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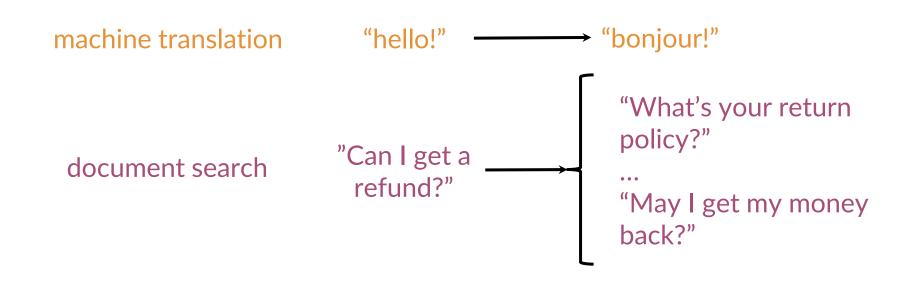
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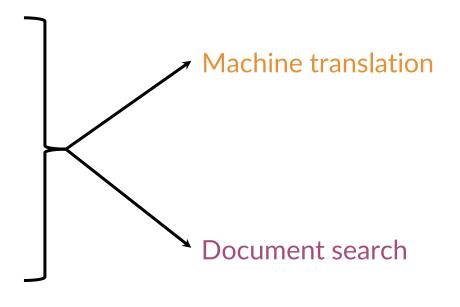
Overview

What you'll be able to do!



Learning Objectives

- Transform vector
- "K nearest neighbors"
- Hash tables
- Divide vector space into regions
- Locality sensitive hashing
- Approximated nearest neighbors





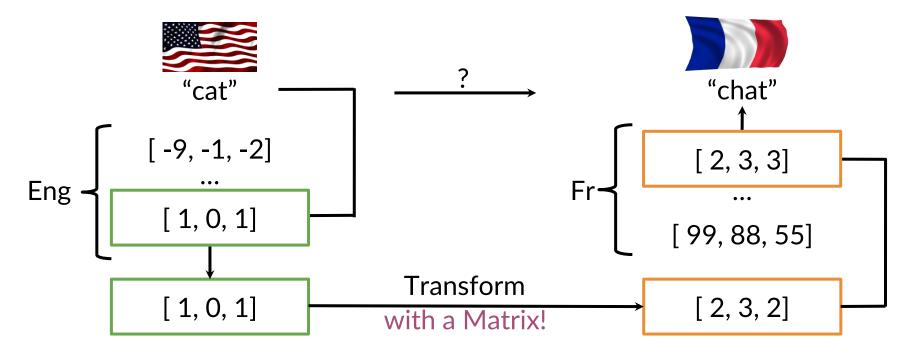
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Transforming word vectors

Outline

- Translation = Transformation
- How to get a good transformation

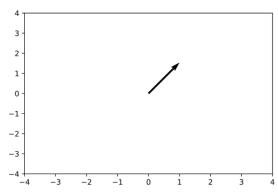
Overview of Translation

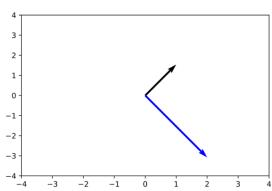


Transforming vectors

$$\begin{pmatrix} 1 & 1 \end{pmatrix} \begin{pmatrix} 2 & 0 \\ 0 & -2 \end{pmatrix} = \begin{pmatrix} 2 & -2 \end{pmatrix}$$

$$\mathbf{X} \qquad \mathbf{R} \qquad \mathbf{Y}$$





Transforming vectors

Try it yourself!

Align word vectors

subsets of the full vocabulary

Solving for R

initialize R

in a loop:

$$Loss = \parallel \mathbf{XR} - \mathbf{Y} \parallel_F$$
 $g = \frac{d}{dR} Loss$ gradient

$$R = R - \alpha g$$
 update

Frobenius norm

$$\parallel \mathbf{X}\mathbf{R} - \mathbf{Y} \parallel_F$$

$$\mathbf{A} = \begin{pmatrix} 2 & 2 \\ 2 & 2 \end{pmatrix}$$

$$\|\mathbf{A}_F\| = \sqrt{2^2 + 2^2 + 2^2 + 2^2}$$

$$\|\mathbf{A}_F\| = 4$$

$$\|\mathbf{A}_F\| = 4$$

$$\|\mathbf{A}\|_F \equiv \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} |a_{ij}|^2}$$

Frobenius norm

```
A = np.array([[2,2],

- ---
A_squared = np.square(A)
A_squared
array([[4,4],
```

