















One-hot encoding Word embedding Word2vec K-mer model t

Difference between One-Hot Encoding vs Embedding

What Is the Difference between **One-Hot Encoding vs Embedding**



SURESH BEEKHANI

Machine Learning Engineer | Data Scientist | Al Agents |





June 20, 2024

Representing Categorical Data in Machine Learning Models

In machine learning, representing categorical data as numerical values is crucial. Two popular techniques for this are:

- 1. One-hot encoding
- 2. Embedding

One-hot Encoding

One-hot encoding is a simple technique, suitable for small datasets with a limited number of categories.

Embedding

On the other hand, Embedding is more suited for large datasets with high-cardinality categorical features. It is beneficial when capturing relationships between categories is important.

Key Differences

Dimensionality

- One-hot encoding: Increases the data dimensionality by creating a new binary column for each unique category. For N categories, it creates N new columns, leading to a high-dimensional, sparse representation. This can be inefficient and impractical for datasets with many categories.
- Embedding: Reduces the dimensionality by representing each category as a dense vector of lower dimensionality (e.g., 8, 16, 32 dimensions). This results in a compact representation that is more manageable and efficient.

Relationship between Categories

One-hot encoding: Treats each category as independent and orthogonal, meaning there is no inherent relationship between the

- (4) What Is the Difference between One-Hot Encoding vs Embedding | LinkedIn categories. Each category is represented by a unique binary vector, where only one element is '1' and all others are '0'.
- Embedding: Captures semantic relationships and similarities between categories by placing similar categories closer together in the embedding space. This is achieved by learning dense vectors that represent the categories in a way that similar categories have similar vectors.

Interpretability

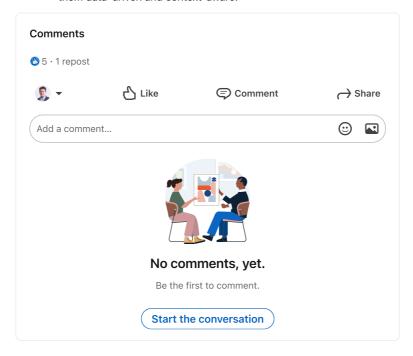
- One-hot encoding: Vectors are easily interpretable since each column directly corresponds to a specific category. This makes it straightforward to understand and analyze the encoded data.
- Embedding: Vectors are dense and harder to interpret directly. The
 meaning of individual dimensions is not as clear as in one-hot
 encoding, as embeddings capture complex relationships learned
 from the data.

Scalability

- One-hot encoding: Becomes inefficient and sparse when dealing
 with high-cardinality categorical features (many unique
 categories). This can lead to the curse of dimensionality, where the
 data space becomes so large that the learning algorithm struggles
 to generalize.
- Embedding: More scalable and efficient for high-cardinality features, as each category is represented in a fixed-size, lowerdimensional vector. This makes embeddings suitable for large datasets with many unique categories.

Learning

- One-hot encoding: A simple deterministic process that does not require any learning. Each category is independently encoded without considering the data distribution or relationships between categories.
- Embedding: Learned from data, typically as part of the training process of a neural network. Embeddings are adjusted during training to capture the relationships between categories, making them data-driven and context-aware.



Enjoyed this article?

Follow to never miss an update.

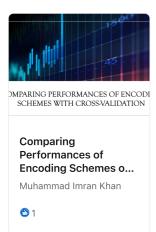


SURESH BEEKHANI

Machine Learning Engineer | Data Scientist | Al Agents | GenAl



More articles for you







♦ 11 · 2 comments





George Bonela

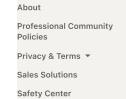
6



Select Language

English (English)

0 0



Accessibility

Careers

Ad Choices

Mobile

Talent Solutions Marketing Solutions

Advertising

Small Business







LinkedIn Corporation © 2025