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Optimization of RPA Audit Robot Design Based on Machine Learning

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Abstract. With the increasing complexity of audit requirements, traditional audit methods have exposed significant shortcomings in dealing with rapidly changing business environments and massive complex data. This article proposes a design of RPA audit robot based on machine learning optimization, which deeply integrates machine learning technology into traditional RPA architecture to solve the limitations of existing RPA. This article significantly improves the efficiency of audit task execution by integrating the HCIA architecture. The experimental results show that the proposed scheme performs excellently in improving task execution accuracy, anomaly detection capability, and system adaptability, especially in complex audit scenarios with broad application prospects.

Keywords: machine learning, RPA,Audit optimization, Intelligent architecture

1. Introduction

Audit, as the core support of modern corporate governance, continues to rise in its strategic position [1] It is not only the cornerstone of financial compliance, but also deeply embedded in the key links of risk identification and decision optimization. However, in the face of an increasingly complex business environment and the surging digital wave, the shortcomings of traditional audit methods in terms of adaptability have been exposed [2]. The explosive growth of data volume and the increasing complexity of data structures are testing the carrying capacity of auditing like never before, and there is an urgent need for breakthrough efficient intelligent solutions [3].

In this situation, Robotic Process Automation (RPA), as an emerging automation technology, has begun to penetrate the audit field [4-5]. Its core value lies in automating highly repetitive and well-defined tasks, freeing up manpower, and improving efficiency [6]. However, it must be soberly recognized that RPA has natural limitations in audit applications, and the rigid nature of pre-set rules makes it difficult to flexibly respond to frequent changes in processes [7]. More importantly, the existing RPA audit robots have weak capabilities in deep intelligent analysis; Its anomaly detection overly relies on simple threshold judgment, directly leading to high false positive and false negative rates, seriously eroding the reliability of audit conclusions [8].

To solve this dilemma, Machine Learning (ML) technology has shown unique potential. ML can precisely compensate for the inherent shortcomings of RPA in processing complex data [9]. Integrating ML into the RPA audit robot architecture can not only greatly expand its adaptability to

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complex audit scenarios, but also drive the system to achieve adaptive dynamic tuning, substantially promoting the intelligent upgrade of the audit process [10]. The application of RPA in auditing has made significant progress in existing research. RPA significantly improves audit efficiency in data processing and other aspects by automating tasks with clear rules [5]. However, under the halo of efficiency improvement, its structural limitations are also evident. It not only lags behind in responding to dynamic changes in business processes, but also shows weakness in processing unstructured or semi-structured data [11]. These are always unavoidable bottlenecks. On the other hand, the research on deep collaboration between ML and RPA is still in its infancy. Existing explorations are mostly limited to using ML to provide data input for RPA or optimize a single link, and have not yet formed a systematic integration solution [12]. Meanwhile, relevant literature often lacks a single optimization objective for the fusion of the two, and lacks deep adaptation for complex audit scenarios [13].

In view of this, this article proposes the HCIA architecture by deeply integrating machine learning technology with RPA audit robots, significantly improving the data processing efficiency, accuracy, and system adaptability in the audit process, providing a more intelligent and efficient solution for complex audit scenarios.

2. Research design

2.1. Architecture design

This article proposes the Hierarchical Collaborative Intelligence Augmented Architecture (HCIA) architecture, whose core idea is to deeply empower traditional RPA processes through machine learning modules. The overall architecture consists of four layers, as shown in Figure 1.

