MTP SCEE 2019-20

Indian Institute of Technology Mandi

Dimensionality Reduction Using Feature Hashing

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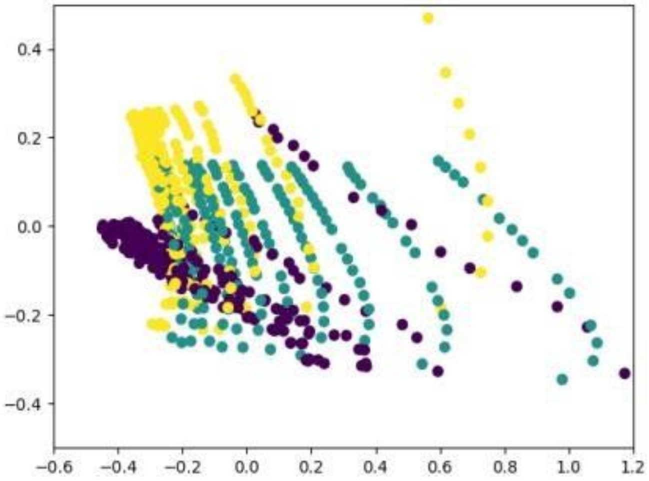
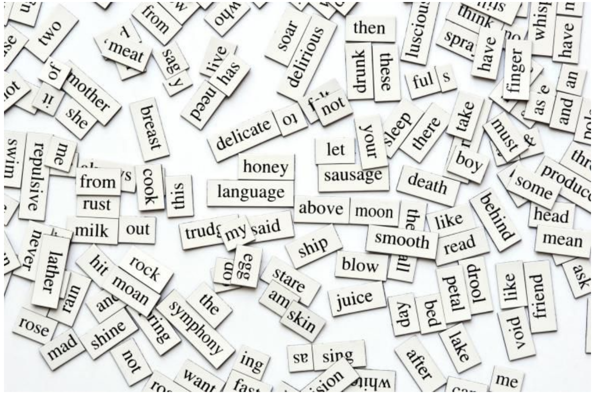
Why Dimensionality Reduction?

1. Collection of Large Data
2. Data size beats Computing Power
3. Vector Representation of Data
4. High Dimensionality of Vectors

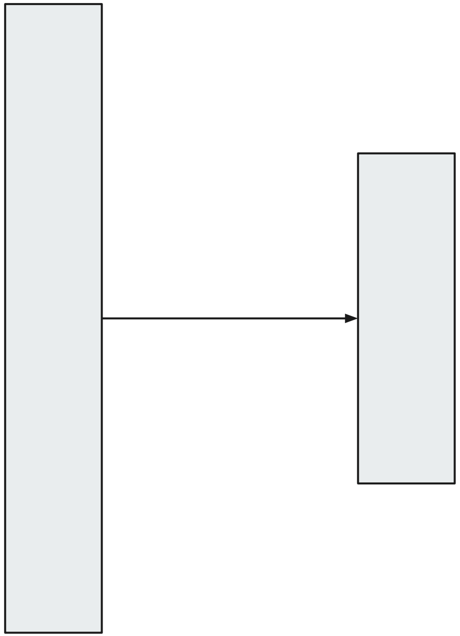
- Size of dataset depend on number of data points as well as on dimension of each data point.
- We can't control the number of data points involved for representing a real world entity model.
- But size of dataset can be reduced by reducing the dimension under which each data point is represented.



- Consider machine learning model which will check the similarity between two given documents.
- Requires large dataset for training that model and a dictionary containing list of attributes for which each data point is represented in vector form.
- Since dictionary can be too large may be of size 10000 to 100000.



- Dimension involved with each data point may become very high.
- This can be solved if somehow these data points (documents) can be represented in vector of much lower dimension.



Our Problem Statement

- *To achieve dimensionality reduction using feature hashing while preserving the similarity between the data objects.*

