RIOS CHANNEL

Martedì 7 luglio 2020

GRAPH POWERED AI

CONTENTS

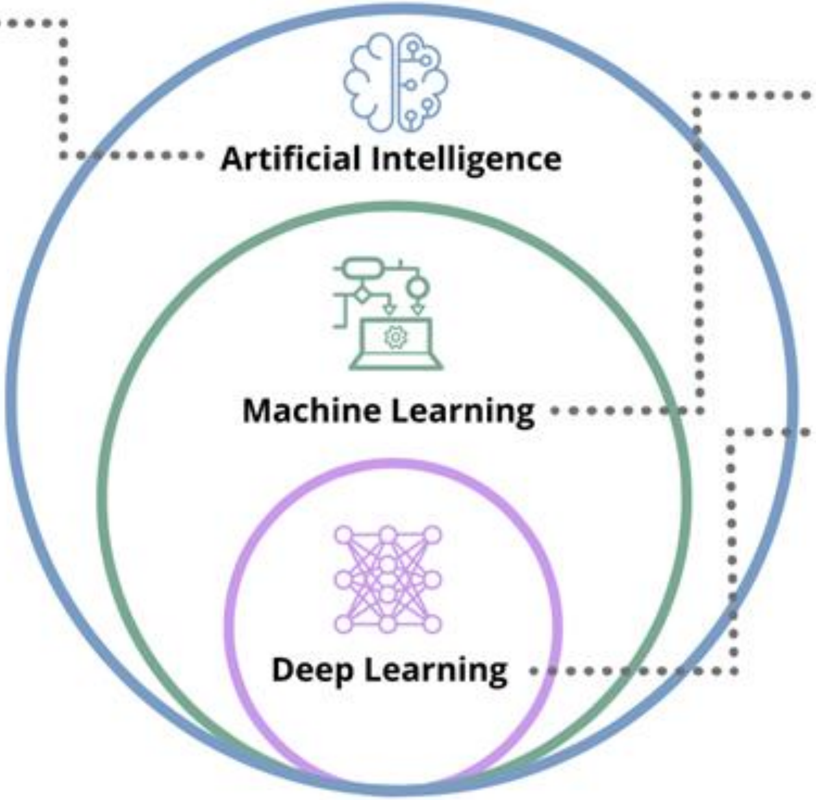
Photo by Yang Jing on Unsplash

1 Present and future of Graph AI

AI CONSISTS OF SEVERAL SUBSETS OF TECHNOLOGIES

Artificial Intelligence (AI)
A computer process that has learned to solve tasks in a way that mimics human decisions

AI solutions today are mostly used for very specific tasks, versus general applications



Machine Learning (ML)
Uses algorithms to help computers learn by task-specific examples and progressive improvements, without explicit programming

Deep Learning (DL)
Uses a cascade of processing layers modeled on neural networks to learn data representations such as features or classifications

SOME DEFINITIONS

➔AI - Artificial Intelligence

- The property of a system that it appears intelligent **to its users**
- Often, but not always, using ML techniques

➔ML - Machine Learning

Machine Learning allows computer programs to **learn** from **data,** by finding functions from historical data to guide future interactions within a **given domain**

➔DL **-** Deep Learning

Deep learning is a subset of machine learning that uses **multiple layers** to cascade learning and work with hierarchical abstractions.

“Machine learning is about analysing data to ‘learn’ a model or using an algorithm that can be applied to make predictions on new data sets. **Machine learning is not tied to a particular representation of data.**

Machine learning algorithms help data scientists **discover** meaning in data sets, and these **insights** can be **expressed as relationships between nodes in a graph**. Graph databases enable efficient storage and traversal of information about relationships. Therefore, **graph data can either be the input or the output of machine learning processing.”**

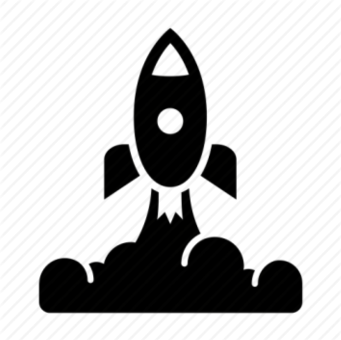
WHY GRAPHS FOR MACHINE LEARNING?

➔ Graph ML can deliver better results for questions you're already asking about data you already have (accuracy)

➔ Graph ML lets you ask new questions of the data you already have

➔ Graphs accelerated machine learning uses graphs to optimize models and speed up processes, offer greater efficiency

➔ Graph provide much-needed data context to AI outcomes, by making them more trustworthy and robust.



Graphs are a foundational building blocks of the next generation of Machine Learning.

