RFI: Developing a Federal AI Standards Engagement Plan

Neo4j Inc. Response

The case for graph technology as a foundation for AI

To our fellow citizens, leaders, and whom it may concern,

The National Institute of Standards and Technology (NIST) has requested information regarding creating a plan for U.S. Federal engagement in the development of technical standards and related tools in support of reliable, robust, and trustworthy systems that use Artificial Intelligence (AI) technologies.

The power and potential of artificial intelligence are expansive and will be used in ways we cannot yet imagine. Despite, and perhaps because of this, we have a duty to guide the development and application of AI in ways that facilitate innovation and fair competition, public trust and confidence, while incorporating the appropriate protections.

We've already seen inklings of what happens when AI is not guided by these principles, such as China's social credit system. This system ranks citizens on their trustworthiness, including whether they jaywalk (using facial recognition), if they buy Chinese-made products, what they post online, and whether they smoke in nonsmoking areas, as reported by CBS News in "China's behavior monitoring system bars some from travel, purchasing property." All 1.4 billion Chinese citizens will have a score by 2020. Those that the system learns are trustworthy receive discounts on energy bills and better interest rates at banks. Those categorized as untrustworthy can reportedly be stopped from buying property, have difficulty with rental contracts and even lose access to high-speed internet. As a society, we need to consciously endeavor to keep AI-based systems aligned with values of independence, fairness, while providing reasonable safeguards.

We are Emil Eifrem and Amy Hodler, the Chief Executive Officer and Analytics and AI Program Manager for Neo4j, Inc., a California-based company. Our expertise are data technologies that specifically deal with how people, processes, locations, and systems are connected and interrelated.

Neo4j helps people make sense of data through graph technologies which naturally store, compute and analyze connections and relationships among data. AI and machine learning systems are more effective, trustworthy, and robust when underpinned by contextual information provided by graph platforms. We can assist the Federal government in understanding the important role that connected data plays in AI and learning systems.

In particular, there are two areas from the NIST RFI that our expertise lead us to comment upon. In the section on "AI Technical Standards and Related Tools Development: Status and Plans" of the RFI document 2019-08818:

- Number 4: "AI technical standards and related tools that are being developed, and the developing organization, including the aspects of AI these standards and tools address, and whether they address sector-specific needs or are cross sector in nature."
- Number 8: "Technical standards and guidance that are needed to establish and advance trustworthy aspects (e.g., accuracy, transparency, security, privacy, and robustness) of AI technologies."

Today, Neo4j leads the graph platform category in installations which include numerous commercial and Federal projects including the Department of Defense, the United States Intelligence Community, as well as state and local government agencies. The U.S. Army has deployed Neo4j for tracking equipment maintenance in their procurement process. MITRE Corp uses Neo4j for managing cybersecurity, and NASA consolidates and references its past research with a Neo4j powered knowledge graph.

The private sector has often been a leader in technical standards, but we also believe that public-private initiatives help fuel innovations and assure transparency. We are major contributors to open source projects and support agencies and non-profit organizations such as our work with the International Consortium of Investigative Journalists (ICIJ) on the Panama Papers, which 3 years on has resulted in more than $1.2 billion in tax fraud investigations.

Working within both government and industry, we've learned that complex data – and its use in AI – is a universal concern and no single company or organization should address those challenges alone. We are offering our suggestions and support in your efforts to develop standards for AI technologies.

Introduction and Summary

For artificial intelligence (AI) to be more situationally appropriate and "learn" in a way that leverages adjacency to understand and refine outputs, it needs to be underpinned by **context**. Context is all of the peripheral information relevant to that specific AI.

AI standards that don't explicitly include contextual information result in subpar outcomes as solution providers leave out this adjacent information. The result is more narrowly focused and rigid AI, uninterpretable predictions, and less accountability.

Graph technologies are a state-of-the-art, purpose-built method for adding and leveraging context from data. Proven repeatedly in deployments worldwide, graph technology is a powerful foundation for AI.

This document explains how graph technology provides much-needed context to AI applications.. It includes examples of how AI outcomes are more effective, trustworthy, and robust when underpinned by the data context that graph platforms deliver.

Artificial Intelligence and Contextual Information

AI today is effective for specific, well-defined tasks but struggles with ambiguity. Humans deal with ambiguities by using context to figure out what's important in a situation and then also extend that learning to understanding new situations.

