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Information Discriminant for Global Exploitation (INDIGO): Information Filtering and Recommender Application on Sensor Network

by Jade Freeman, Michael Lee, Tim Gregory, and Mark Dennison

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DEVCOM Army Research Laboratory

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14. ABSTRACT
In the current era of perpetual advancing digital technology, ubiquitous smart sensors and devices are widely adopted to inform situational awareness, courses of actions, and decision making. Seismic, acoustic, chem-bio sensors, passive infrared, mounted cameras, and multi-modal sensors on unmanned ground and aerial vehicles are just a few examples. While the technology has greatly enhanced decisionmakers' ability to understand, forecast, decide, and act fast, it has heightened the risk for drowning in information as they are inundated with growing sources of data. This is further exasperated by scarce communication resources in the field where transporting data is already expensive. Managing an excessive volume of information remains a challenge that continues to burden cognitive ability and stress communication networks. Motivated by this, we posit a sensor-to-user information prioritization framework to deliver the right information to the right person at the right time. We explore a paradigm called Information Discriminant for Global Exploitation (INDIGO) to dynamically filter, prioritize, and recommend relevant information based on the context-and-user aware reinforcement learning approach. Initial evaluation of INDIGO in the lab simulation and a field experiment showed promising results and a potential toward advanced capabilities of information mediation with further development.

15. SUBJECT TERMS
Military Information Sciences, value of information, filtering, recommender, sensor, cursor on target, ATAK

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1. Introduction

Today's information environment is fueled by an exploding number of devices with stand-alone or built-in sensors, applications, and systems on connected networks. Smartphones, portable computers, wearable devices, traffic cameras, environmental sensors, and diverse unmanned and manned platforms pump out information in constant stream everywhere and anytime. Consequently, achieving real-time situational awareness (SA) is easier than ever before. However, managing and exploiting continuously flowing data from ever-growing sources present challenges to extracting the right information at the right time. Further, data acquisition, transaction, and processing are often costly with limited resources under a stressed environment.

The *New York Times'* article reported that "since the attacks of 9/11, the amount of intelligence gathered by remotely piloted drones and other surveillance technologies has risen 1,600 percent."[1] It also reported military leaders' concerns that growing information from various sensor platforms present significant challenges to even experienced analysts and operators to process and analyze to form critical and high-value intelligence and SA. Particularly, in the combat environment, physical sources such as heat, noise, and vibration, as well as cognitive sources such as information overload, complexity, and distraction, affect the Soldier's ability to perform with speed and accuracy.[2] The impact of information overload on computing/network resources and cognition has been widely researched in the military context. These studies point to the need to find a way to mitigate information overload and prevent intelligence analysts from sharing poorly analyzed data that only degrades the decision-making process.[3] However, there have not been many, to the extent of our knowledge, technological solutions to address information overload in military. Such solutions can be implemented into tactical information systems to aid systematic and automated filtering for the mission critical, pertinent, and timely relevant data. SA tactical devices should provide the operators with task-relevant information while suppressing extraneous information to avoid excessive information presented on tactical device.[2]

Given the negative effect of stress on attention level in which the individual becomes oblivious to the threats of the external environment, the way in which information is provided to operators must vary according to operational context.[4] As the human intelligence assesses the value of information according to the goals, requirements, and contexts surrounding the state, situation, and environment, artificial intelligence tools can automate information discrimination process.

Human–machine teaming approach implements an algorithm to exploit the information consumption pattern under the changing operational context.

In this work, we explore a recommender framework for filtering and prioritizing information in dynamic real-time learning. We present the Information Discriminant for Global Exploitation (INDIGO) system with preliminary discussion on the existing systems and methodology and discuss how we leverage them in this framework. We also discuss the results from the lab simulation and the lessons learned from a field exercise.