Try it yourself!

```
A_Frobenious = np.sqrt(np.sum(A_squared))
A_Frobenious
4.0
```

Frobenius norm squared

$$\|\mathbf{X}\mathbf{R} - \mathbf{Y}\|_F^2$$

$$\mathbf{A} = \begin{pmatrix} 2 & 2 \\ 2 & 2 \end{pmatrix}$$

$$\|\mathbf{A}\|_F^2 = \left(\sqrt{2^2 + 2^2 + 2^2 + 2^2}\right)^2$$

$$\|\mathbf{A}\|_F^2 = 16$$

Gradient

$$Loss = \|\mathbf{X}\mathbf{R} - \mathbf{Y}\|_F^2$$

$$g = \frac{d}{dR}Loss = \frac{2}{m} \left(\mathbf{X}^T (\mathbf{X}\mathbf{R} - \mathbf{Y}) \right)$$

Implement in the assignment!

Summary

- $XR \approx Y$
- minimize $\|\mathbf{X}\mathbf{R} \mathbf{Y}\|_F^2$

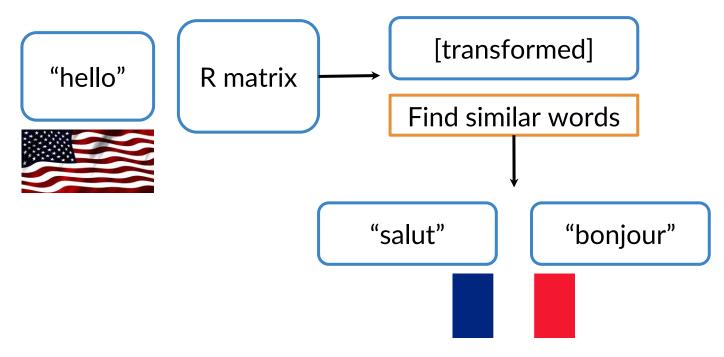


K-nearest neighbors

Outline

• K closest matches — K-nearest neighbors

Finding the translation



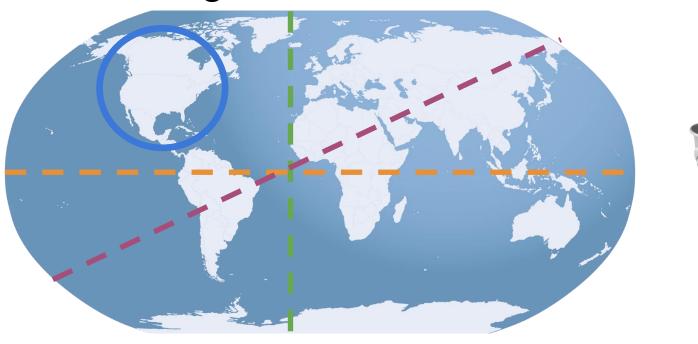
Nearest neighbours







Nearest neighbors



Hash tables!



Summary

- K-nearest neighbors, for closest matches
- Hash tables



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Hash tables and hash functions

Outline

Hash values

Hash functions

Hash tables

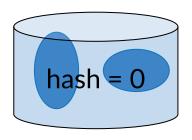


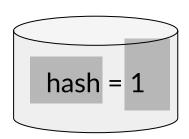


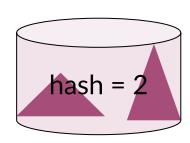


hash = 2

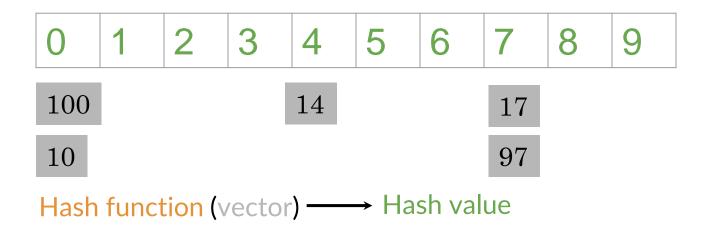
Hash tables







Hash function

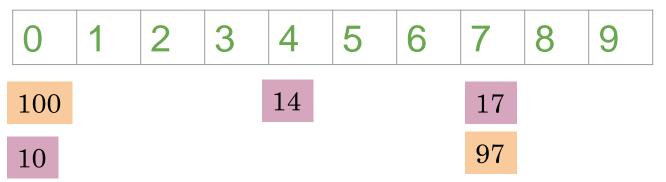


Hash value = vector % number of buckets

Create a basic hash table

```
def basic_hash_table(value_1,n_buckets):
   def hash_function(value 1,n buckets):
             return int(value 1) % n buckets
   hash_table = {i:[] for i in range(n_buckets)}
   for value in value 1:
             hash value =
hash function(value, n buckets)
   return hash table
```

Hash function



Hash function by location?