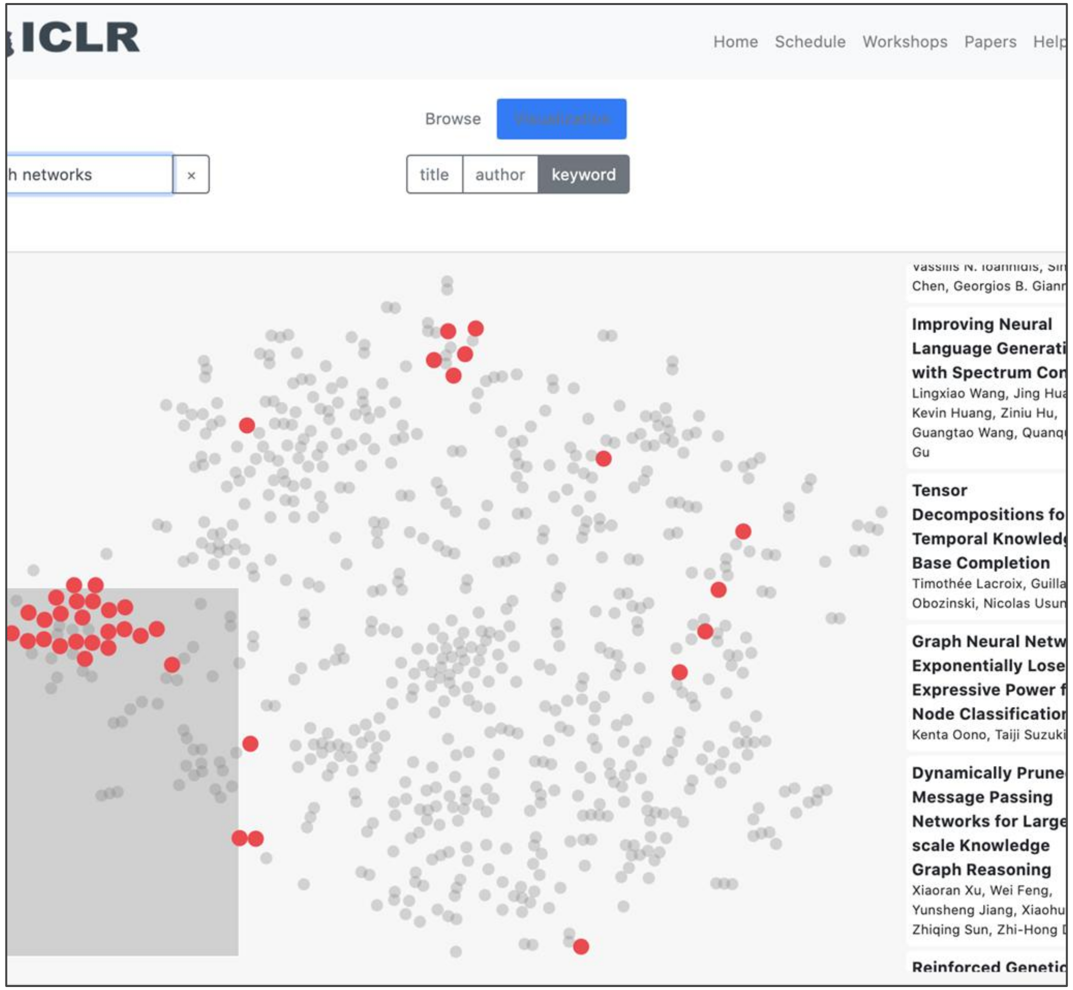
“The application of graph processing and graph databases will grow at 100% annually through 2022 to continuously accelerate data preparation and enable more-complex and adaptive data science.”

Gartner predicts

GRAPH ML IS GROWING IN AI RESEARCH

ICLR2020 International Conference on Learning Representations - https://iclr.cc/

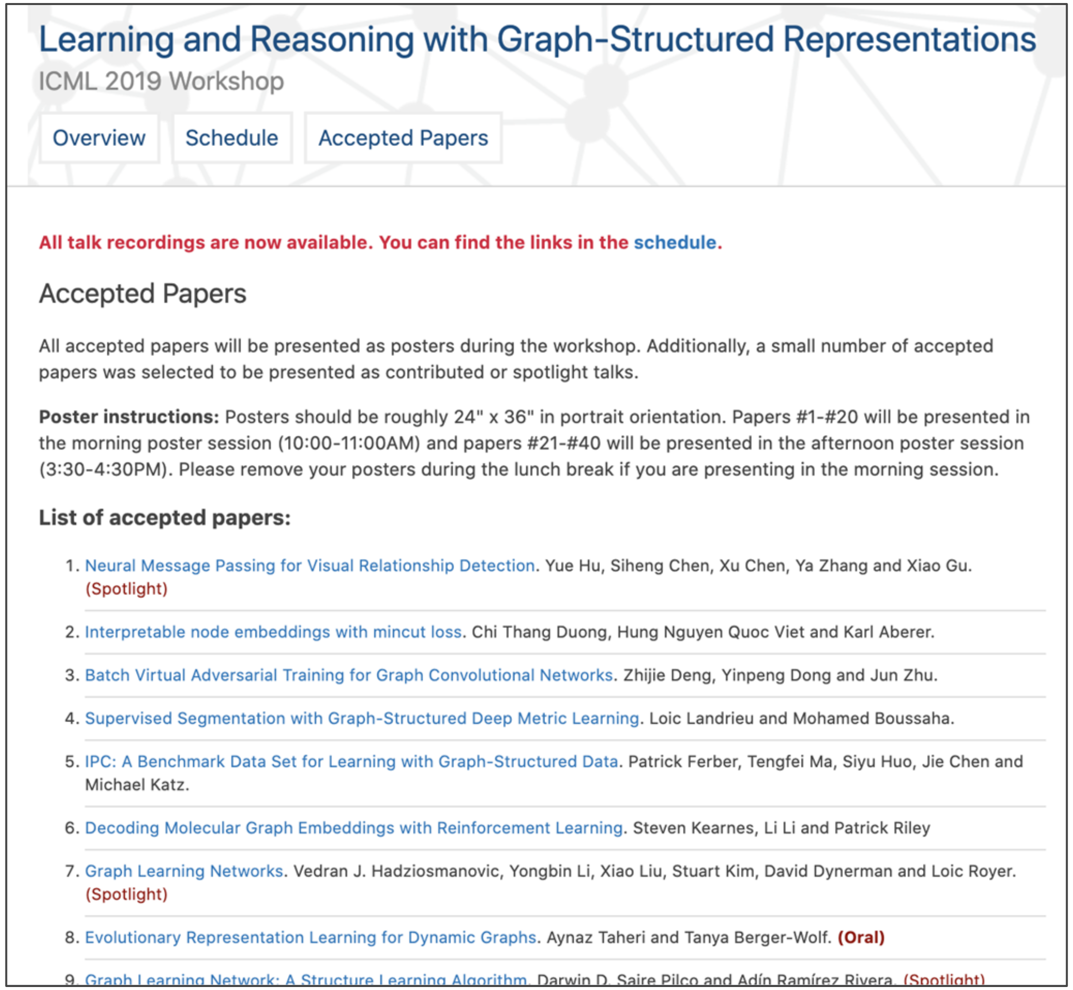
https://iclr.cc/virtual_2020/papers.html?filter=keywords



GRAPH ML IS GROWING IN AI RESEARCH

ICML 2019 International Conference on Machine Learning

Workshop about “**Learning and Reasoning with Graph-Structured Representations**”



Learning and Reasoning with Graph-Structured Representations

ICML 2019 Workshop

Overview | Schedule | Accepted Papers

All talk recordings are now available. You can find the links in the schedule.