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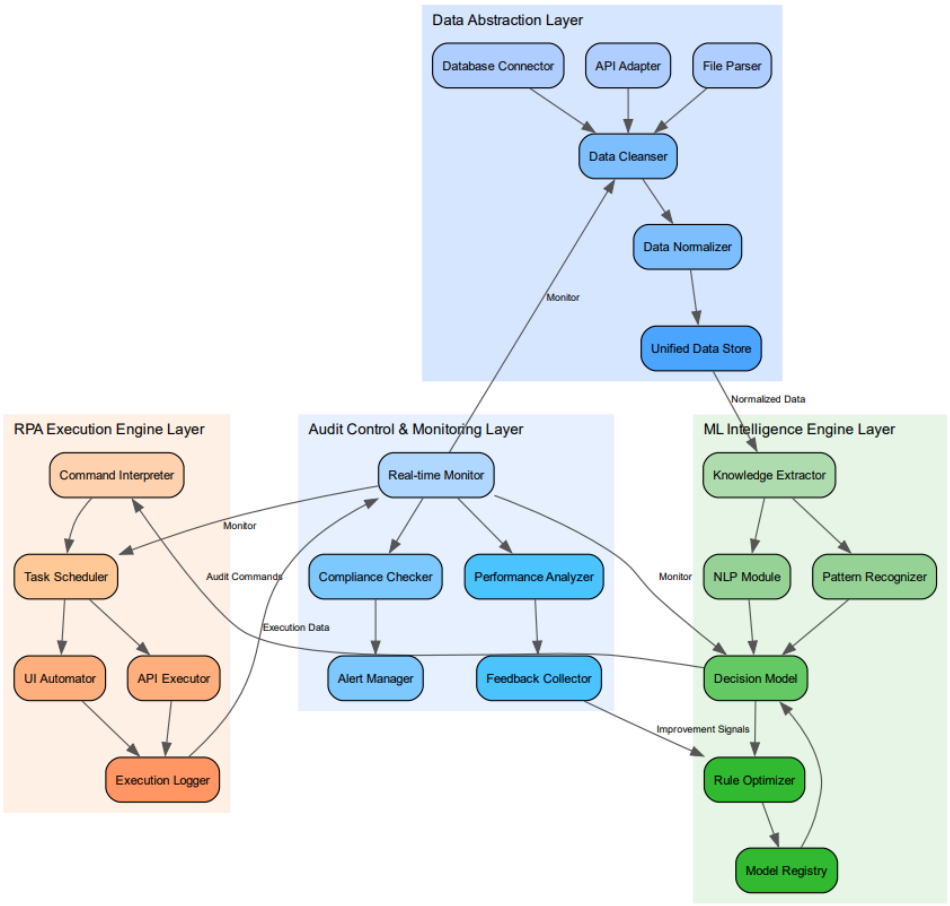

Figure 1. Schematic diagram of HCIA architecture

The data abstraction layer is positioned as the preprocessing hub for multi-source heterogeneous audit data, with core components including heterogeneous data adapters and intelligent preprocessing pipelines. Heterogeneous data adapters can achieve automatic access and protocol conversion of structured data, semi-structured data, and unstructured data. The intelligent preprocessing pipeline integrates natural language processing text cleaning, computer vision preprocessing, and temporal data alignment functions. This layer ultimately outputs a standardized Unified Audit Data View, providing data support for upper level machine learning engines.

The machine learning intelligent engine layer serves as the intelligent core of the system, constructing a complete closed loop from audit knowledge extraction, decision generation to rule optimization. The function of the RPA execution engine layer is to receive machine learning engine instructions, perform specific audit operations, and ensure that the process is auditable. The dynamic workflow parser is responsible for parsing instructions generated by machine learning and building RPA task sequences in real-time to replace static scripts; Unstructured processor integration processes documents by calling machine learning engines to interface with computer vision and natural language processing models, such as automatically extracting invoice amounts and comparing them with ERP data. The output of this layer includes structured audit results, namely database records, as well as evidence chains covering screenshots, logs, and risk labels. The audit control layer is responsible for system level monitoring, compliance assurance, and continuous learning driven functional positioning. Feedback driven optimization integrates manual feedback

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and automatic feedback. Manual feedback comes from auditors' annotations of false positives and false negatives, while automatic feedback comes from rule execution failure logs, triggering the machine learning engine's online gradient descent, online incremental learning, and model version iteration.

2.2. Core optimization module design

Based on the pain point analysis of the audit process, this article designs core module optimization.