Our Methodology

- *Motive*

Reduce d dimensional Vector to N dimensions
Where N << d

$$<a, b> \cong <a', b'>$$

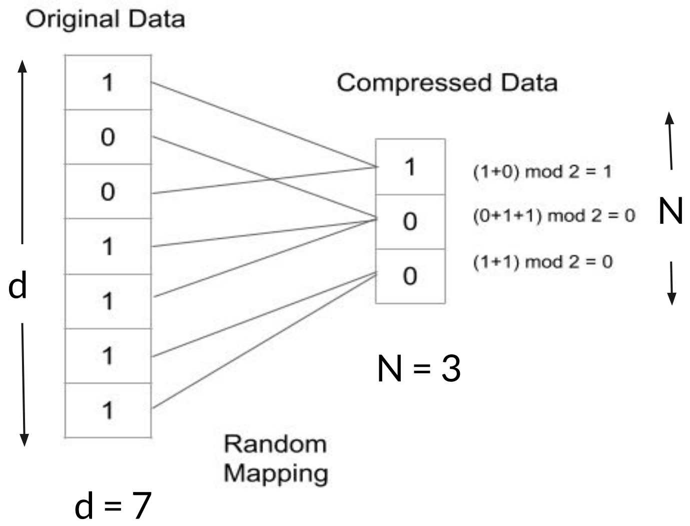
a, b **- N dimensional vectors**

Where , a', b' **- N dimensional vectors**

- *Compression scheme for Binary data*

- Sparse Data
- s - sparse data

$N = O(s^2)$



- Theorem Used for Binary Data

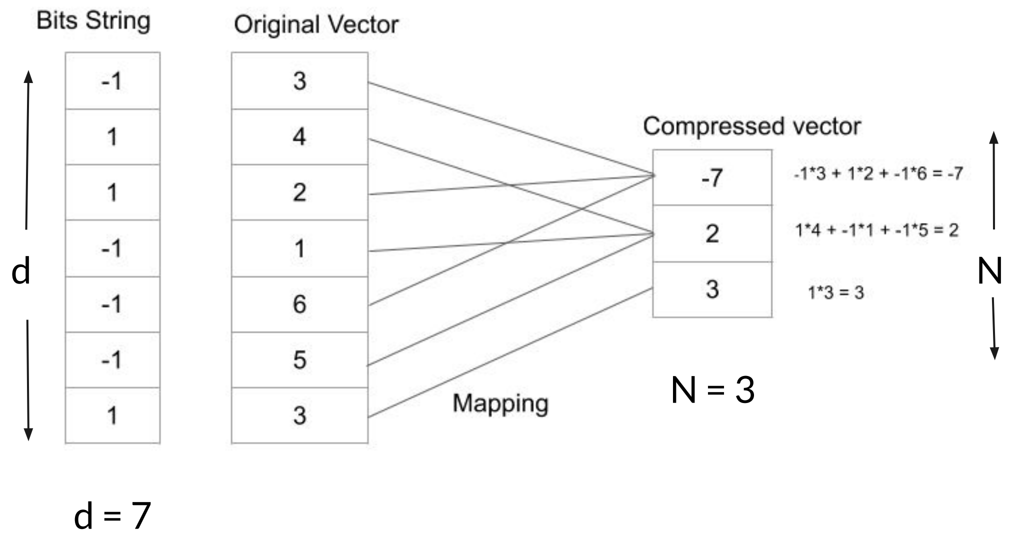
Theorem 1. *Consider a pair of binary vectors* $\mathbf{u_i}, \mathbf{u_j} \in \{0,1\}^d$ *such that the maximum number of* 1*s in any vector is at most* s*. If we set* $N = 10 \times s^2$*, and compress them into binary vectors* $\mathbf{u_i}', \mathbf{u_j}' \in \{0,1\}^N$ *via algorithm of [4], then the following holds with probability* 9/10

$$\langle \mathbf{u_i}, \mathbf{u_j} \rangle = \langle \mathbf{u_i}', \mathbf{u_j}' \rangle.$$

Source - Efficient Dimensionality Reduction for Sparse Binary Data

- Real Valued Data

- Random Mapping
- Random Bits



- Theorem Used for Real valued data

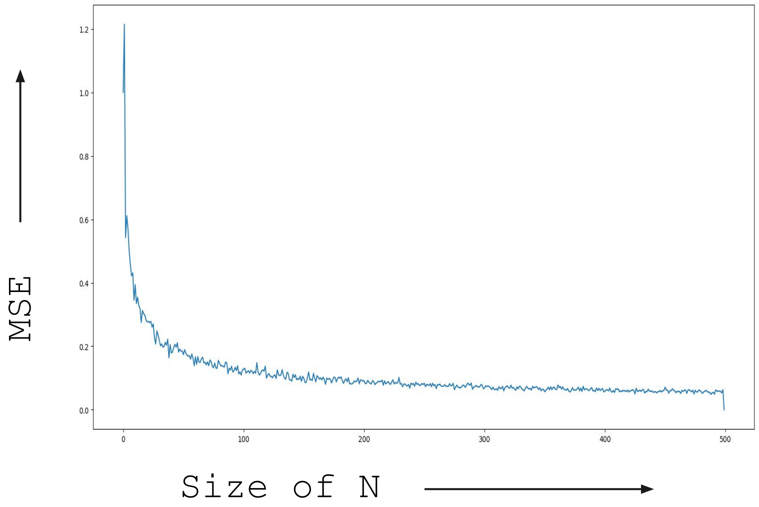
Consider a pair of normalised real valued vectors $\mathbf{u_i}, \mathbf{u_j} \in R^d$. *If we set* $N = 10/\epsilon^2$, *(where* ϵ *is the error tolerance, and* N *is the reduced dimension) and compress them into* $\mathbf{u_i}', \mathbf{u_j}' \in R^N$ *using the feature hashing algorithm of [1], then the following holds with probability* $9/10$

$$\langle \mathbf{u_i}, \mathbf{u_j} \rangle = \langle \mathbf{u_i}', \mathbf{u_j}' \rangle.$$

Source - feature hashing for large scale multitask learning

- *Defining N for Real Valued Data*

Trade off between Error and Storage



- *Why these compression scheme ?*

- ❑ Solves for high dimensional sparse data which is most common form of data now days.
- ❑ Independent of dimension and depends only on sparsity of data.
- ❑ Retain similarity between any 2 data points

Our Challenges

*–To come up with a data structure(code) which can maintain a random mapping while handling **insertions** and **deletions** for features in a growing dataset.*

- *Random Mapping*

- Used compression scheme demands highly random mapping .
- Highly random mapping is must for Uniform mapping of features from high dimension to lower dimension.