Accepted Papers

All accepted papers will be presented as posters during the workshop. Additionally, a small number of accepted papers was selected to be presented as contributed or spotlight talks.

Poster instructions: Posters should be roughly 24" x 36" in portrait orientation. Papers #1-#20 will be presented in the morning poster session (10:00-11:00AM) and papers #21-#40 will be presented in the afternoon poster session (3:30-4:30PM). Please remove your posters during the lunch break if you are presenting in the morning session.

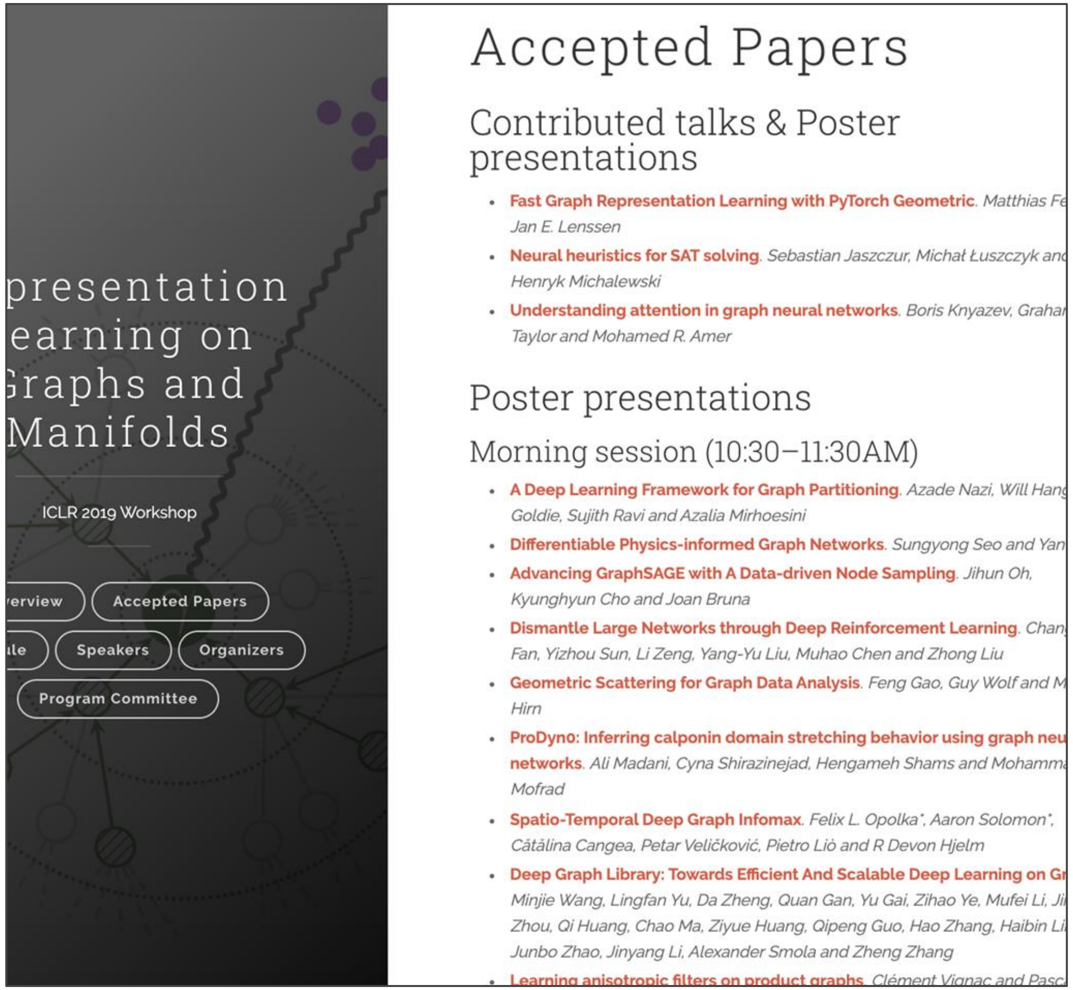
List of accepted papers:

1. Neural Message Passing for Visual Relationship Detection. Yue Hu, Siheng Chen, Xu Chen, Ya Zhang and Xiao Gu. (Spotlight)
2. Interpretable node embeddings with mincut loss. Chi Thang Duong, Hung Nguyen Quoc Viet and Karl Aberer.
3. Batch Virtual Adversarial Training for Graph Convolutional Networks. Zhijie Deng, Yinpeng Dong and Jun Zhu.
4. Supervised Segmentation with Graph-Structured Deep Metric Learning. Loic Landrieu and Mohamed Boussaha.
5. IPC: A Benchmark Data Set for Learning with Graph-Structured Data. Patrick Ferber, Tengfei Ma, Siyu Huo, Jie Chen and Michael Katz.
6. Decoding Molecular Graph Embeddings with Reinforcement Learning. Steven Kearnes, Li Li and Patrick Riley
7. Graph Learning Networks. Vedran J. Hadziosmanovic, Yongbin Li, Xiao Liu, Stuart Kim, David Dynerman and Loic Royer. (Spotlight)
8. Evolutionary Representation Learning for Dynamic Graphs. Aynaz Taheri and Tanya Berger-Wolf. **(Oral)**
9. Graph Learning Network: A Structure Learning Algorithm. Darwin D. Saire Pilco and Adín Ramírez Rivera. (Spotlight)