2. Information Filtering: Recommender System

One of the goals of information filtering is not to waste resources by moving low-value, noncritical information across the network and systems. To that end, cost and outcome are factors in determining the value of information. Costs can be the resources expended for acquisition and dissemination of the information. Cost, such as monetary amount or network and computational resources to store, transport, and process data, can be quantified. Likewise, outcomes can be measured quantitatively (e.g., monetary gain or statistical risk) and probabilistically modeled. Conversely, costs and outcomes that are abstract, such as cognitive burden, distraction, sense of accomplishment, SA, and so forth, are often measured qualitatively. Defining universal standards against these qualitative measurements with considerations for diverse and dynamic human/environment factors can be challenging. Further, predetermined policies for valuating outcomes require complete knowledge of the operational environment.

How users value the information is affected by many contextual factors: the environment that the user is experiencing, the user's intuition about what objects will satisfy those goals, and domain-specific knowledge that the user might have.[5] Recommender systems use active information-filtering techniques to exploit past user behavior to suggest information tailored to an end user's goals.[5] One step further, a recommender system can determine the value of information given situational contexts by observing and learning how the interaction is affected by the contextual factors.

Gadepally et al.[5] argued the value of recommender systems for the Department of Defense and intelligence community. One of their proposed applications of a recommender system was for incidence response in cyber domain, where the recommender systems would model a variety of factors, such as the time since the vulnerability's discovery, severity of the exploit, existence of a patch, difficulty of deploying the patch, and impact of the patch on users. The recommender system can learn from past user behavior about important cyber security news item and suggest a course of action for patching the vulnerability.

3. Existing Work on Information Filtering Based on Value of Information

Suri et al.[6] presented an approach that considered the information objects generated by sensors as well as Soldiers, including tracks, detection, pictures, reports, and other types of information objects that would represent user context. The policy for value of information determination consisted of evaluating the metadata of the information object, source, pedigree, and designated importance level. The valuation function used prescribed numeric weighting scheme on the metadata for the information object to calculate relative importance.

Tortonesi et al.[7] proposed a similar approach for prioritizing information and content filtering based on recipient-specific value to each piece of information under consideration. Their approach for the calculation of value of information depended on factors such as the priority of applications, the number of requests for a specific type of information, the timeliness of relevance of the information object with respect to the request origination time, and the proximity to the information source location with respect to the requester. Likewise, this prioritization policy was predetermined and configured in the application, assigning the priority level according to these factors.

4. INDIGO Framework

INDIGO is a proof of concept for a recommender-based predictive analytic system to discriminate and filter for relevant information to a user. INDIGO uses a recommender algorithm to perform information discrimination and filtering. INDIGO's workflow consists of four phases of data pipelines: data aggregation, information recommender, data dissemination, and user feedback loop to the recommender. The framework is designed to use Tactical Assault Kit (TAK) systems and support Cursor-on-Target (CoT) messages from heterogenous sensors.

4.1 Top-K Deep Contextual Bandit

Top-K Deep Contextual Bandit (TKDCB)[8] is a recommender algorithm for information selection developed by the US Army Combat Capabilities Development Command (DEVCOM) Army Research Laboratory (ARL). TKDCB implements top-K ranking approaches in information object selection under the contextual multi-armed bandit (MAB) framework. MAB is a type of reinforcement learning, where the algorithm builds its model based on a reward function at each time step (trial iteration) rather than training on existing data. TKDCB is an extension to contextual multi-armed bandit (CMAB) and Learning-to-Rank techniques to optimize the reward approximation and select the optimal set of information objects. In TKDCB, the stochastic reward function is modeled with a neural network on the relationship between rewards and contexts. In other words, TKDCB approaches the problem of learning to correctly identify *K*-number of high reward value information objects from a set of *N* using CMAB given historical interactions and the context. To briefly describe the algorithm, at each trial round *t*, the optimal object $\mathrm{d}^*_{(\mathrm{i}),\mathrm{t}}$ is determined from the collection of *N* objects where *(i)* is the *i-th* prioritized ranking of the object *d* according to the estimated rewards using a MAB method. Then, TKDCB selects the top *K* $d^*_{(j),t}$,*j=1,...,K*. Finally, the reward function is updated on $A^*_t = \{d^*_{(i),t}\}_{i=1,\dots,K}$ with their observed rewards and the corresponding contexts.

4.2 Tactical Assault Kit

TAK is a suite of georeferenced imagery and communications tools that allow for scaled operational planning, and data sharing (https://tak.gov). In this workflow, we leverage TAK products and services. TAK is used to pass information between the INDIGO system and the operator.

