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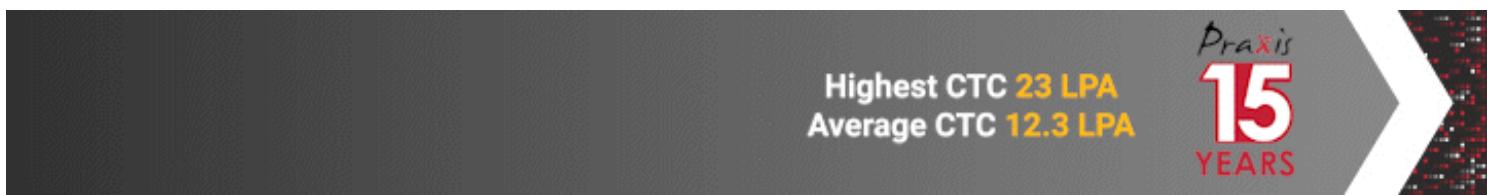
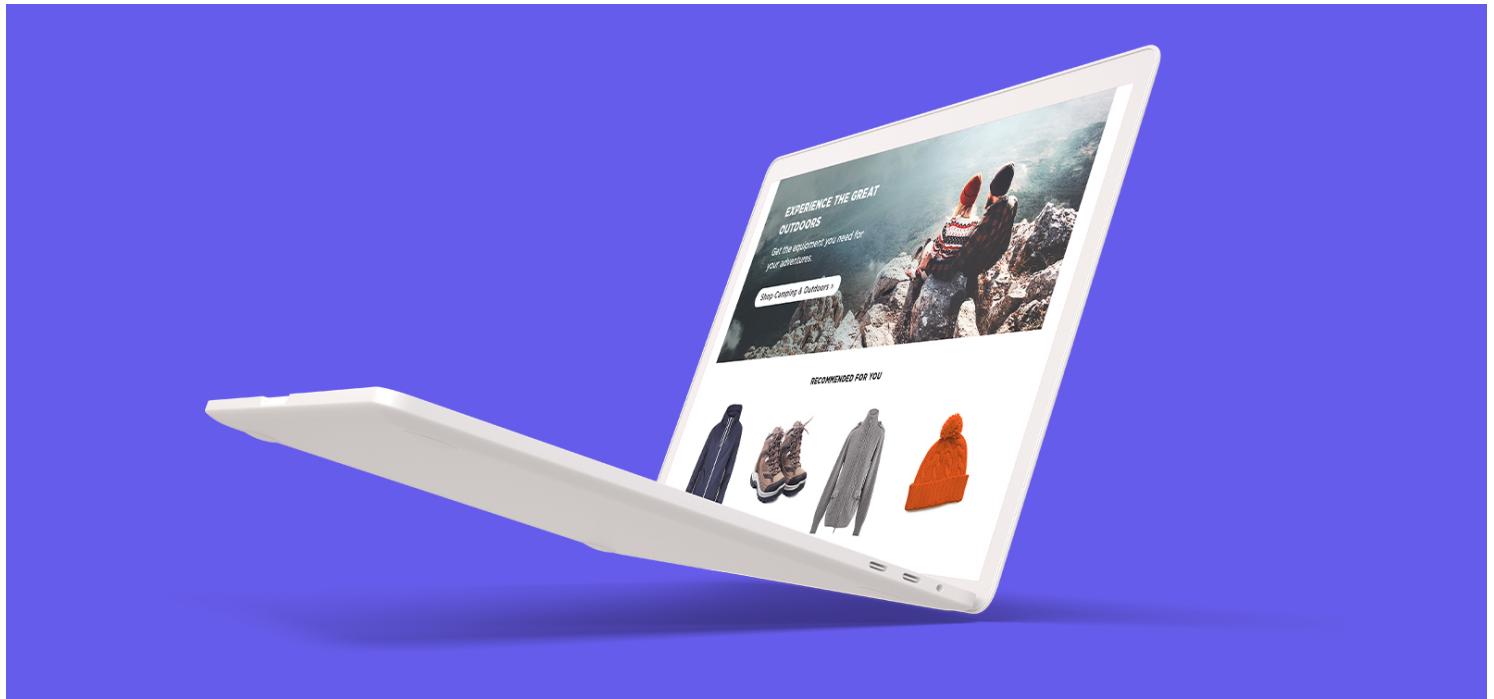
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Cold-Start Problem in Recommender Systems and its Mitigation Techniques

The recommender systems face a problem in recommending items to users in case there is very little data available related to the user or item. This is called the cold-start problem.

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Let's start with understanding what actually the cold-start means.