GRAPH ML IS GROWING IN AI RESEARCH

NeurIPS Annual Conference on Neural Information Processing Systems

NeurIPS 2019 Workshop about "Graph Representation Learning"



GRAPH NEURAL NETWORKS

Many studies on extending deep learning approaches for graph data have emerged: graph neural networks (GNNs) are divided into into four categories:

➔recurrent graph neural networks

➔convolutional graph neural networks,

➔graph auto-encoders

➔spatial-temporal graph neural networks

JOURNAL OF LaTeX CLASS FILES, VOL. XX, NO. XX, AUGUST 2019 1

A Comprehensive Survey on Graph Neural Networks

Zonghan Wu, Shirui Pan, *Member, IEEE*, Fengwen Chen, Guodong Long, Chengqi Zhang, *Senior Member, IEEE*, Philip S. Yu, *Fellow, IEEE*

***Abstract*—Deep learning has revolutionized many machine learning tasks in recent years, ranging from image classification and video processing to speech recognition and natural language understanding. The data in these tasks are typically represented in the Euclidean space. However, there is an increasing number of applications where data are generated from non-Euclidean domains and are represented as graphs with complex relationships and interdependency between objects. The complexity of graph data has imposed significant challenges on existing machine learning algorithms. Recently, many studies on extending deep learning approaches for graph data have emerged. In this survey, we provide a comprehensive overview of graph neural networks**

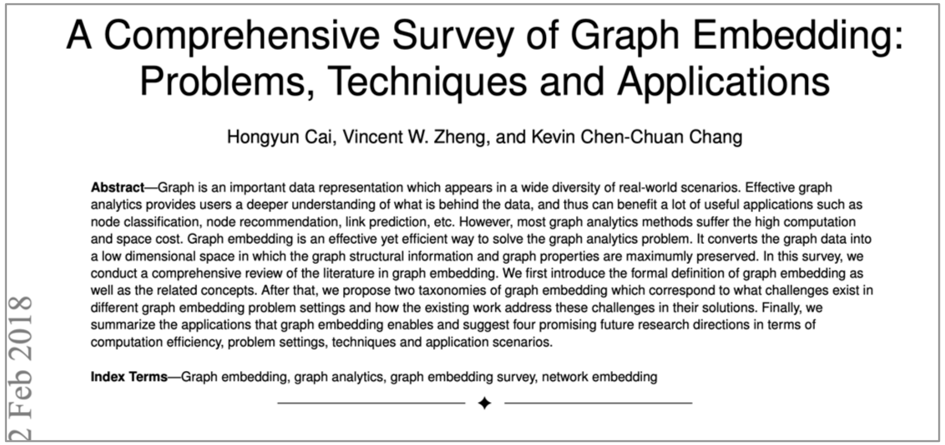
example, we can represent an image as a regular grid in the Euclidean space. A convolutional neural network (CNN) is able to exploit the shift-invariance, local connectivity, and compositionality of image data [9]. As a result, CNNs can extract local meaningful features that are shared with the entire data sets for various image analysis.

While deep learning effectively captures hidden patterns of Euclidean data, there is an increasing number of applications where data are represented in the form of graphs. For examples, in e-commence, a graph-based learning system can

GRAPH EMBEDDING

Graph embedding converts a graph into a low dimensional space in which the graph information is preserved.
By representing a graph as a (or a set of) low dimensional **vector(s)**, graph algorithms can then be computed efficiently.

Embedding transforms graphs into a feature vector, or set of vectors, describing topology, connectivity, or attributes of nodes and relationships in the graphs



A Comprehensive Survey of Graph Embedding: Problems, Techniques and Applications

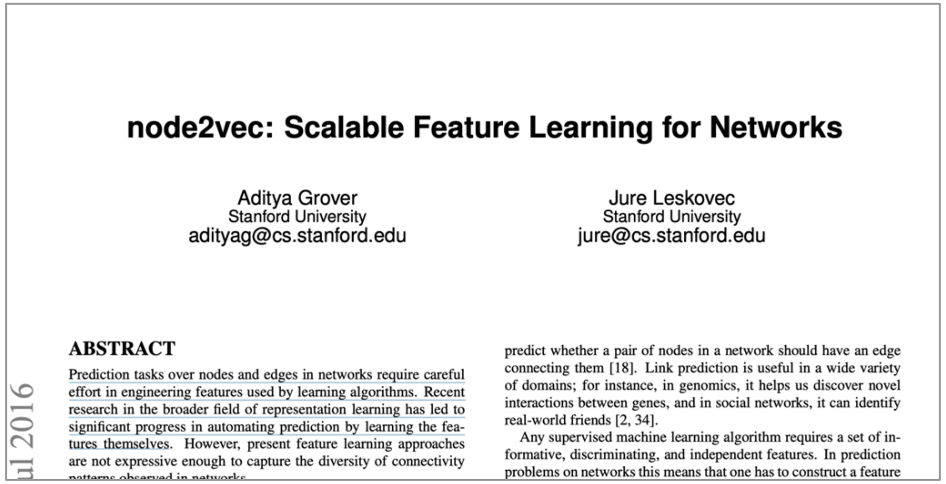
Hongyun Cai, Vincent W. Zheng, and Kevin Chen-Chuan Chang

Abstract—Graph is an important data representation which appears in a wide diversity of real-world scenarios. Effective graph analytics provides users a deeper understanding of what is behind the data, and thus can benefit a lot of useful applications such as node classification, node recommendation, link prediction, etc. However, most graph analytics methods suffer the high computation and space cost. Graph embedding is an effective yet efficient way to solve the graph analytics problem. It converts the graph data into a low dimensional space in which the graph structural information and graph properties are maximumly preserved. In this survey, we conduct a comprehensive review of the literature in graph embedding. We first introduce the formal definition of graph embedding as well as the related concepts. After that, we propose two taxonomies of graph embedding which correspond to what challenges exist in different graph embedding problem settings and how the existing work address these challenges in their solutions. Finally, we summarize the applications that graph embedding enables and suggest four promising future research directions in terms of computation efficiency, problem settings, techniques and application scenarios.