For example, if we are making travel plans, our decisions vary significantly depending on whether the trip is for work or pleasure. And once we learn a complicated or nuanced task, like driving a manual transmission, we easily apply that to other scenarios, such as other vehicles. We are masters of abstraction and recycling lessons learned.

For artificial intelligence to make human-like decisions that are more situationally appropriate, it needs to incorporate **context** – all of the adjacent information. Context-driven AI also ensures the explainability and transparency of any given decision, since human overseers can map and visualize the decision path within the contextual dataset.

Without context, AI requires exhaustive training, strictly prescriptive rules, and specific applications. Moreover, since it's impossible to anticipate every possible situation, we often find AI solutions wanting when new situations arise. Sometimes outcomes are even malefic, such as unverifiable results, biased recommendations, or harmful interpretations.

For example, Microsoft's Twitter bot, Tay, learned from Twitter users how to respond to tweets. After interacting with real social media users, however, Tay learned offensive language and racial slurs. Another example is Amazon's AI-powered recruiting tool, which was shut down after showing bias against women candidates (as reported by Reuters).

In both of these cases, the machine learning models were trained on existing demographic data that lacked the appropriate context. Tay's model drew more often from the loudest and most outrageous opinions, reinforcing those as the norm. Amazon's recruiting tool amplified and even codified discriminatory practices because its existing dataset was too narrow.

And how do we identify whether an AI-based solution is suboptimal, incorrect, or bad? Do we wait until something wretched happens? Knowing if an AI has gone off-course requires a larger frame of reference to identify how millions of data points and procedures come together. If we fail to evaluate AI outcomes within a larger context, we risk accelerating unintended outcomes as data and technologies become more complex.

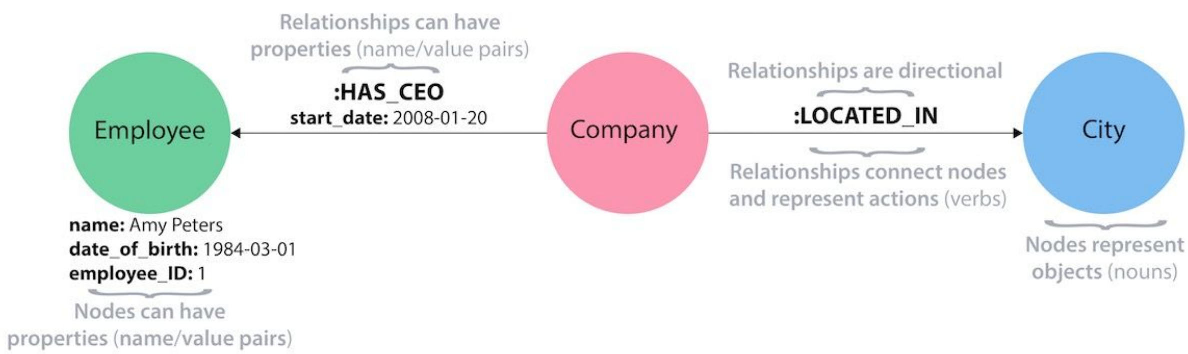
Explainability is also critical for accountability. Particularly in nuanced situations, such as creditworthiness or criminal sentencing, unchecked AI runs the potential of putting entire groups at a disadvantage. Context-driven AI helps us understand and explain the factors and pathways of logic processing so organizations better understand AI decisions.

Graph Technology as a Fabric for Context and Connections

There are no isolated pieces of information, only rich, connected domains all around us.

Graph theory and technologies were specifically developed as a way to represent connected data and analyze relationships. Very simply, a graph is a mathematical representation of any type of network and a graph platform is designed to treat the relationships between data as equally important as the data itself.

A graph platform stores and uses data as we might first sketch it out on a whiteboard – showing how each individual entity connects with or is related to others. It acts as a fabric for our data, imbuing it with context and connections. Graph technologies enrich our data so it is more useful, much in the same way that individual stars in the sky become more meaningful as a constellation, or when we understand how to use them for navigation.



Fundamental elements of the property graph model

Graph technologies were originally custom-built and used internally by game-changing companies like Facebook, Google, Uber, Netflix, Twitter, and LinkedIn because relational databases fell short of their need to find connections between people, places, locations, and systems in their data. In 2002, Neo4j invented the property graph model and went on to build a graph database so organizations could quickly traverse millions of data connections per second.

Graphs are used across multiple industries including, government, financial services, healthcare, retail, manufacturing, and more. Graph technology deployments encompass a broad variety of use cases that include fraud detection, cybersecurity, real-time recommendations, network & IT operations, master data management and customer 360.