Android Tactical Assault Kit (ATAK) is a geospatial infrastructure and military SA app that enables operators to navigate using GPS and a terrain map overlayed with real-time events on an Android device (https://tak.gov). See Fig. 1 for ATAK user interface view.

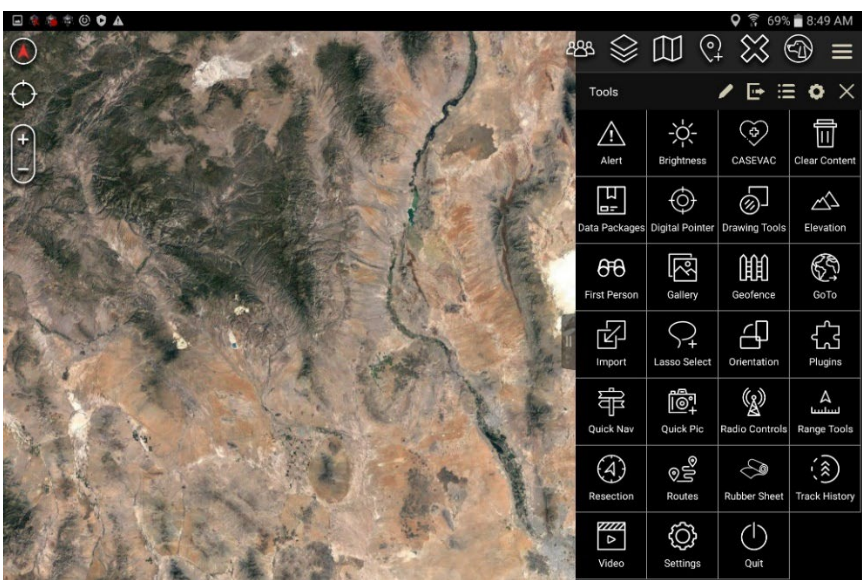

Fig. 1 ATAK user interface view

We developed the ATAK plug-in to receive filtered CoT messages from the recommender server via the TAK server for user's view on the device and to send back the user response/interaction data. See Fig. 2 for INDIGO system components and workflow.

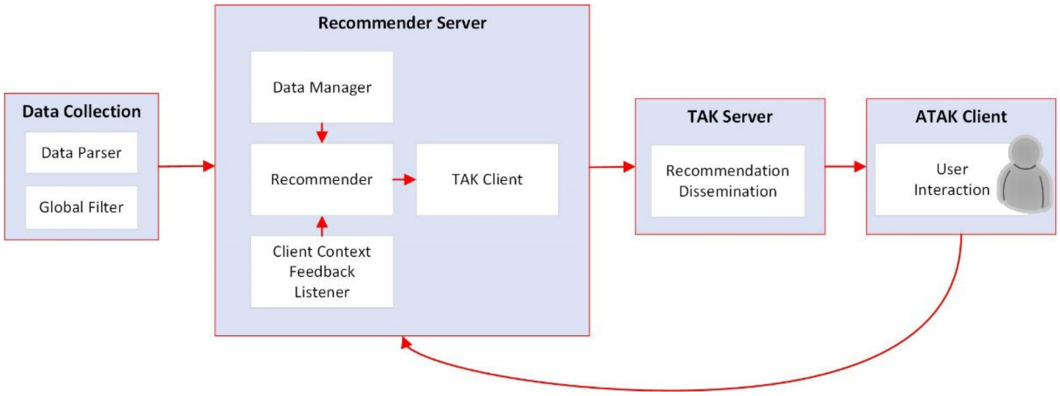

Fig. 2 INDIGO system components and workflow

4.3 Workflow Overview

Incoming sensor data are passed through the initial data processing of raw sensor messages into a structured uniform data format and ingested into the data listener. A rule-based initial global data stream prefilter is implemented at this phase. Then, the messages are transformed and stored in the data manager. The data manager is where the data are logged during the phases of recommendation, dissemination, feedback, and reward/model update. Once the sensor data are sent to the recommender system, the data are then transformed and aggregated in the data manager so that the data are suitable for the recommender algorithm. Meanwhile, contextual data from the users are provided to the recommender server, which are merged with the sensor data. Both the user contexts and the sensor data are run through the algorithm. The algorithm provides Top-K-recommended sensor objects that are disseminated to the user via the TAK client and then the TAK server, which mediates and relays the data to the ATAK instances.