Index Terms—Graph embedding, graph analytics, graph embedding survey, network embedding

NODE2VEC

Node2vec is an algorithm to generate vector representations of nodes on a graph
Given any graph, it can **learn continuous feature representations for the** nodes, which can then be used for various downstream machine learning tasks involving predictions over nodes and edges predicting the most probable labels of nodes in a network [33]



node2vec: Scalable Feature Learning for Networks

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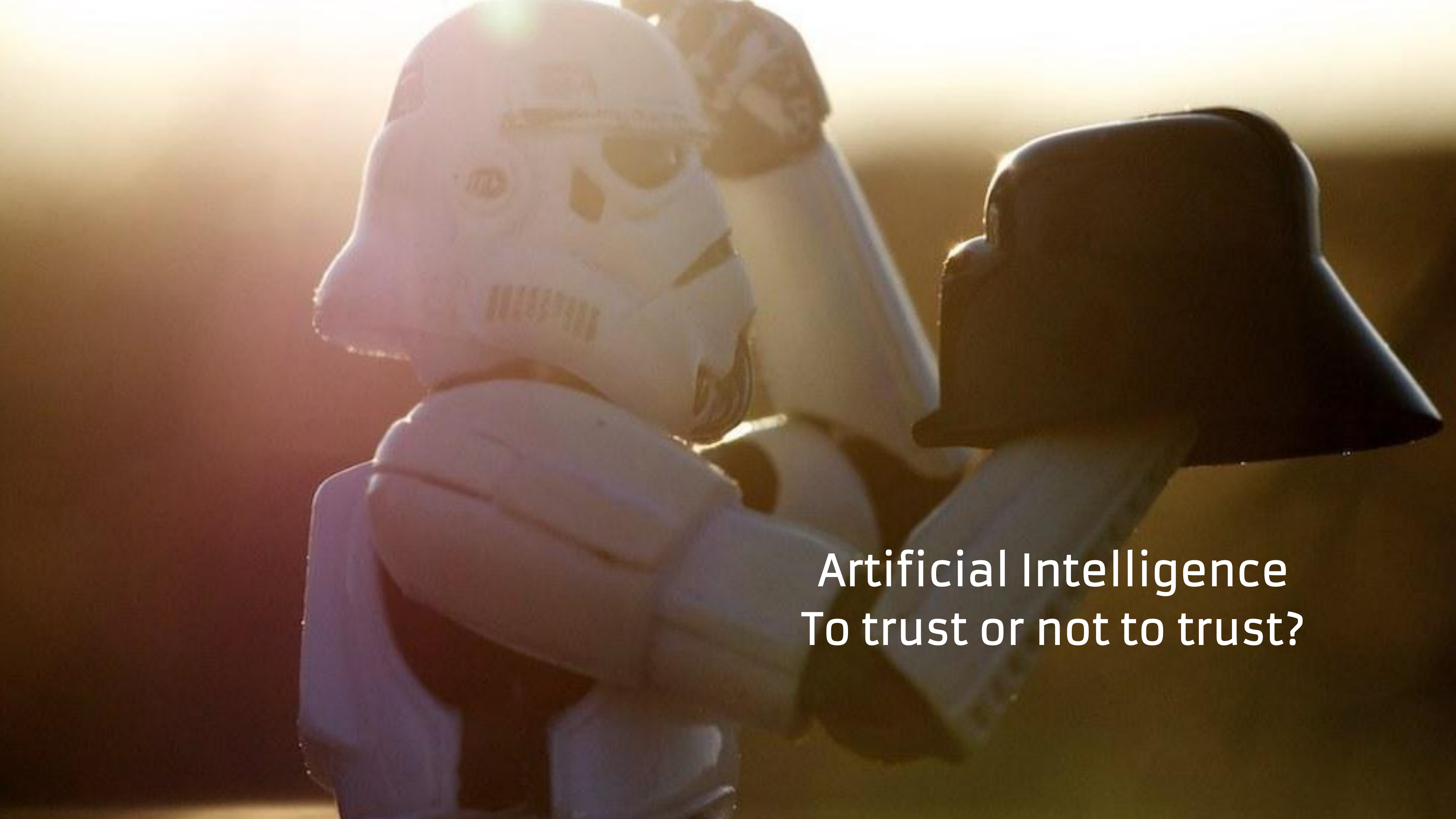
ABSTRACT

Prediction tasks over nodes and edges in networks require careful effort in engineering features used by learning algorithms. Recent research in the broader field of representation learning has led to significant progress in automating prediction by learning the features themselves. However, present feature learning approaches are not expressive enough to capture the diversity of connectivity patterns observed in networks.

predict whether a pair of nodes in a network should have an edge connecting them [18]. Link prediction is useful in a wide variety of domains; for instance, in genomics, it helps us discover novel interactions between genes, and in social networks, it can identify real-world friends [2, 34].