More recently, graph technologies have been increasingly integrated with machine learning and artificial intelligence solutions. These applications include using connections to predict with better accuracy, to make decisions with more flexibility and fairness, to track verifiable data lineage, and to understand decision pathways for improved explainability.

For any machine learning or AI application, data *quality* – and not just quantity – is foundational. If we use contextual data, we create systems that are more reliable, robust, and trustworthy. We believe that graph technologies – which naturally store and analyze connections – cohesively advance these goals.

Furthermore, graph technology has been recognized as a major leap forward in machine learning. In *Relational inductive biases, deep learning, and graph networks,* a recent paper from DeepMind, Google Brain, MIT and the University of Edinburgh, researchers "...advocated for building stronger relational inductive biases into deep learning architectures by highlighting an underused deep learning building block called a graph network, which performs computations over graph-structured data." The authors found that graphs had an unparalleled ability to generalize about structure, which broadens applicability because, "...graph networks can support relational reasoning and combinatorial generalization, laying the foundation for more sophisticated, interpretable, and flexible patterns of reasoning."

In fact, the amount of research being published on the use of graphs with AI has also skyrocketed in recent years as can be seen in the below chart showing graph-related research from 2010 to 2018.

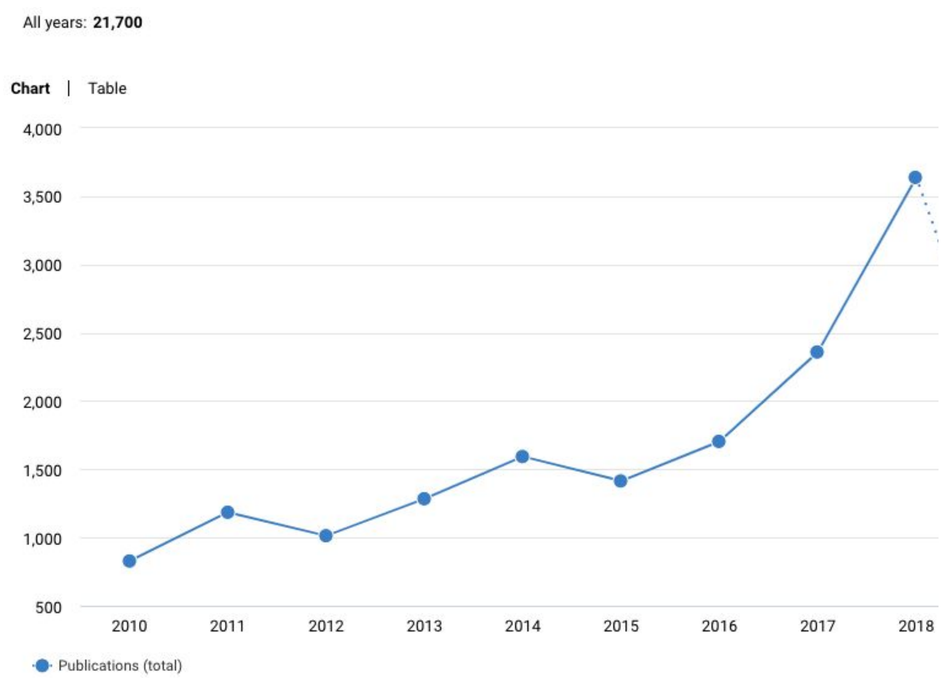


Chart from the [Dimensions knowledge system](#) for research discovery using the search terms, "graph neural network" OR "graph convolutional" OR "graph embedding" OR "graph learning" OR "graph attention" OR "graph kernel" OR "graph completion".

Context Makes AI More Robust

Incorporating context into AI-based systems increases robustness by improving predictions and flexibility.

Better Predictions

One of the greatest challenges in training artificial intelligence models is gathering enough relevant data. And yet current methods don't incorporate existing relationships within data, essentially throwing out predictive information. Using context adds relevant information and results in better predictions – all with only the data we already have.

According to Stratistics MRC, the global fraud detection and prevention market was valued at $17.5 billion in 2017 and is expected to grow to $120 billion by 2026, and there's been over 48,000 U.S. patents for graph fraud and anomaly detection issued in the last 10 years. Many financial services companies are looking for graphs to reveal predictive patterns, find unusual behavior, and score influential entities. All of this contextual information is then loaded into their machine learning models.