Locality sensitive hashing, next!

Summary

Hash function (vector) → Hash value



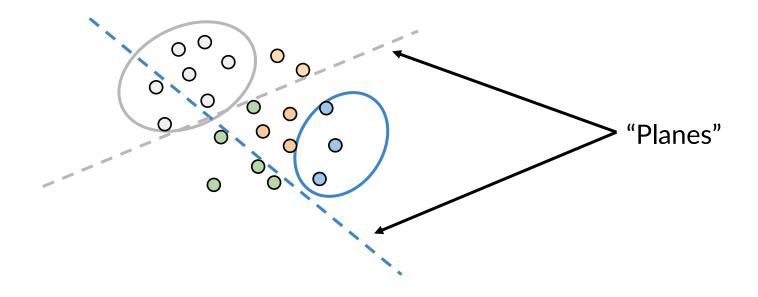
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Locality sensitive hashing

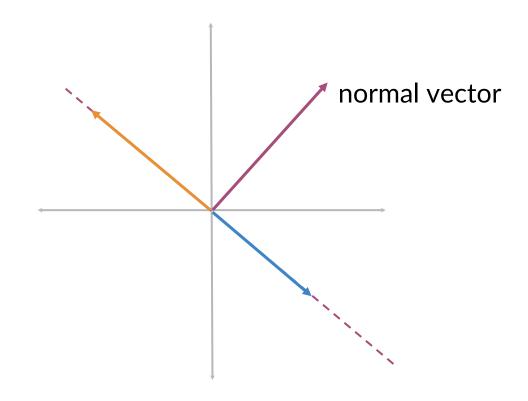
Outline

Locality sensitive hashing with planes in vector spaces

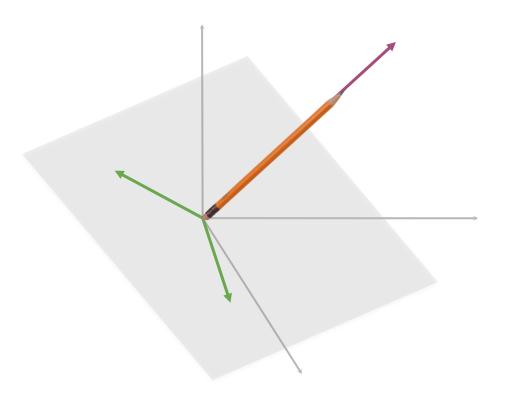
Locality Sensitive Hashing

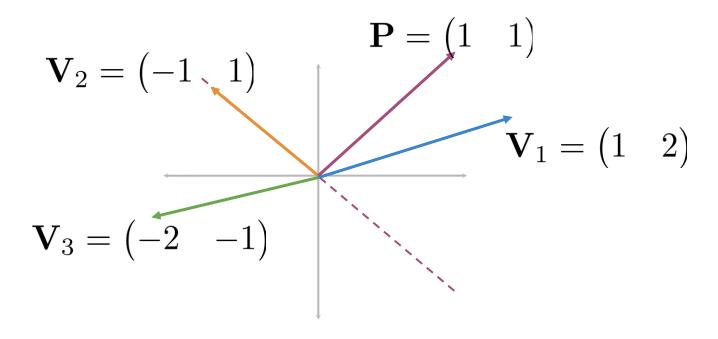


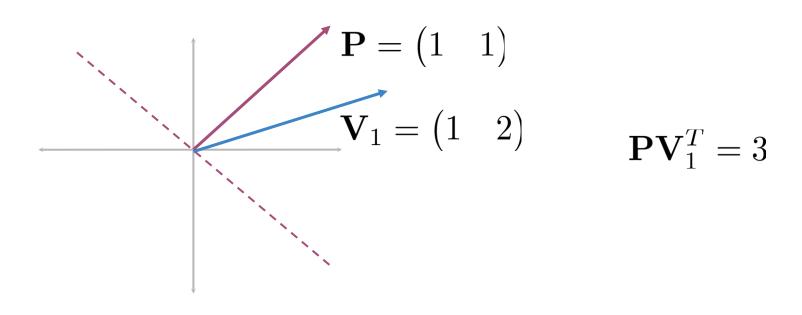
Planes

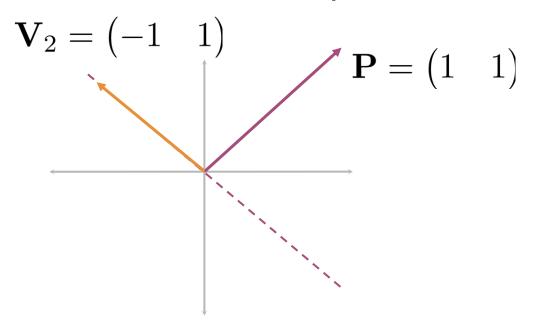


Planes

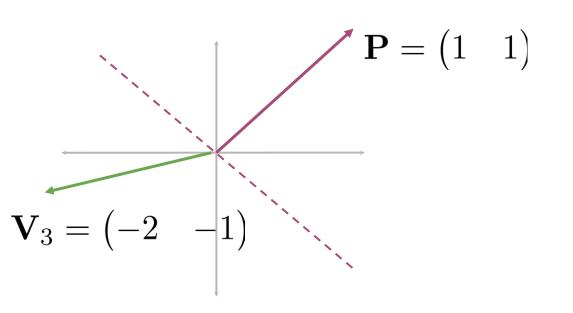




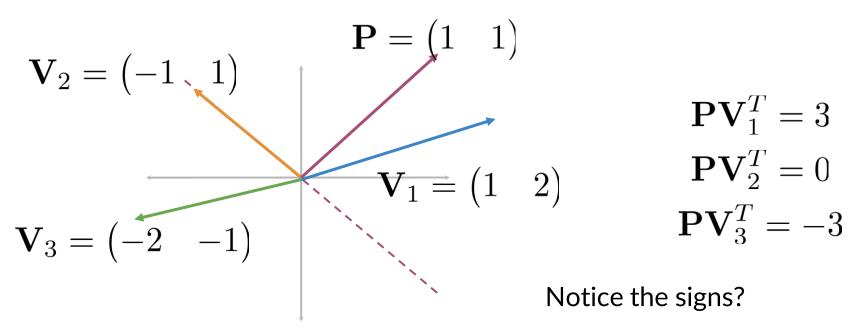




$$\mathbf{P}\mathbf{V}_2^T = 0$$