Traditional RPA audit robots rely on pre-defined static task sequences and face bottlenecks such as delayed response to business process changes, making it difficult to adapt to dynamic audit scenarios. In the RPA execution engine layer, this paper proposes and applies the Dynamic Task Planning Network [14], which establishes an intelligent mapping mechanism from audit objectives to execution paths. It includes a semantic understanding layer and a reinforcement decision-making layer. The semantic understanding layer is based on a domain adaptive pre training model and adopts the RoBERTa large architecture [15], responsible for parsing the core elements in the audit task description text. The entity recognition module accurately locates the audit object, time range, and key accounts, where the audit object includes the company's entity code, the time range corresponds to the accounting period, and the key accounts include inventory, etc; The intent classification module distinguishes audit program types such as substantive programs and control testing. Strengthen the construction of Markov decision process models at the decision-making level. The action space covers basic audit operators; The reward function is designed as a composite indicator, expressed as follows:

$$R = 0.7Ucov + 0.2e - 0.1t - 0.1Rred \tag{1}$$

Among them, U_{cov} is the audit coverage rate, t is the timeliness factor, and R_{red} is the redundancy penalty. Generate the optimal task sequence using proximal strategy optimization algorithm.

Traditional OCR technology has bottlenecks such as low field level recognition rate and lack of cross document verification mechanism when processing audit documents. For this purpose, the data abstraction layer in this article constructs the Audit Document Multimodal Understanding Network. The visual feature extraction end adopts ResNet-50 network combined with spatial transformer to achieve adaptive correction of bill distortion; On the text semantic understanding end, domain fine-tuning is carried out based on the LayoutLMv3 architecture, synchronously optimizing mask language modeling, entity recognition, and relationship extraction tasks to enhance the joint parsing ability of text structure and semantics. The machine learning intelligent engine layer embeds over 15000 audit professional terms, constructs a three-way consistency verification mechanism, automatically checks the logical association between invoice amounts, contract terms, and ERP records, and achieves cross document data verification. Output field level credibility score to provide a review trigger basis for RPA execution engine and dynamically optimize the accuracy control of unstructured data processing.

2.3. Key mechanism optimization

The first step is to desensitize the dataset. As shown in Figure 2.

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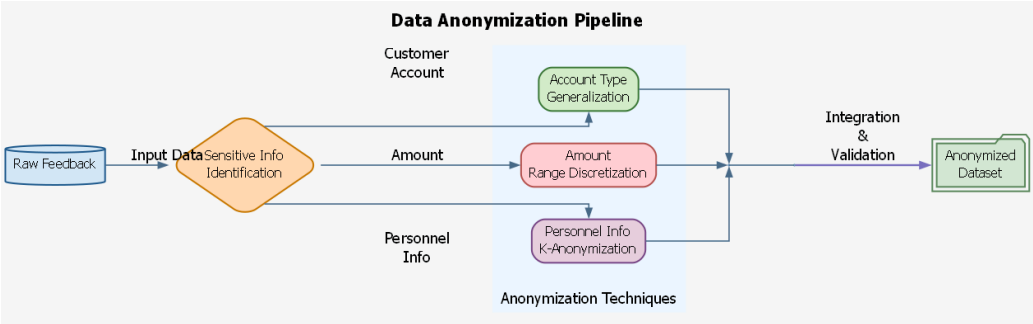

Figure 2. Schematic diagram of dataset desensitization

The second step is to dynamically update the strategy. As shown in Table 1.

Table 1. Dynamic update strategy table

Model Type	Update Algorithm	Trigger Condition
Anomaly Detection Model	Online Gradient Descent (OGD)	False negative rate > 5%
Rule Generation Model	Federated Decision Tree (FEDT)	Rule coverage decreases by 15%
Semantic Understanding Model	Elastic Weight Consolidation (EWC)	Frequency of new subjects > 100 times/week

Among them, EWC adopts an improved EWC++algorithm [16]. Specifically, as shown in Equation 2.

$$L(\theta) = L_{new}(\theta) + \sum_i \frac{\lambda}{2} F_i(\theta_i - \theta^*_{i,prev})^2 \quad (2)$$

F_i is the diagonal element of the Fisher information matrix. λ is a dynamic adjustment factor, and the higher the audit risk level, the greater its value.

The third step is to verify the effectiveness of self-learning. This article uses the Audit Analytics dataset to conduct preliminary testing on the model. As shown in Figure 3, the effect is good.