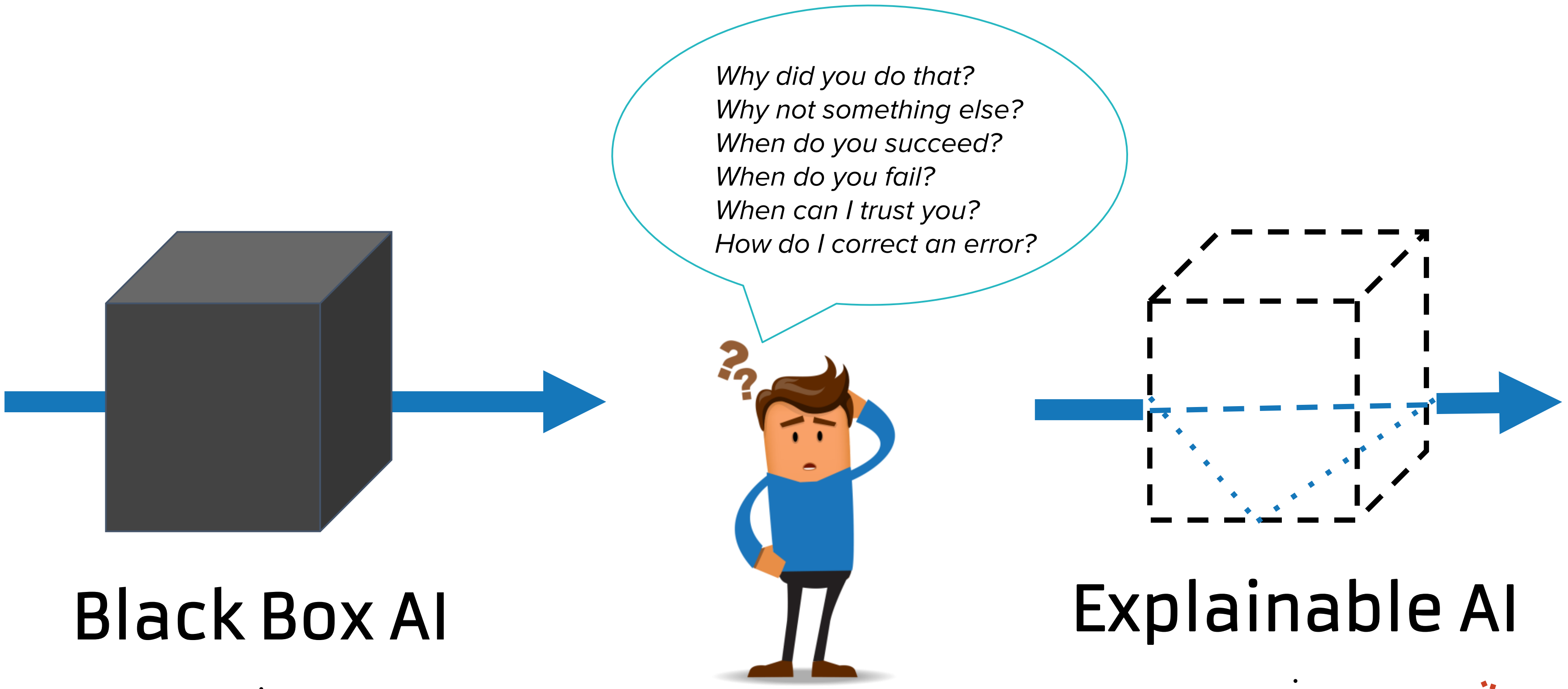
Any supervised machine learning algorithm requires a set of informative, discriminating, and independent features. In prediction problems on networks this means that one has to construct a feature

2 Explainable AI



Artificial Intelligence
To trust or not to trust?

BLACK BOX EFFECT



➔machine learning models are opaque, non-intuitive, and difficult for people to understand

➔black box models may reflect human biases and prejudices

LARUS

HOW CAN WE GUARANTEE THE RELIABILITY OF AI?

When machines make decisions, we want them to be clear on what stage they have reached in this process. And when they are unsure, we want them to tell us.

Transparency is especially relevant is in applications like:

➔medical diagnoses
➔crime prediction
➔personality scoring
➔lending decisions
➔high-scoring cases of suspected fraudulent activity
➔GDPR

LARUS

EXPLAINABLE AI

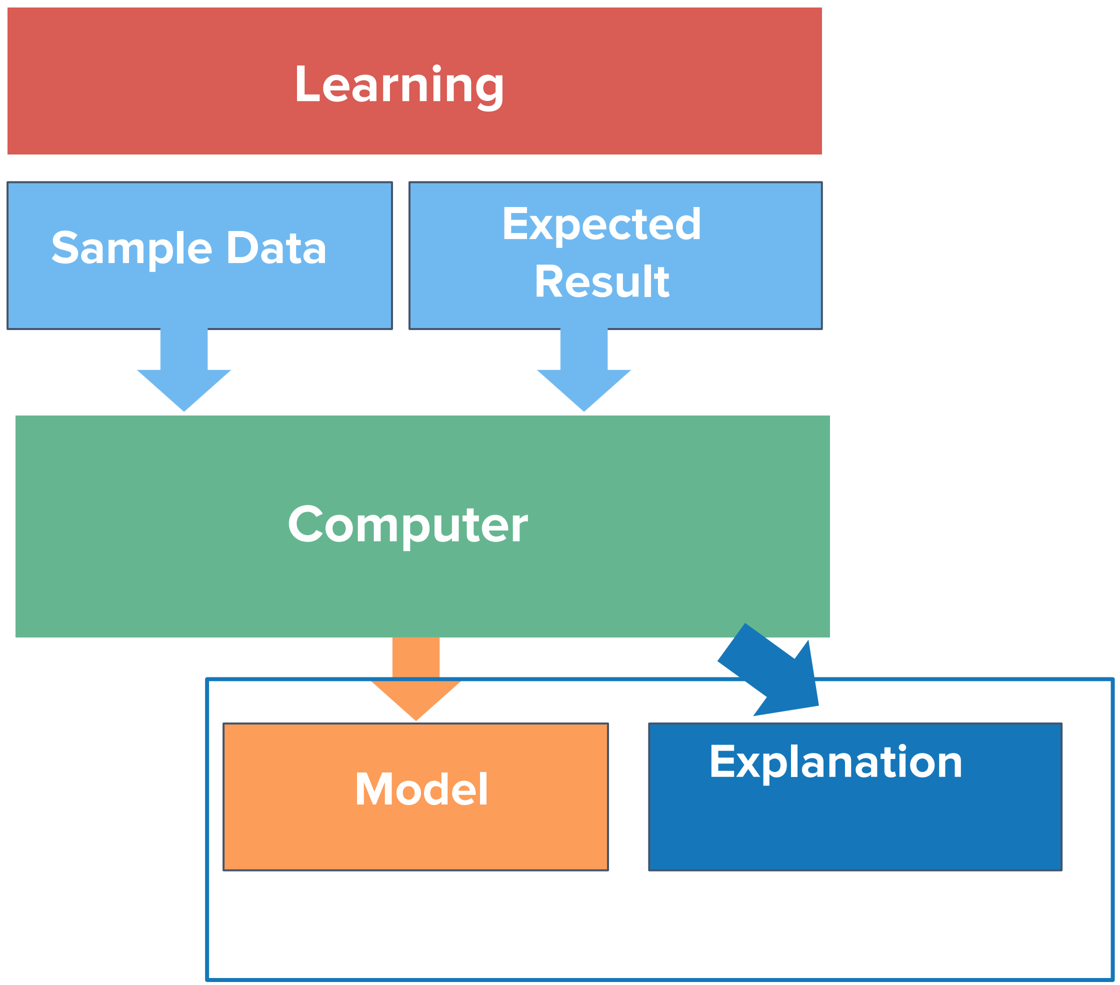
Explainable AI (XAI) is the class of systems that provide **visibility** into how an AI system makes decisions and predictions and executes its actions.