Even beyond the obvious fit in financial services, people are using graph algorithms in various industries to create more predictive “features” that train AI models for higher accuracy and precision. For example, the Association for the Advancement of Artificial Intelligence used graphs to detect clusters of interactions between doctors and pharmacies to improve opioid fraud predictions as described in “Graph Analysis for Detecting Fraud, Waste, and Abuse in Health-Care Data.”

Today’s data is highly connected and has uneven concentrations, which basic statistics and averages completely miss. Graph algorithms are specifically developed to leverage the topology of data through connections: find communities, uncover influential components, and infer patterns and structure. Incorporating the predictive elements of context into machine learning greatly increases model accuracy and precision.

Situational Flexibility

Situational awareness and appropriateness is another concern for AI where context-based learning and action are critical. For example, consider how we want an age-appropriate chatbot sensing and responding differently in an interaction with a 7-year-old versus a 30-year-old. In fact, an investigation highlighted an egregious example: a mental health chatbot created for use by children was unable to understand a child explicitly reporting underage sexual abuse as reported in the BBC news, “Child advice chatbots fail to spot sexual abuse.”

AI-based systems need to be flexible, which includes designing AI in a way that views user interaction as critical to the design and implementation of autonomous decision-making systems. This user-centric thinking could have helped prevent the recent loss of two Boeing 737 MAX aircraft, which investigations revealed were partly due to the failure to incorporate pilot behavior into automated systems.

Contextual information also helps an AI solution flex within new situations that it is untrained for, reducing failures and equipping it with new data or unexpected scenarios. For example, a semi-autonomous car might be programmed to slow down in rainy weather, but we would also want it to expand its AI application to incorporate contextual information such as falling temperature and an approaching bridge.

Beyond mere flexibility, we believe that contextual data helps AI solutions properly deal with adversarial attacks. For example, researchers tricked a Tesla into changing lanes with stickers as noted in the Vox article, “It’s disturbingly easy to trick AI into doing something deadly.”

Finally, when AI solutions are based on contextually aware and dynamic backends they are more broadly applicable. In turn, they will spur new innovations and broaden competition. We know that graph technologies are inherently cross-sector, with Neo4j’s graph platform used globally by:

- 20 of the top 25 financial services firms
- 7 of the top 10 software firms
- 3 of the top 5 logistics firms
- 7 of the top 10 retailers
- 3 of the top 5 airlines

- 4 of the top 5 telecommunications firms
- And 3 of the top 5 hospitality companies.

Context Makes AI More Reliable and Trustworthy

Adding contextual information enables AI-based systems to be more reliable, fair, and trustworthy.

Reliability

In order for AI solutions to be reliable and fair, we need to know what data was used to train our models and why. Unfortunately, this isn't as straightforward as we might think. If we consider a large cloud service provider or a company like Facebook with an enormous amount of data, it's difficult to know what exact data was used to inform its algorithms.

Graph technology adds the required context for this level of explainability. For example, graph technology is often used for data lineage to meet data compliance regulations such as GDPR or the upcoming California Consumer Privacy Act (CCPA). A data lineage approach is also used on NASA's knowledge graph to find past "lessons learned" that are applicable to new missions. When we store data as a graph, it's easier to track how that data is changed, where data is used, and who used what data.

Understanding and monitoring data lineage also guards against the manipulation of input data. For example, corporate fraud research has shown that when the significance of input data is common knowledge, people will game the system to avoid detection. Imagine a utility system or network infrastructure where we were confident in our monitoring software, but could no longer rely on the input data. The whole system would become immediately untrustworthy.

Finally, context-driven AI systems avoid excessive reliance on any one point of correlated data. For example, organizations are beginning to apply AI to automate complex business dependencies in areas such as data centers, batch manufacturing, and process operations. With contextual coordination, they avoid the trap of noisy, non-causal information and use root-cause analysis to maximize future efficiency. Contextual information helps us identify the root cause of a problem as opposed to just treating a symptom.

Fairness

Understanding the context of our data also reveals the potential biases inherent in existing data as well as how we collect new data and train our models.

For instance, existing data may be biased by the fact that it was only collected for one gender, which is a known issue in medical studies as noted by Elysium Health in, "Do Clinical Trials Have a Sex Problem?" Or perhaps an AI's human language interactions were trained on a narrow age or accent range. Graphs ensure situational/contextual fairness by bringing context to the forefront of AI solutions.