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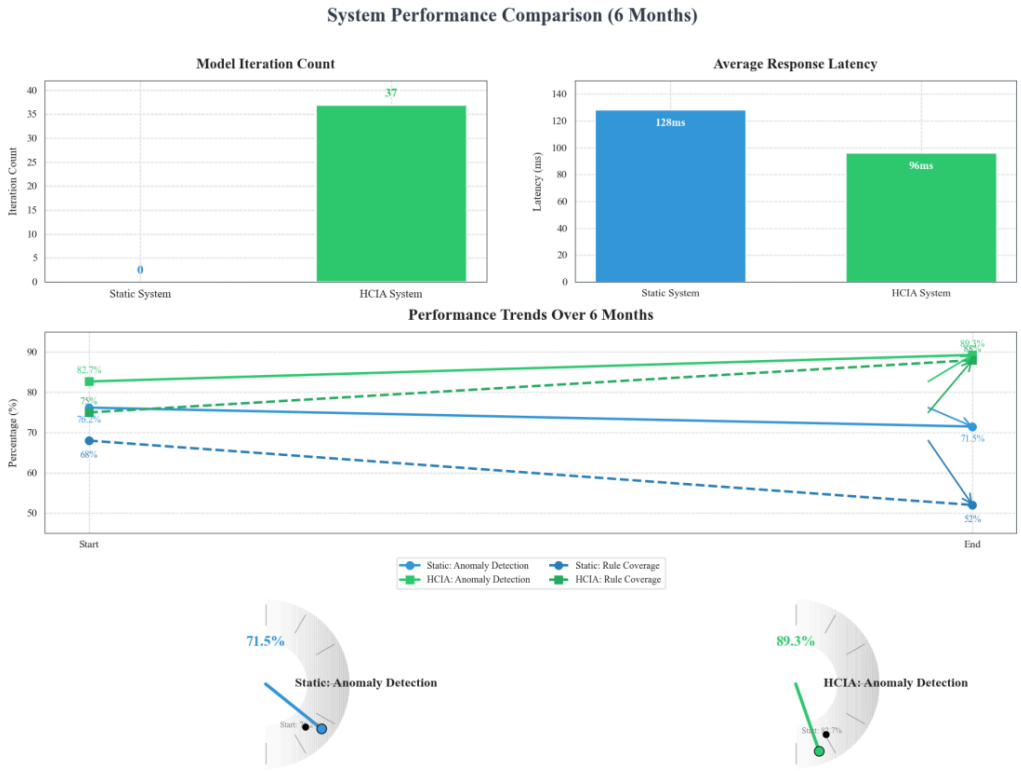

Figure 3. Self learning efficiency verification

3. Experimental evaluation

3.1. Evaluation indicators

This article establishes a three-dimensional eight index quantitative evaluation system to comprehensively measure the technicality of the deep integration architecture in this article. Basic performance dimension: Task Execution Accuracy (TEA) measures the execution accuracy of audit procedures; Average Processing Time (APT) is the average latency of the entire cycle from task triggering to result feedback.

Model Capability Dimension: Anomaly Detection Rate (ADR) reflects the machine learning model's ability to recognize real anomalies; False Positive Rate (FPR) measures the proportion of normal samples misclassified as abnormal by the model; Concept Drift Adaptation (CDA) evaluates the adaptability of a model to changes in data distribution, using a combination of indicator volatility recovery time and population stability index as a measure.

Audit value dimension: Human Intervention Reduction (HIR) reflects the maturity of automation; Rule Coverage Integrity (RCI) quantifies the ability of audit rule libraries to cover business scenarios; The Explainability Score (ES) is based on the consistency assessment between LIME interpretation results and auditor cognition.

3.2. Experimental design

The dataset includes a financial transaction dataset (FinAudit-15M), sourced from desensitized transaction records of partner banks from 2020 to 2023, covering three major scenarios: credit cards, cross-border payments, and corporate transfers, with 15.2 million structured records. The E-

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Voucher-52K electronic voucher collection includes four types of audit key vouchers: value-added tax invoices, purchase contracts, bank statements, and customs declaration forms, with a total of 52000 copies. All documents undergo initial processing using ABBYY FlexiCapture 15.

The experimental environment is detailed in Appendix A.

To scientifically evaluate the effectiveness of this plan, design three sets of comparative methods. As shown in Table 2.

