独立行政法人での料金設定等
			地方独立行政法人化の意思決定
			公的医療機関等に関する分析結果

Table 10: Extracted topics from Izumi's questions and answers (cont.)

和泉なおみ（共産党）(Naomi Izumi, JCP)

Togikai dayori	Net report	From questions	From answers
羽田新飛行ルート	羽田新飛行ルート (4)		羽田の新飛行経路
			羽田新飛行経路における着陸時の進入角度の引き上げ
			羽田新飛行経路の運航
			羽田新飛行経路の実施
IR	カジノ誘致 (4)		**IR**
			今年度も依存症対策など
			IR の委託調査
			IR に関する世論
	都市政策 (6)		文化的価値
			神宮外苑のまちづくりへの意見等
			神宮外苑地区のスポーツクラスター
			首都高日本橋地下化に伴う大型車の交通機能確保策
			都市再生
			日本橋周辺の再開発
	気候変動対策 (3)		ゼロエミッション東京戦略
			二〇三〇年に向けた温室効果ガスの排出削減目標
			二〇三〇年目標の実現に向けた取り組み
	防災対策 (6)		河川の水害対策
京成本線荒川橋梁			京成本線の荒川橋梁かけかえ
			京成本線の荒川橋梁部周辺における堤防強化に対する都の対応
			地域の防火防災功労賞
			防災対策における地域コミュニティの役割
		住宅耐震化	住宅の耐震化
オリ・パラ大会	東京オリ・パラ大会 (8)		大会に関する経費の縮減と透明化
			大会を契機に都が取り組む大会関連経費
			大会経費
			組織委員会の情報公開
			大会後の組織委員会の文書の検証
			組織委員会の文書の保存期間
			清算人
			平和の祭典に向けた取り組み
			東京二〇二〇大会期間中の第五福竜丸展示館
	横田基地 (1)		横田基地周辺における PFOS など有機フッ素化合物の検出
			PFOS 等
	再質問 (4)		
			料金設定
			決裁手続
			羽田空港の機能強化に係ります進入角度や落下物対策
			住宅の耐震化