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Cold-Start Problems and its Types

Recommender systems are a sort of information filtering technology that aims to offer information items that are likely to be of interest to the user. The cold start problem occurs when the system is unable to form any relation between users and items for which it has insufficient data. There are two types of cold-start problems: –

1. **User cold-start problems:** When there is almost no information available about the user, the user cold-start problem arises.
2. **Product cold-start problems:** When there is almost no information about the product, the product cold-start problem arises.

Reasons for Cold-Start Problem

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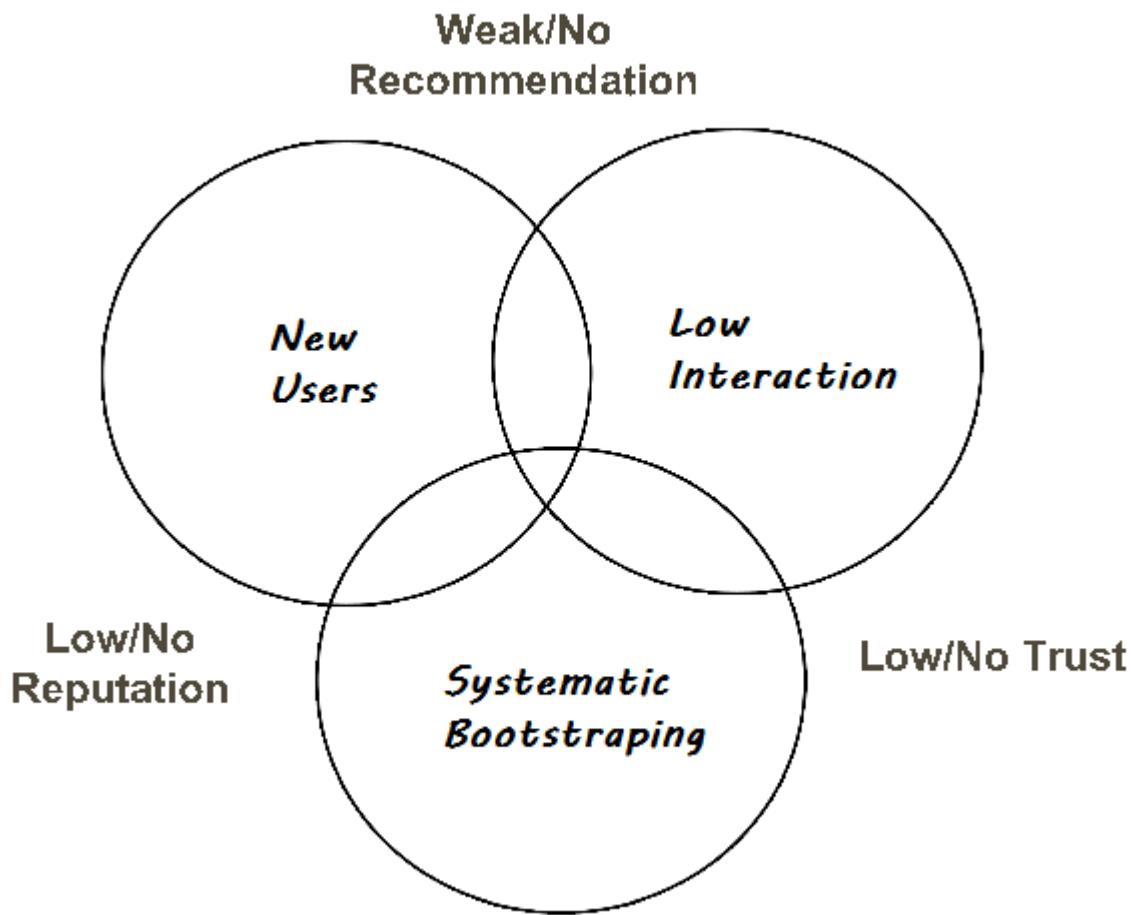


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Commonly there are three main reasons for which the system fails to give recommendations namely Systematic Bootstrapping, Low Interaction (Few instances available), and the entry of new users.



[Image Source \(https://www.researchgate.net/figure/Beyond-the-cold-start-problem-new-items-may-fail-in-trust-if-new-users-with-low_fig1_263575914\)](https://www.researchgate.net/figure/Beyond-the-cold-start-problem-new-items-may-fail-in-trust-if-new-users-with-low_fig1_263575914)

Systematic Bootstrapping

Systemic bootstrapping refers to the starting of the system when there is almost no information on which the recommender may rely. As all assets and users are new, this example demonstrates the drawbacks of both the minimal interaction and the New user cases. As a result, several of the approaches established to cope with those two scenarios are unsuitable for system bootstrapping.

Low Interaction

When things are added to the catalogue, the item cold-start problem occurs when they have no or very few interactions. This is particularly problematic for collaborative filtering algorithms, which generate recommendations based on the item's

interactions. A pure collaborative algorithm cannot recommend an item if there are no interactions available.