The filtered data are visualized as a GPS icon on the user's mapping device or system and the user will interact further with the sensor object to investigate, choose to ignore, or clear away from device if the data are deemed to be irrelevant or useless. These user interactions and behavior on the recommended objects are generated as the feedback to the recommender server, which listens, collects, and sends it to the recommender algorithm for reward/model updates.

5. Experiments and Results

5.1 Lab Simulation

5.1.1 Data

We conducted a simulation using CoT[9] data from a previous field experiment. The CoT messaging format is used to package the sensor data in an XML format with the embedded sensor information object. Figure 3 is an example of the CoT message. The CoT XML schema provides placeholders to include common metadata (e.g., timestamp, latitude, longitude, information object identifier) as well as detailed messages about the events generated from the sensor.


```xml
<?xml version="1.0" ?>
<event version="2.0" uid="US-XXX-XXXX8.2-XXX" type="a-f-G-U-C" time="2023-09-13T18:23:49.000Z"
        start="2023-09-13T18:23:45Z" stale="2023-09-14T18:23:45Z" how="h-e">
        <point lat="3X.XXXX" lon="-1XX.XXX" ce="XX.0" hae="X" le="XX.0"/>
        <detail>
                <takv os="28" version="3.12.1.1-XXX" platform="ATAK"/>
                <contact callsign="US-XXX-XXXX8.2-XXX"
                        endpoint="US.US-XXX-XXXX8.2-XXX:4242:tcp"/>
        </detail>
</event>
```


Fig. 3 Example of CoT message

In this simulation, the context information on the sensor event is described within the 27 features from the CoT message. Using a playback simulator, 200,000 messages were sent, extracted, parsed, loaded, and transformed during the data collection phase. Before the messages were sent to the recommender server, any data outside of a 5-km radius from the simulated ATAK user's location were filtered out.

Each CoT message sent to the user would be either accepted or rejected, implying whether the message was indeed of interest to the user. This action feedback was sent to the recommender server to update the model with observed reward from the user action, where "ACCEPT" messages were encoded as 1 and "REJECT" messages were encoded as zero. In the absence of a real user interacting with the messages, we generated simulated user feedback under three hypothetical cases that a user would accept the messages. From the context provided in the CoT message, the recommender model must correctly learn to identify these specific cases, from which the event messages would be indeed of interest to the user.

5.1.2 Results

We ran 1,000 iterations of INDIGO instances where INDIGO would select and send K number of CoT messages out of N available messages. Here, we also call the available messages as the *arms,* a common reference used in MAB methodology. Three cases of experiment were conducted under 1) $N = 25$, $K = 5$; 2) $N = 50$, $K = 10$; and 3) $N = 75$, $K = 10$. We employed epsilon-greedy with 5% and Thompson's sampling methods as the recommender algorithms. These two methods were chosen since they are popular MAB methods among many, but other methods could be implemented without significantly altering the INDIGO architecture. We evaluated the recommender algorithm performance using cumulative regret up to the time step of the iteration as a metric. Regret is the difference between the rewards from the selections and the ground truth. Details on the MAB methods and cumulative regrets can be found in Freeman and Rawson.[8] Random selection of messages was also evaluated for the purpose of baseline comparison.

As shown in Fig. 4, a smaller number of incoming messages ($N = 25$ arms) performed better than larger number of messages ($N = 50$ or 75) for both MAB methods. This might indicate that an increased number of messages presents more difficulties in learning the correct set of user preferred messages.