XAI explains the **rationale** for the decision-making process, surfaces the strengths and weaknesses of the process, and provides a sense of how the system will behave in the future[1]

[1]The Defense Advanced Research Projects Agency (DARPA) program on XAI identifies these as key characteristics of XAI: Turek, Matt, Explainable AI, Program Information, Defense Advanced Research Projects Agency, https://www.darpa.mil/program/explainable-artificial-intelligence, Accessed on October 20, 2019.

NO AI WITHOUT EXPLANATION

➔Produce more explainable models, while maintaining a high level of learning performance (prediction accuracy)
➔Enable human users to understand, appropriately trust, and effectively manage the emerging generation of artificially intelligent systems
➔Ensure impartiality in decision-making, to detect, and consequently, correct from bias in the training dataset.



3 Fujitsu Deep Tensor

FUJITSU DEEP TENSOR

Our Partner **Fujitsu** Laboratories of America has developed the very first explainable AI, called **Deep Tensor,** capable of showing the reasons behind AI-generated findings and to make them explainable, allowing human experts to validate the truth of AI produced results and gain new insights.

uses Deep Tensor with Knowledge Graph to Explain and Basis Behind AI-Generated Findings

aboratories Ltd.,Fujitsu Limited

Kawasaki, Japan, September 20, 2017

ed and Fujitsu Laboratories Ltd. today announced that they have developed te
he reason and academic basis for findings from AI that have been trained on la
data. This is done by connecting the proprietary AI technology Deep Tensor(1), v
achine learning on graph-structured data, with graph-structured knowledge bas
graph(2), which brings together expert knowledge such as academic literature.

ed prevalence of machine learning technologies such as deep learning, in whic
ds characteristics of data on its own after being trained on large volumes of dat
h the application of this technology to mission-critical fields such as medicine a
s is because there are questions of accountability regarding experts' AI-based f
ult for humans to evaluate the reason behind the findings gained using these
s.

Fujitsu Laboratories have now successfully developed technology that shows th
r an AI inference by connecting the results of Deep Tensor findings with knowle

https://www.fujitsu.com/global/about/resources/news/press-releases/2017/0920-02.html

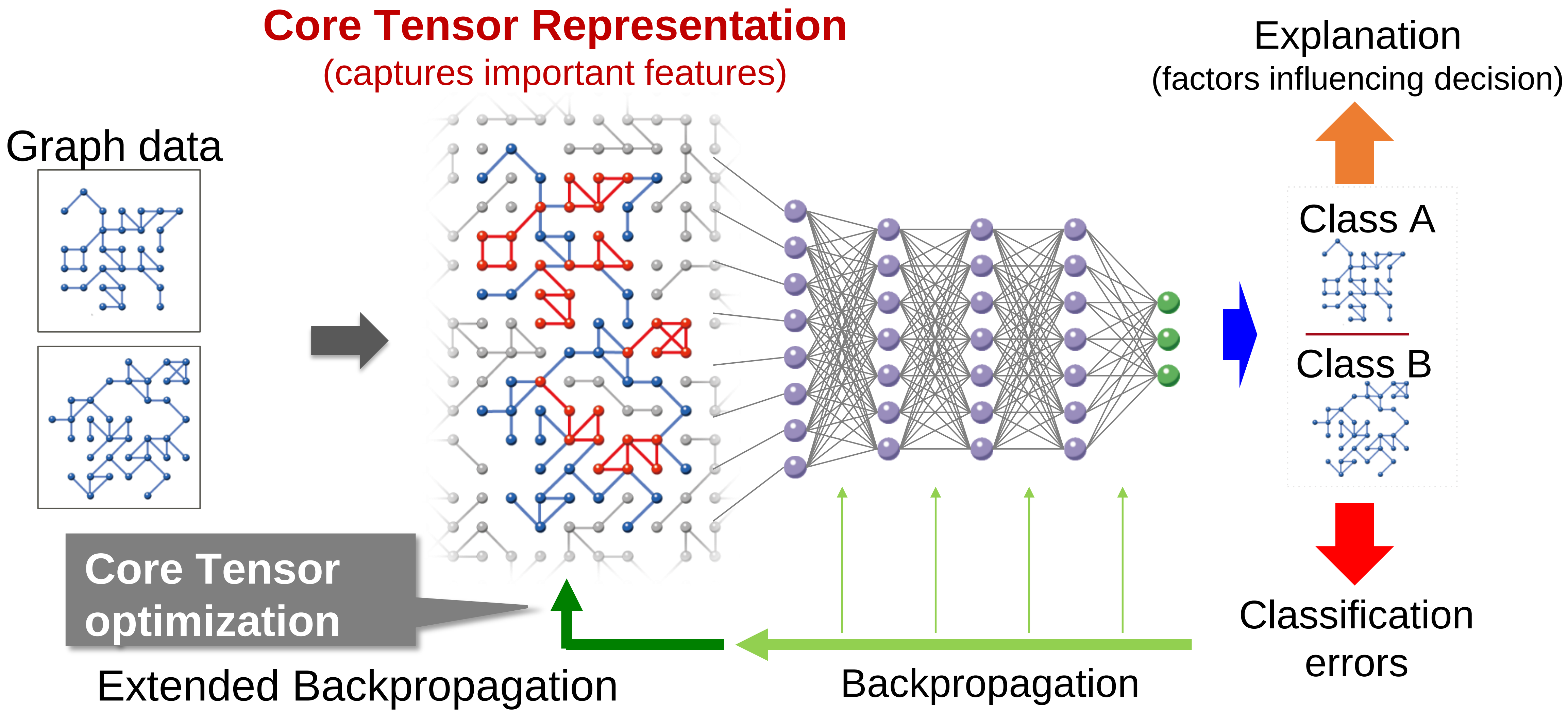
HOW FUJITSU DEEP TENSOR REALIZE EXPLAINABLE AI?