If only a few interactions are available, a collaborative algorithm can recommend it, but the quality of those recommendations will be poor. This raises a new issue, one that is not tied to new products, but rather to unpopular items.

New User

The new user case occurs when a new user enrolls in the system and the recommender is required to offer recommendations for a set length of time without depending on the user's previous interactions, as none have been recorded yet.

This issue is especially important when the recommender is part of the service provided to users, because a user who receives poor-quality recommendations may opt to leave the system before giving enough interaction to allow the recommender to understand his or her interests.

When dealing with new users, the primary technique is to ask them to offer certain preferences in order to create an initial user profile. You may have seen such interaction on Netflix.

Mitigation Techniques

Many solutions to minimize the cold-start problem have been created due to a large number of recommender algorithms available, as well as system type and features. The basic strategy is to use hybrid recommenders to offset the drawbacks of one category or model by combining them with another.

All three types of cold-start problems we have discussed so far have a lack of user engagements in common, and there are some similarities in the techniques available to solve them. Let's see them one by one;

Representative Approach

If we lack sufficient knowledge of users and objects, we can rely on those who represent the set of items and users. That is the underlying idea of representative-based approaches. Representatives can be users whose linear combinations of preferences closely resemble those of other users.

When a new user joins the site, we may ask them to rate a few contents, and then use that information to deduce the ratings of other products. In this manner, we can enhance suggestions for new users by charging consumers a modest fee to rate select goods.

Feature Mapping

The matrix factorization technique may be used to solve feature mapping. The basic concept is that a matrix factorization model depicts user-item interactions as the product of two rectangular matrices whose content is learnt using known interactions via machine learning. Each user will be assigned a row in the first matrix, and each item will be assigned a column in the second matrix; this set is called a latent factor. Latent factors are rows or columns that are linked with a certain individual or object.

When a new item is added, there are no related latent factors, and the lack of interactions prevents them from being learned, as was done with previous things. If each item is linked with certain attributes (for example, author, year, publication, actors), an embedding function may be defined that, given the item features, estimates the corresponding item latent factors. The embedding function may be built in a variety of ways, and it is trained using data from warm things that are already accessible. By the feature mapping, we can have a reasonable recommendation.

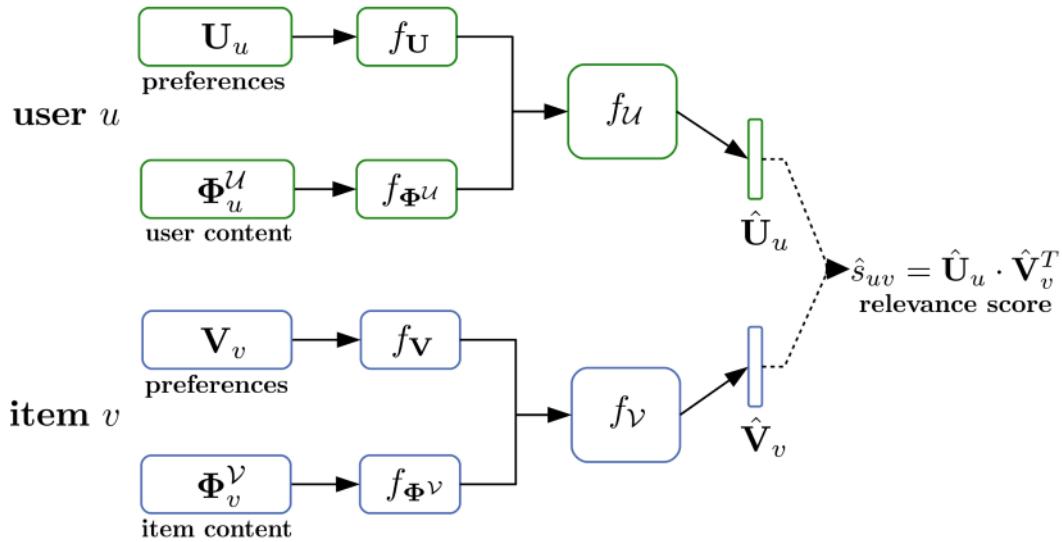
Hybrid Approach

Another new technique that is related to feature weighting is the development of a hybrid content-based filtering recommender in which characteristics, either of the items or of the people, are weighted depending on the user's sense of significance. Different criteria (such as the actors, director, region, and title) will be weighted differently in order to select a movie that the consumer would enjoy.

Deep Learning-Based Mitigation Approaches

Dropout-Net

The basic concept is simple but effective. Their idea is that by randomly deleting ratings of things and users when training deep learning-based recommendation systems (e.g., collaborative filtering with multiple layers), we may make it resilient against cold items.