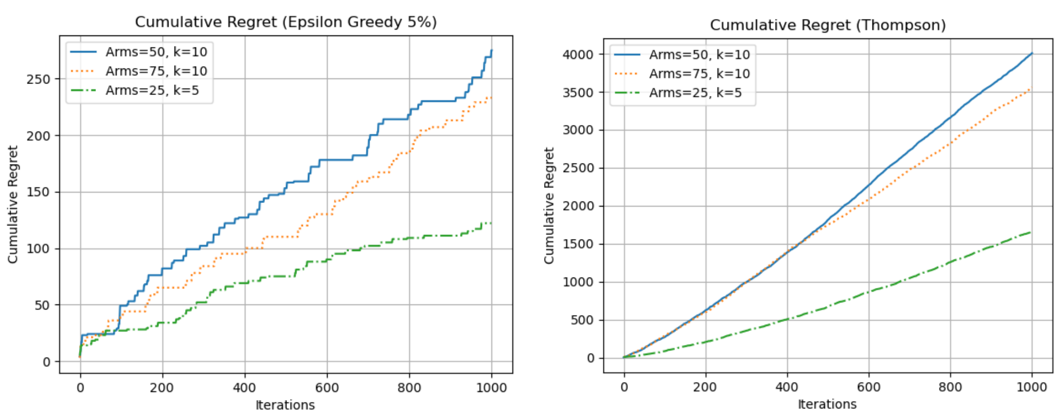

Fig. 4 Comparing performances across varying number of incoming and selected messages

Both MAB methods, epsilon-greedy with 5% and Thompson's sampling, performed better than no recommender algorithm implementation (i.e., random selection) in terms of correctly predicting the user acceptance on select messages. Across N and K, epsilon-greedy 5% outperformed Thompson's sampling approach, while random methods performed the worst, suffering the most regrets as shown in Fig. 5.

In summary, the simulations demonstrated that INDIGO ingested, parsed, and extracted CoT messages. Further, INDIGO's recommender algorithms selected and filtered messages using the context features from the CoT events and the user feedback.

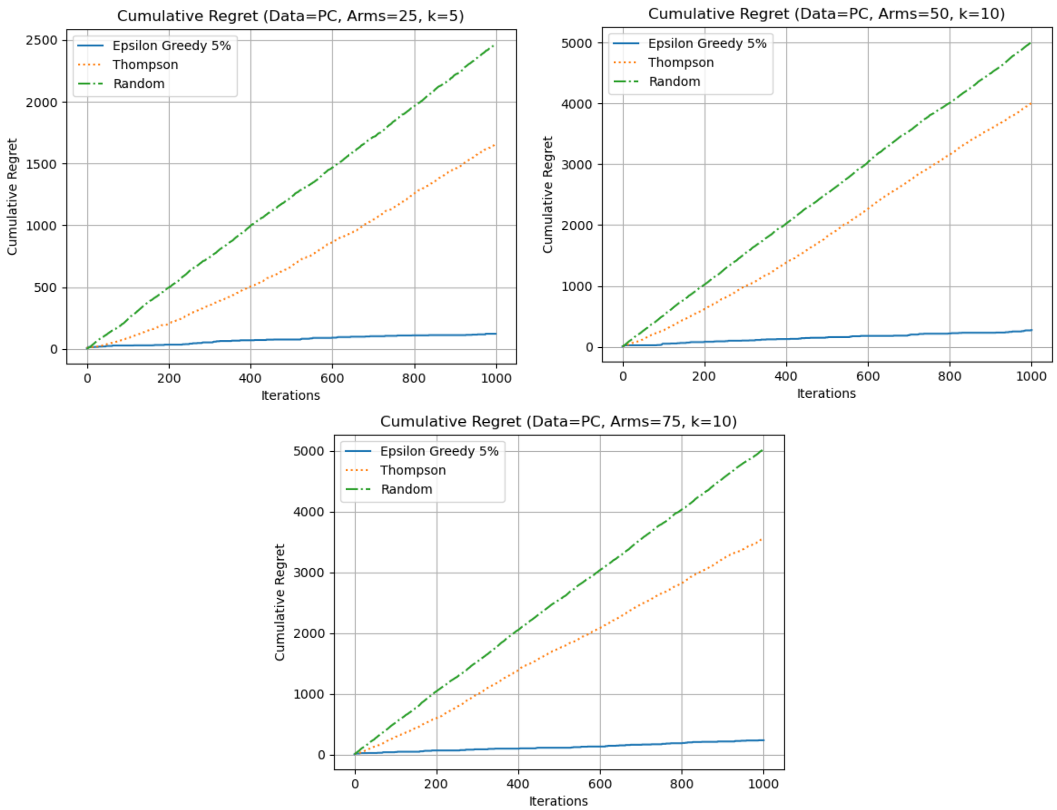

Fig. 5 Comparing performances between MAB and random selection methods across varying number of incoming and selected messages