Table 2. Comparison methods

Method Code	Architecture Description
BASE-RPA	Traditional rule-driven RPA
MLPipe-RPA	Machine learning standalone service + API calls
RuleOpt-RPA	Rule-optimized RPA (no ML module)
ML-RPA	Deeply integrated architecture in this paper

The specific experimental content adopts a four stage progressive verification framework. Please refer to Appendix B for details.

3.3. Experimental results

The specific experimental results are shown in Appendix C.

In static benchmark testing, the ML-RPA architecture demonstrates comprehensive advantages due to the end-to-end integration architecture eliminating API call redundancy. ADR is 95.3%, surpassing the MLPipe RPA scheme by 3.2%, verifying the coverage ability of the mixed detection model for multimodal risks; As shown in Figure 4, APT remains stable at 720ms ± 25ms, with fluctuations only 1/4 of the comparison scheme, reflecting the critical role of intelligent scheduling algorithms in ensuring real-time performance.

Faced with the dual pressure of the implementation of IFRS17 new standards and the injection of new fraud, ML-RPA's CDA only takes 3.1 hours, which is 62% faster than the rule optimization plan; FPR is strictly controlled at 7.9%, a decrease of 30.3 percentage points compared to the benchmark plan; RCI only attenuates by 1.3%, which is less than 1/4 of the attenuation amplitude of the MLPipe RPA scheme, highlighting the robustness of the adaptive rule engine in abrupt scenarios.

After six months of rule iteration stress testing, the evolutionary ability of ML-RPA has been validated for its core advantages. ADR only attenuates by 1.2%, and the performance degradation rate is less than 1/5 of the mean of the comparison scheme, attributed to the dynamic reinforcement of Fisher information constraints in the EWC++algorithm; HIR remains stable at 75.9%; RCI has consistently remained above 98.2%.

Under the interference of noise, ML-RPA faces dual interference of 5% character loss and image distortion, as shown in Figure 4, while TEA still reaches 96.5%, which is 33.1 percentage points higher than traditional OCR; ES is as high as 4.6/5.0.

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Figure 4. Comparison of TEA and APT results

4. Conclusion

This study proposes the HCIA architecture by deeply integrating machine learning technology with RPA audit robots, effectively improving the intelligence level of the audit process. By introducing dynamic task planning and multimodal document understanding, the limitations of traditional RPA in dealing with dynamic scenarios have been significantly improved. The experimental results show that the proposed architecture exhibits significant advantages in task execution accuracy, anomaly detection rate, and system adaptability, especially in unstructured data processing, cross document consistency verification, and dynamic adjustment of audit rules. In addition, the HCIA architecture demonstrates strong robustness in complex audit scenarios such as rule changes and new types of fraudulent behavior, providing a practical and feasible solution for the efficient deployment of future audit automation systems.

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Appendix

Appendix A

Table A.1 Experimental environment

Category	Component Name	Spec/Version
Hardware Platform	Computing Node	4× NVIDIA A100-SXM4-80GB
	Memory Subsystem	8× 64GB DDR4-3200 ECC RAM
	Storage System	2× Intel Optane P5800X (1.6TB)
Software Stack	Operating System	Ubuntu Server 22.04 LTS
	Container Engine	Docker 20.10.23
	Orchestration Management	Kubernetes 1.26.4
Machine Learning	AI Framework	PyTorch 2.0.1 + CUDA 11.8
	Federated Learning Module	NVIDIA FLARE 2.3.0
	Graph Computing Engine	DGL 0.9.1 + CUDA
Data Processing	Time-Series Database	InfluxDB 2.6.1
	Document Processing Acceleration Library	NVIDIA DALI 1.21.0
RPA Execution	Automation Platform	UiPath 2023.4.3 Enterprise
	Process Monitoring Tool	Elastic APM 7.17.9
Testing Tools	Load Testing Framework	Locust 2.15.1
	Blockchain Verification	Hyperledger Caliper 0.4.4

Appendix B

1. Static environment benchmark testing

In this stage, the core performance of the system is evaluated in a stable business environment, using FinAudit-15M test shards as the input benchmark. Design dual task scenarios. One is credit card anomaly screening, processing 100000 transactions in a single batch, simulating the daily audit pressure of banks; The second is three order matching verification, which involves cross checking 5000 value-added tax invoices with purchase orders and receipt records. Strictly control the hardware environment and data input sequence. At this stage, establish performance baselines for each method and verify the completeness of basic functions.