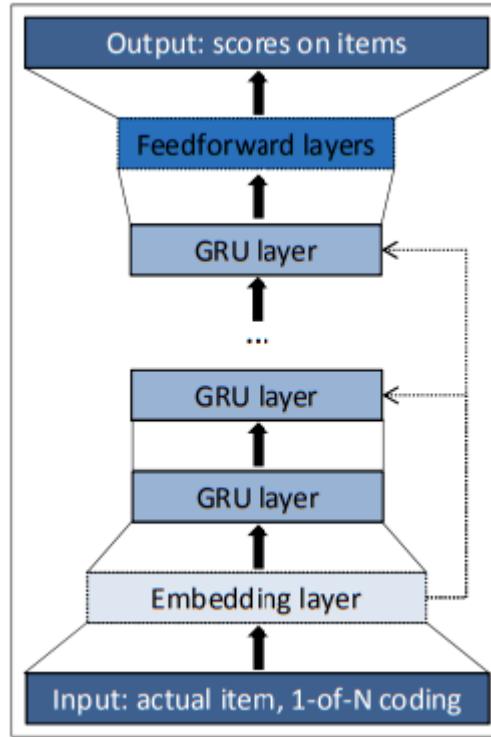


DropoutNet architecture diagram. For each user u , the preference \mathbf{U}_u and content Φ_u^U inputs are first passed through the corresponding DNNs f_U and f_{Φ^U} . Top layer activations are then concatenated together and passed to the fine-tuning network f_u which outputs the latent representation $\hat{\mathbf{U}}_u$. Items are handled in a similar fashion with f_V , f_{Φ^V} and f_v to produce $\hat{\mathbf{V}}_v$. All components are optimized jointly with back-propagation and then kept fixed during inference. Retrieval is done in the new latent space using $\hat{\mathbf{U}}$ and $\hat{\mathbf{V}}$ that replace the original representations \mathbf{U} and \mathbf{V} .

The above information is taken from the original research paper of [Volkovs et. al](#) (<https://proceedings.neurips.cc/paper/2017/file/dbd22ba3bd0df8f385bdac3e9f8be207-Paper.pdf>). The essential point here is that, unlike normal dropouts in neural network training, they drop the features rather than the nodes. By doing so, they may reduce the neural network's reliance on specific ratings and make it more generalizable to items/users with fewer ratings. Their approach's strength is that it can be utilized with any neural network-based recommender system, and it also works for a cold start.

Session-Based RNN

This method attempts to make use of each user session by feeding it into an RNN. They trained a version of the Gated Recurrent Unit (GRU) with the input being the current state of the session and the output being the item of the next event in the session.



The architecture of Session-Based RNN
[\(https://arxiv.org/pdf/1511.06939.pdf\)](https://arxiv.org/pdf/1511.06939.pdf)

The GRU layer(s) form the network's core, and between the last layer and the output, additional feed-forward layers can be added. The projected preference of the items, i.e. the likelihood of being the next item in the session for each item, is the output. When using several GRU layers, the preceding layer's hidden state becomes the input for the next. Optionally, the input can be linked to GRU layers located farther down the network. Take a look at the entire architecture, which illustrates the representation of a single event inside a timeline of occurrences.

This network is helpful, for example, in smaller e-commerce sites with a limited number of user sessions.

Conclusion

Through this post, we could understand the cold-start problem in the recommender system and its major causes. Mitigation techniques discussed here can help you to overcome this issue out of which hybrid approach can make your system robust because it considers many aspects of the product.