5.2 Live Experiment

5.2.1 Bold Quest/Island of Marauder 2023

Bold Quest 23/Island of Marauder (BQ23/IM) exercise was a US joint service and multipartner nations exercise held at Camp Pendleton, California. The overall objective of the BQ23/IM exercise is to demonstrate and assess coalition capabilities on interoperability and information sharing focused on fire kill chain. During the exercise, INDIGO was deployed within the ground SA capability area where Friendly Force Tracking near the target and ground-to-air information were captured on various tactical command and control devices and tracked on common operating picture (COP) systems in near-real time.

As shown in Fig. 6, INDIGO was configured to operate within its own subnetwork. INDIGO used two network interfaces on the local host for data captures. One interface connected to the ground SA network to receive CoT messages and one interface connected to the INDIGO subnetwork. This type of network configuration was intended to prevent network traffic on the INDIGO network from reaching the ground SA network.

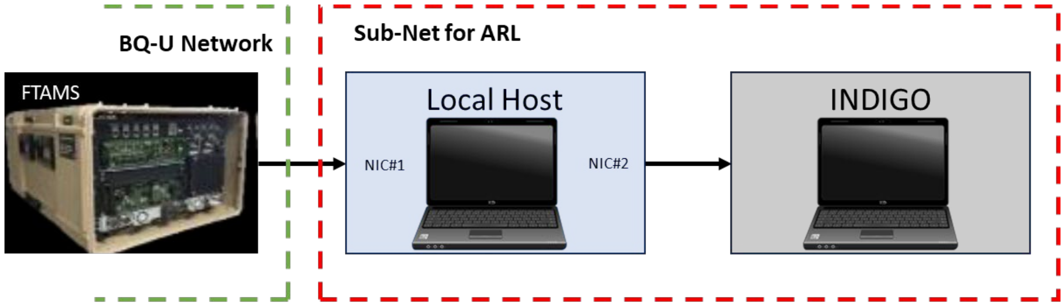

Fig. 6 INDIGO network connection setup

5.2.2 Key Questions for Experiment

For the purposes of INDIGO experimentation at BQ23/IM, the following questions were investigated:

1) Information Ingest and Processing: Can the INDIGO technology support data ingest and processing from high volume of data?

2) Information Dissemination and Machine Learning: Can the INDIGO technology support information filtering, dissemination, feedback collection, and model update on the ground SA data?

For the Question 1, the key objective was to test and validate the INDIGO's capability to ingest CoT data from the ground SA mission network. For the Question 2, the key objective was to assess the recommender engines' ability to intake and model incoming data, filter, disseminate, and obtain feedback to update the model. Both questions were to address architectural soundness of INDIGO using the data from real-world mission environments.

At BQ23/IM, INDIGO successfully connected to the mission network. Also, with minimum modification, INDIGO successfully ingested the data from the ground SA systems. The recommender model within the system also successfully processed, filtered, and processed the data. Therefore, Questions 1 and 2 have been validated positively.

In summary, INDIGO was tested for mission command information ingress and egress with a complete feedback loop for the recommender model. Further, INDIGO was validated on the architectural soundness of the system under real-world settings presented by the ground SA thread.

5.2.3 Other Observations

From observing the data from the ground SA exercise, insights were gained on the critical need to process CoT messages to extract key contextual information within the details of the messages. To support heterogenous data from the joint services and coalition partners, INDIGO needs to expand the capability to extract contextual features of the message under a general scheme. For example, an embedded video in a message can serve as a key feature in discriminating high value from non-relevant information given other historical contexts.