Discrimination has been shown to affect arrest rates, which in turn become embedded in prosecution data. When biased input data is used for predictive policing, it causes a vicious cycle of increased arrests and policing. The Royal Statistical Society published an Oakland, CA simulation analysis of a machine learning approach often used for predictive policing and found, “...that rather than correcting for the apparent biases in the police data, the model reinforces these biases.”

Fair-use of our personal data is an important part of AI based systems. Contextual data can assist in privacy efforts because relationships are extremely predictive of behavior. This means we can learn from peripheral information and collect less information that is less personally identifiable. In the book, “Connected,” James Fowler describes studies have shown that even with little or no information about an individual, we can predict a behavior such as smoking based on the behavior of friends, or even friends of friends.

Trust and Explainability

Training a machine learning model is mostly done on existing data, but not all situations can be accounted for ahead of time. This means we’ll never be completely sure of an AI reaction to a novel condition until it occurs.

Consequently, AI deployments need to dynamically integrate contextual information. For example, researchers have developed an application that predicts the legal meaning of "violation" based on past cases. However, legal concepts change over time and need to be applied to new situations. Because graph technologies capture and store relationships naturally, they help AI solutions adjust faster to unexpected outcomes and new situations.

To increase public trustworthiness of AI, predictions must be more easily interpretable by experts and explainable to the public. Without this, people will reject recommendations that are counterintuitive. Graph technologies offer a more human-friendly way to evaluate connected data, similar to drawing circles to represent entities and lines to show how they are connected on a whiteboard.

There are also new ways to learn based on contextual information. For example, companies like eBay are mapping the potential pathways a person might take from one purchase to another in order to recommend another selection. In the example of a music download, there’s a lot of context around a person and their selection: the artist, album, publishing decade, music genre, etc.. The paper, “Explainable Reasoning over Knowledge Graphs for Recommendation” details how to use graph technology and machine learning to predict the path (from song to artist, album, genre, or decade, etc.) that a person would likely take to get to their next song purchase.

We can use graphs to relay the complex data of people, songs, albums, and their relationships into practical machine learning measures while *retaining* the various potential paths from one purchase to another. We better understand and describe such AI-powered recommendations and decision making when we have likelihood combined with context.

Oversight opportunities also benefit from increased AI explainability. When homeowners insurance increases for an individual, it's frustrating; when rates increase for an entire demographic, it's discrimination. Without efficient AI explainability, it will take regulators considerable more effort to determine the root cause of such discrimination.

We're excited by recent work that appears to offer a leap forward for machine learning explainability. Particularly promising is the idea of graph native learning which involves computing machine learning tasks within a graph structure itself to make use of its natural context.

Implementing artificial intelligence in a way that is underpinned by connected data as suggested above, results in AI solutions that are much more generally applicable. However, perhaps even more significant will be the extreme transparency afforded by this approach: Graph native learning enables us to *input* connected data, *learn* while keeping data connected, and then *output* AI outcomes in the same graph format, which helps those accountable to accurately *interpret* results. In addition, the intermediate states of learning become uniquely observable in that same connected format, which means experts track and validate an AI's decision paths.

With the advancement of native graph learning, we can interpret and explain how an AI comes to a particular conclusion – which is a far cry from the black box approach used today.

Conclusion

Context must be incorporated to guide AI breakthroughs that are more generally applicable, to support just implementations of AI technologies, and to create trusted automated systems. Without standards for including context, it will be more difficult to encourage the use of adjacent information, resulting in suboptimal AI solutions and outcomes.

Although any new standards endeavor is difficult and imperfect, NIST is making the necessary first steps in encouraging reliable, robust, and trustworthy systems that use AI technologies. Furthermore, when considering such a broad and evolving area of technology, widely applicable standards and tools – such as integrating context – should be part of any AI foundation.

The federal government does have a role in creating guidelines that promote AI aligned to key American values of independence, fairness, and trust. Specifically, to advise that AI systems incorporate the contextual factors of flexibility and situational appropriateness, explainability and transparency, protection against data manipulation, and verifiability.

Finally, graph technologies are unarguably the state-of-the-art method for adding and leveraging context. These technologies are used worldwide across a diverse array of industries. Please contact us if we can be of assistance in gathering or understanding how connected data influences artificial intelligence.

With our sincerest regards,
Emil Eifrem, Neo4j CEO
Amy E. Hodler, Neo4j Analytics and AI Program Manager

Additional Resources

1. Introduction to Graph Databases
2. Graph Algorithms: Practical Examples in Apache Spark and Neo4j; Chapter 8: Using Graph Algorithms to Enhance Machine Learning
3. How Graphs Enhance AI