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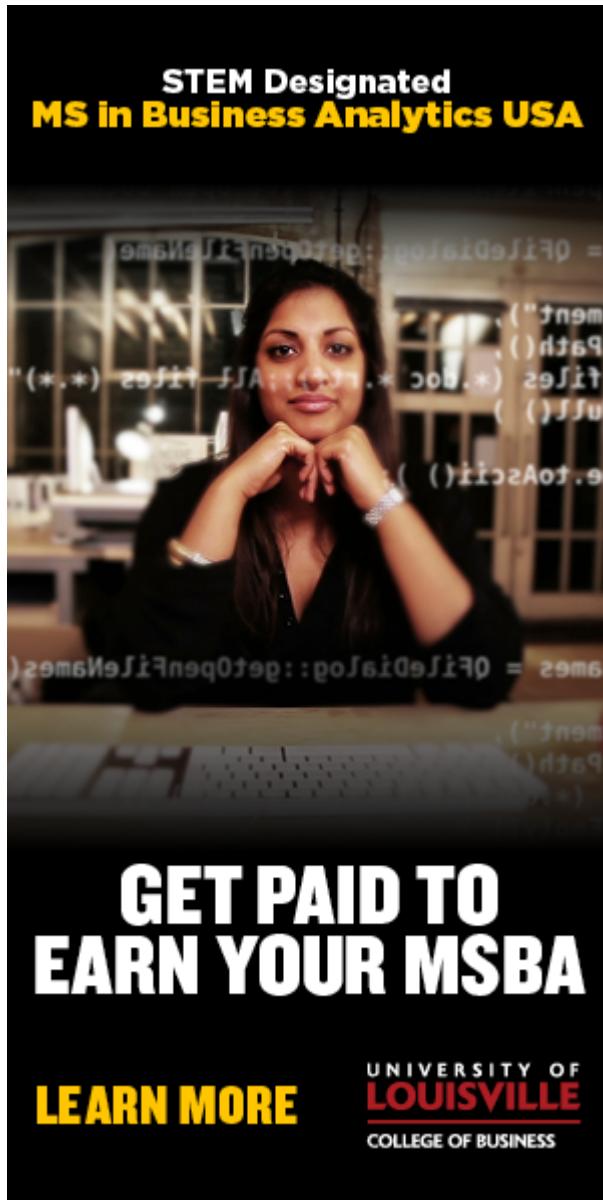
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Vijaysinh is an enthusiast in machine learning and deep learning. He is skilled in ML algorithms, data manipulation, handling and visualization, model building.