Further, it has been observed that overall, there were more than a 1,000 messages per minute on average during the peak hours of the BQ23/IM daily exercises (see Fig. 7). Although this is an aggregate amount across the entire systems under disparate ownership, the future battlefield will require information exploitation across multi-domain and multi-action partners. Therefore, automated information mediation capabilities to connect and share various and disparately produced information must be considered to maximize information exploitation. The mission command scenarios and the data network settings at the BQ23/IM exercise provided a complex information environment and deeper questions on how the information should be filtered and disseminated in real time from the perspective of users in addition to the system capability.

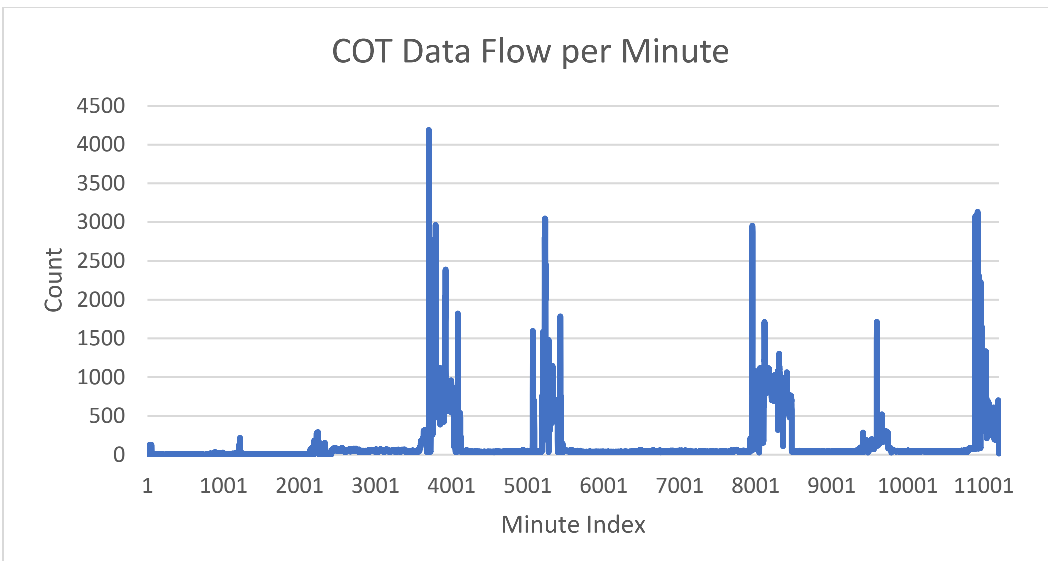

Fig. 7 Average number of CoT messages per minute received from ground SA mission network

6. Conclusion and Future Work

We have been developing the INDIGO system, an information filtering and prioritization system that can learn the information needs of tactical operators where data sources are abundant, but network connectivity is scarce and cognitive load is stressed in austere locations. The design of INDIGO is particularly aiming to learn and adapt to the contextual information regarding the users and the environment, without the need to have a full understanding about dynamic and complex relationships between the users and the environment.

INDIGO has been evaluated in lab simulations and at a live experiment, where INDIGO shows promising potential for mediating the high velocity, high volume of the information to filter for relevant information. Building upon this validation and lessons learned, we are currently evaluating the limitations of the system as we are working on further development and enhancement. The current effort has been focused on one-user case and we plan to extend INDIGO to apply a collaborative-filtering approach under muti-user case. One potential approach is Graph Neural Network[10] for better learning from the relations and associations within and between the information objects and the users. Further, INDIGO is being enhanced for integration with virtual COP platform, the Cross Reality Common Operating Picture.[11]

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List of Symbols, Abbreviations, and Acronyms

ARL	Army Research Laboratory
ATAK	Android Tactical Assault Kit
BQ23/IM	Bold Quest23/Island of Marauder
CMAB	contextual multi-armed bandit
COP	common operating picture
CoT	Cursor-on-Target
DEVCOM	US Army Combat Capabilities Development Command
GPS	global positioning system
INDIGO	Information Discriminant for Global Exploitation
IT	information technology
MAB	multi-armed bandit
SA	situational awareness
TAK	Tactical Assault Kit
TKDCB	Top-K Deep Contextual Bandit

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