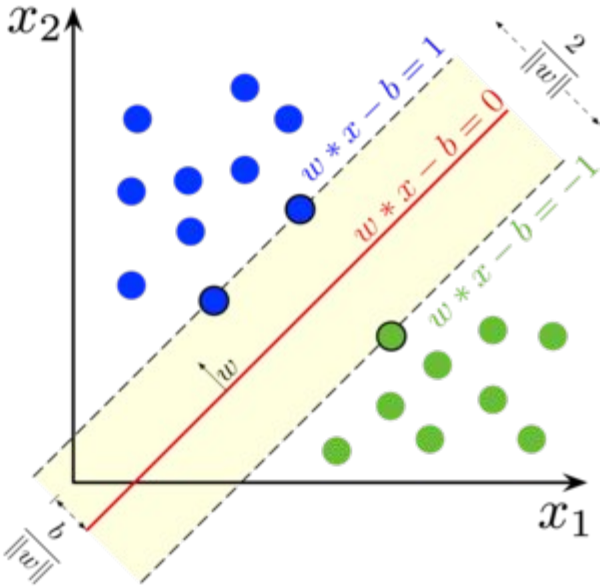
- Insertion and Deletion Handling

- Since dataset can be growing.
- New features can be added and deleted.
- Our code should be compatible with the proper feature insertion and deletion.
- Improper handling of mapping may result in risks of non uniform mapping.

Future Application

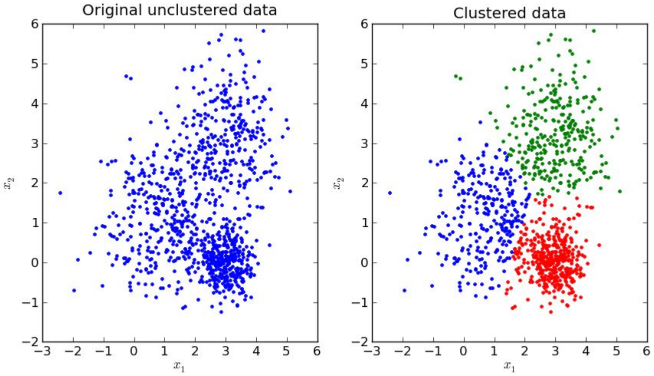
- *In classifier*

- Consider a d dimensional dataset for a Binary classification problem.
- Let any data point be represented as X.
- Let curve learned as a classifier be A as a d dimensional vector.
- For classification Inner product of A and X will be involved.

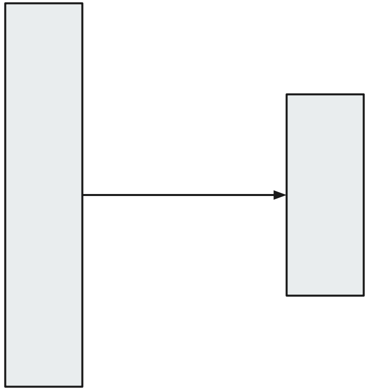


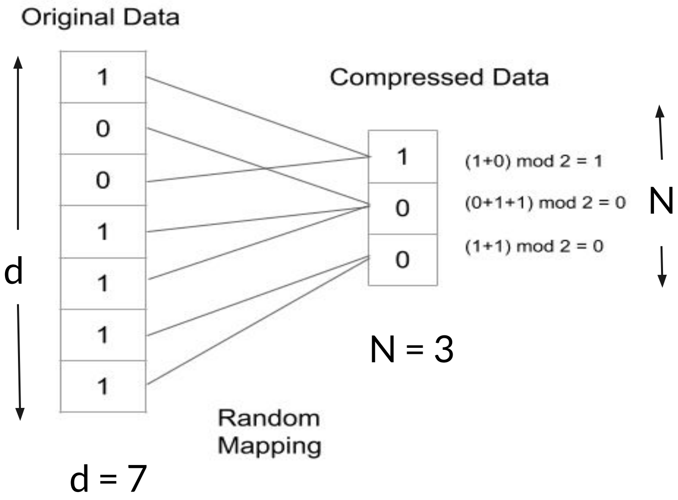
- *In clustering*

- Our compression scheme guarantee to maintain similarity between data points.
- Clustering Algorithms involves clustering of similar data objects.



- Thank You





Original Data
Compressed Data
1
0
0
1
1
1
1
d
1
0
0
(1+0) mod 2 = 1
(0+1+1) mod 2 = 0
(1+1) mod 2 = 0
N
N = 3
Random Mapping
d = 7