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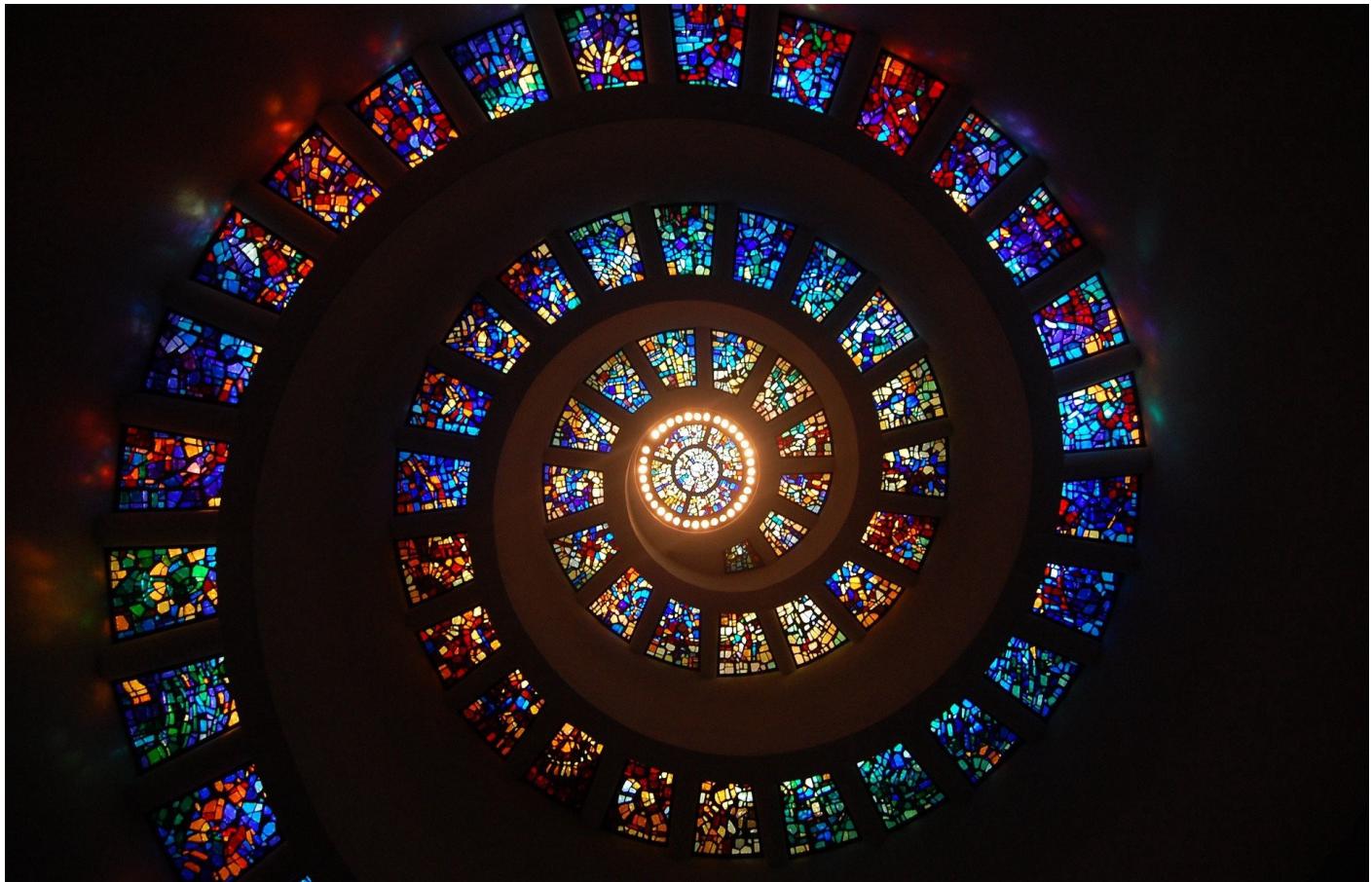
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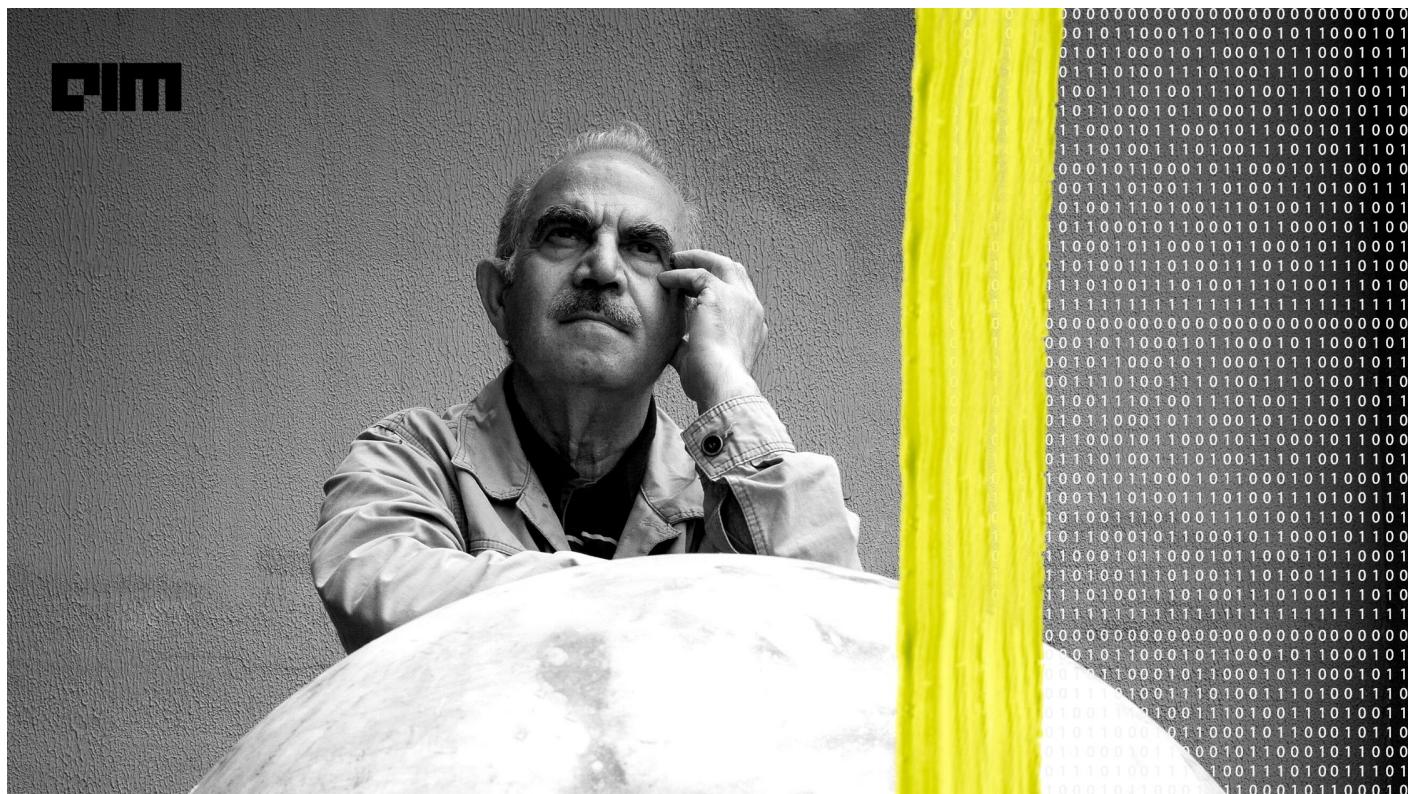