2. Dynamic adaptive stress testing

To test the robustness of the system in response to business changes, two rounds of drift injection experiments were designed. Firstly, there is a change in accounting standards, simulating the implementation of the new IFRS 17 revenue standard and modifying the 15% business rule; Next is the upgrade of fraud patterns, injecting new types of gang fraud topologies. This stage exposes the system's adaptive capability deficiencies in the dynamic changes of the audit environment.

3. Special evaluation of unstructured processing

Focus on the electronic credential evidence set and design a dual challenge task. One is the analysis of complex terms, extracting key elements such as payment terms and breach of contract responsibilities from procurement contracts; The second is cross document consistency auditing, which achieves triangulation of invoice amount, customs declaration number, and ERP records.

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Artificially injecting two types of interference, including image distortion and text blur. At this stage, verify the actual usability of the unstructured processing module.

4. Continuous learning for long-term validation

Simulate a complete audit quarter and build a closed-loop evolutionary environment. Insert 200 manually calibrated samples per week; Implement a standard iteration once a month. Observe the iteration trajectory of the model version and the attenuation law of the indicators. This stage verifies the stability and evolutionary effectiveness of long-term deployment.

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Appendix C

Table C.1 Specific experimental results table

Evaluation indicators	Method	Stage 1	Stage 2	Stage 3	Stage 4	Mean increase
TEA	BASE-RPA	98.2%	86.7% ↓	72.4%	79.1% ↓	-16.4%
	MLPipe-RPA	99.1%	91.5%	88.3%	92.6%	+2.7%
	RuleOpt-RPA	99.0%	93.2%	84.7%	90.3%	+1.9%
	ML-RPA	99.7%	96.8%	96.5%	97.2%	+2.4%
APT(ms)	BASE-RPA	680	892 ↑	1,210	954 ↑	+31.2%
	MLPipe-RPA	730	805	920	849	+14.1%
	RuleOpt-RPA	710	825	1,050	887	+20.0%
	ML-RPA	720	735	780	745	+3.5%
ADR	BASE-RPA	73.8%	64.1% ↓	-	58.9% ↓	-18.2%
	MLPipe-RPA	92.5%	84.7%	-	86.1%	+0.9%
	RuleOpt-RPA	87.3%	80.2%	-	78.5%	-4.1%
	ML-RPA	95.3%	93.6%	-	94.1%	+1.8%
FPR	BASE-RPA	24.6%	38.2% ↑	-	41.7% ↑	+43.5%
	MLPipe-RPA	9.2%	14.1%	-	12.9%	+28.3%
	RuleOpt-RPA	16.4%	22.3%	-	24.0%	+31.7%
	ML-RPA	7.1%	7.9%	-	7.5%	+5.6%
CDA	BASE-RPA	-	32.8h	-	-	-
	MLPipe-RPA	-	19.2h	-	-	-
	RuleOpt-RPA	-	8.7h	-	-	-
	ML-RPA	-	3.1h	-	-	-
RCI	BASE-RPA	82.7%	74.5% ↓	-	68.2% ↓	-15.8%
	MLPipe-RPA	93.4%	87.9%	-	90.1%	-3.2%
	RuleOpt-RPA	95.1%	91.3%	-	92.6%	-2.5%
	ML-RPA	98.8%	97.5%	-	98.2%	-0.5%
HIR	BASE-RPA	42.1%	27.5% ↓	-	22.8% ↓	-40.1%
	MLPipe-RPA	65.3%	58.7%	-	62.1%	-4.9%
	RuleOpt-RPA	68.2%	63.4%	-	65.0%	-4.6%
	ML-RPA	76.5%	74.3%	-	75.9%	-0.8%
ES	BASE-RPA	-	-	3.1	-	-
	MLPipe-RPA	-	-	4.0	-	-
	RuleOpt-RPA	-	-	3.8	-	-
	ML-RPA	-	-	4.6	-	-