This special lecture has been given by Prof. Zhuang Chenyi who joined Artificial Intelligence Research Center (AIRC), AIST as a researcher in April 2018. And through the introduction we could know that during October 2017 and March 2018, he was a post-doctor in Kyoto University. He received the BS degree in SE from Nanjing University in 2011, the MS degree and PhD degree in Informatics from Kyoto University in 2014 and 2017, respectively. And his current research themes are data mining, machine learning and urban computing.

In this special lecture, the prof. Zhuang Chenyi talked about the “Representation Learning to Make Computers Better Understand Graph-Structured Data”, it could be divided into five parts. The first part, the speaker introduced the basic knowledge about the graphs, and he also gave us the reasons that why he chooses graph? As we know, graph is a general language for describing structured data from the real world and for modeling complex systems. For instances, in computational social science, simulation, computer vision, chemistry and biology research areas, a lot of problems can be modeled as data mining tasks on graphs (e.g., social networks, point clouds, images, protein-gene interactions). And about the reason the speaker told us that, although there are so many graph-structured data surrounding us, a problem of significant importance is how to make computers better understand these structured data. After that, in order to consider both of the semantic information on data points, edges and the geometric characteristics, the key technical challenges and how our methods work will be discussed. Thus, he introduced several technologies to talk about graphs and graph laplacian. At the same time, graph fourier transform (GFT) has been talked in part three. In the fourth part, the more details about GFT and representation learning have been discussed with us. Finally, the Prof. Zhuang Chenyi gives us the potential research directions by using a graph representation learning study which aims to learn task-independent graph features.

It is my pleasure to take part in this special lecture, due to I am very interesting in data management and data analyze, I think this special lecture cold help me well in data. In our daily life, data is anywhere, from the internet we could gather texts, images and so on. But there still has big gap between computer and human, how to make computer to understand data easily is a big problem need to solve. Firstly, about the meaning of graph, Graphs are a ubiquitous data structure, employed extensively within computer science and related fields. Social networks, molecular graph structures, biological protein-protein networks, recommender systems—all of these domains and many more can be readily modeled as graphs, which capture interactions (i.e., edges) between individual units (i.e., nodes). As a consequence of their ubiquity, graphs are the backbone of countless systems, allowing relational knowledge about interacting entities to be efficiently stored and accessed.

At the same, why the prof. Zhuang Chenyi chose graph as his research area, he through several directions to explain the reason. The first reason is that, the graph links predictions. He gave an example from freebase knowledge graph to explain this reason. Freebase was a large collaborative knowledge base consisting of data composed mainly by its [community](https://en.wikipedia.org/wiki/Online_community) members. It was an online collection of structured data harvested from many sources, including individual, user-submitted [wiki](https://en.wikipedia.org/wiki/Wiki) contributions. And freebase aimed to create a global resource that allowed people (and machines) to access common information more effectively. About the second reason is that, image is a special instance, for example, as we know, if the inputs is an image as a 2D grids, through kernels which is a filtering matrix, we could get the outputs which convolved representation. However, there still has some challenges need to consider, for example, the graph structure is irregular, and there may be attribute on the edges and there may be attributes on the nodes. In contrast, how to jointly consider the structure and edge and node information is a big challenge.

Thus, based on the current challenges, graph and the graph laplacian have been introduced. In the mathematical field of graph theory, the Laplacian matrix, sometimes called admittance matrix, Kirchhoff matrix or discrete Laplacian, is a matrix representation of a graph. The Laplacian matrix can be used to find many useful properties of a graph. Together with Kirchhoff's theorem, it can be used to calculate the number of spanning trees for a given graph. The sparsest cut of a graph can be approximated through the second smallest eigenvalue of its Laplacian by Cheeger's inequality. It can also be used to construct low dimensional embeddings, which can be useful for a variety of machine learning applications. Meanwhile, there are many mathematical formulas have been talked in this lecture. For example, in the part of graph definition, the speaker talked about the graph signal, graph adjacency matrix and the graph degree diagonal matrix. Laplace operator is also be divided into 2 situations, the first situation is on the real number line, the laplace operator is the second derivative, and then if we discretize the real number line by its dyadic points, the discretized laplace operator is the sum of all the differences of function f(x) evaluated at all its neighbors.

About the graph fourier transform which is a function of time (a signal) into the frequencies that make it up, in a way similar to how a musical chord can be expressed as the frequencies (or pitches) of its constituent notes. We need to calculate the fourier basis such as the eigenvetors of the laplace matrix, through this we could get n different eigenvectors and the corresponding n different eigenvalues. An example about apply the heat kernel to the Minnesota road map has been introduced by using GFT based filtering. In this lecture, we also compare the classic GFT based filtering and the representation learning. As we have known that he classic GFT based filtering, which could manually define the filtering functions and unsupervised ( no training needed ). At the same time, the representation learning could make the filtering function trainable, and it could automatically learn the filtering function from training data, which means it is supervised.

In conclusion, this special lecture is mainly a technical report lecture. The author elaborated on the key technologies through mathematical formulas.