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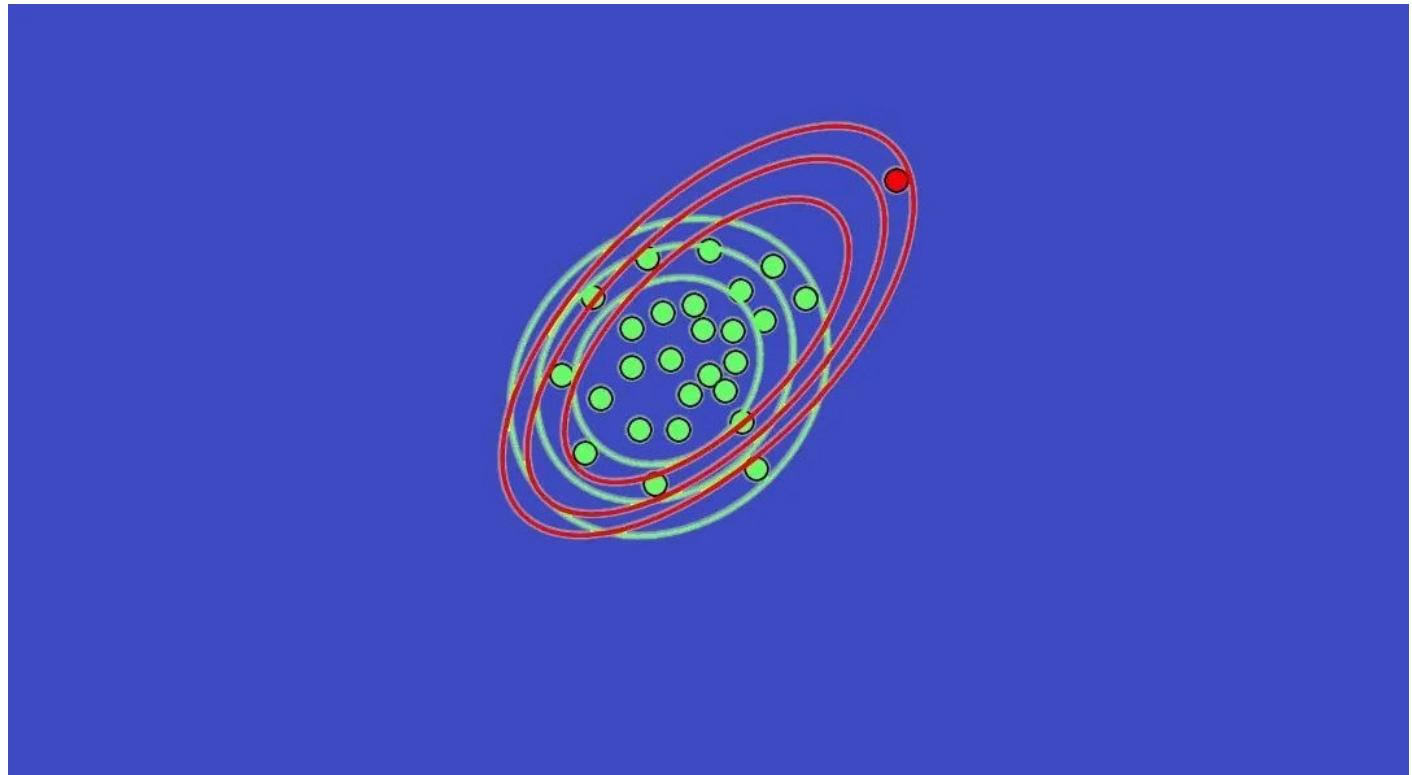