Fujitsu's **new deep learning technology** connecting the proprietary AI technology **Deep Tensor**, which performs machine learning on a **knowledge graph.**

➔step 1, it identifies factors within the input data that significantly contribute to the inference result.

➔step 2, it establishes a correspondence between those factors and the nodes in a knowledge graph.

DT EARNS FROM GRAPH DATA NATIVELY, AUTOMATICALLY EXTRACTING FEATURES



LARUS

Let us fix your Data to get a better AI

Data Platform Design & Development

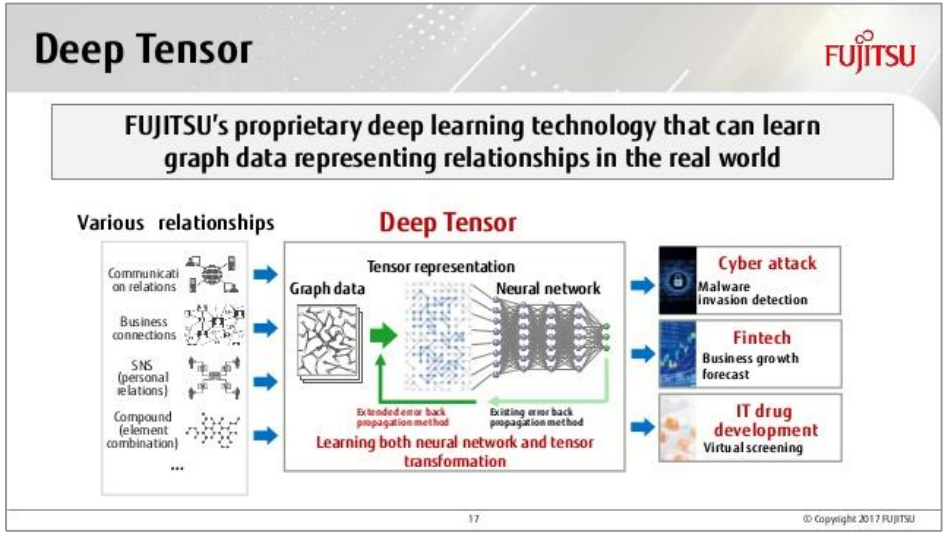
Data Visualization

Machine Learning and AI graph based technology

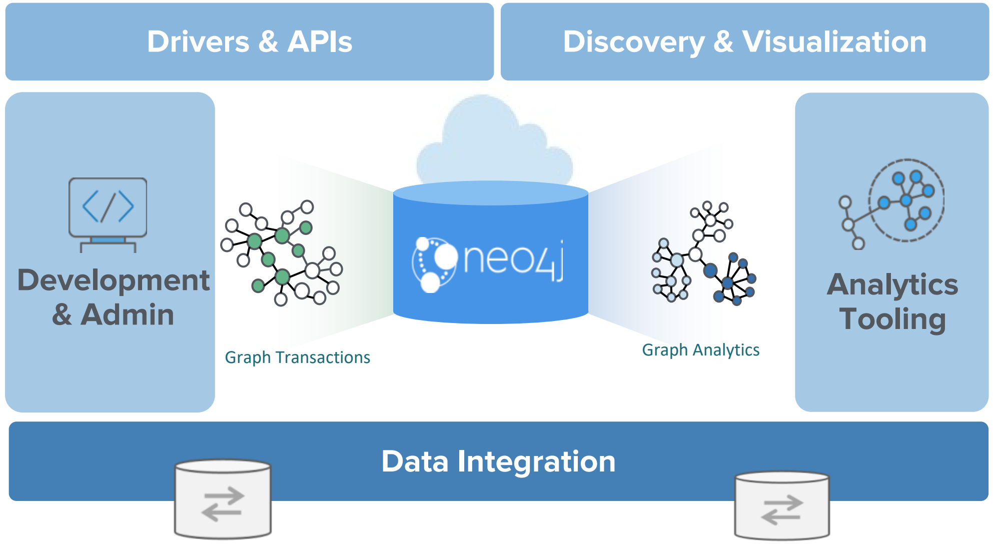
Strategic Advisoring for AI Projects

LARUS

WE PARTNERS WITH FUJITSU AND DEEP TENSOR FOR BETTER AI



Fujitsu Deep Tensor



Neo4j Graph Data Platform

Thank you!