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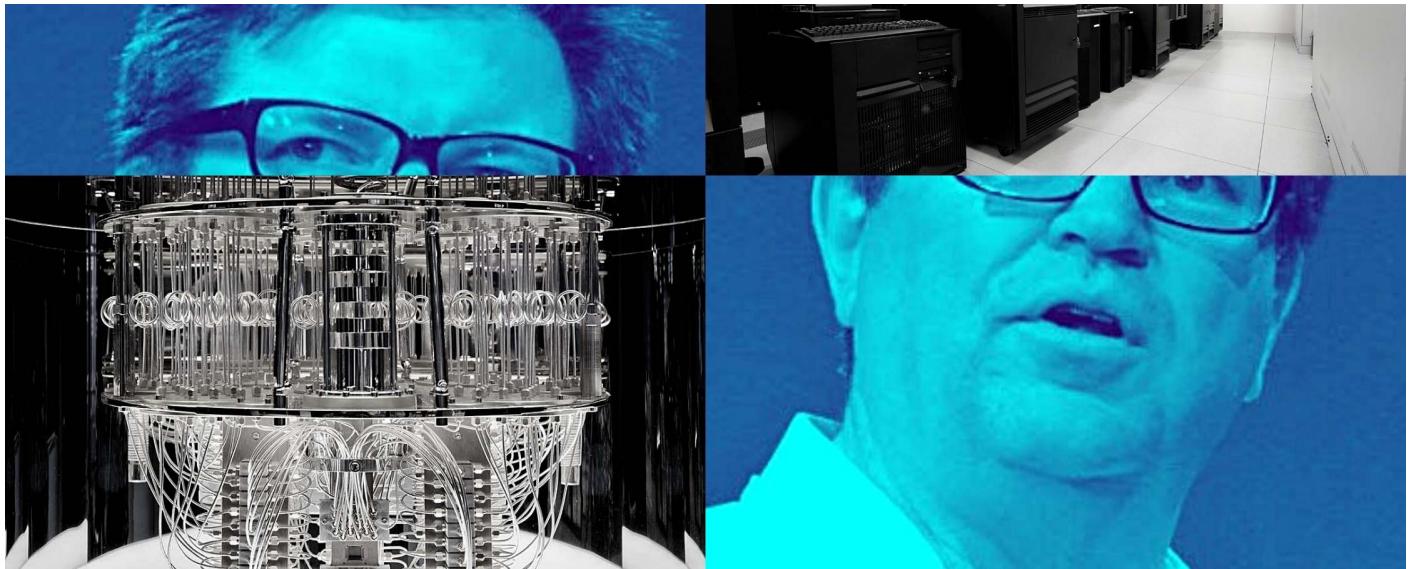
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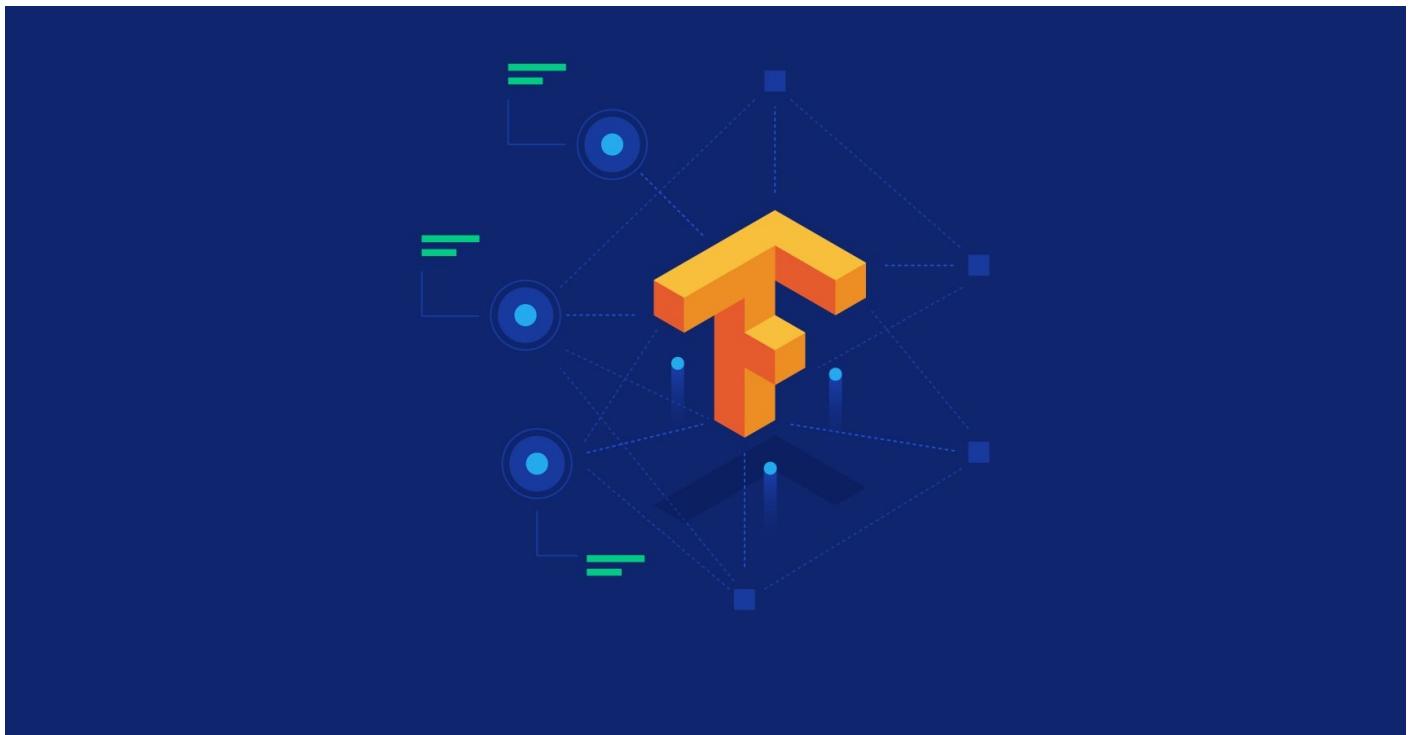
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