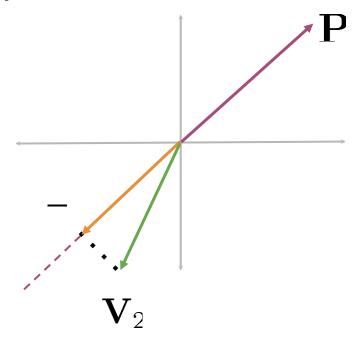


$$\mathbf{PV}_3^T = -3$$

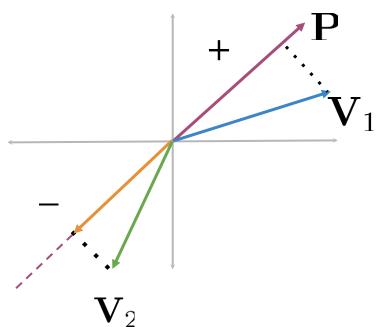


Visualizing a dot product Projection $||\mathbf{P}\mathbf{V}_1^T||$

Visualizing a dot product



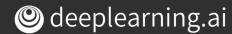
Visualizing a dot product



Sign indicates direction

```
def side_of_plane(P,v):
    dotproduct = np.dot(P,v.T)
    sign_of_dot_product = np.sign(dotproduct)
    sign_of_dot_product_scalar= np.asscalar(sign_of_dot_product)
    return sign_of_dot_product_scalar
```

Try it!



Summary

Sign of dot product — Hash values



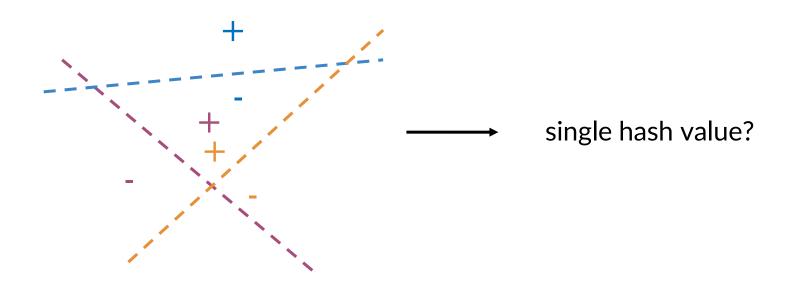
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Multiple Planes

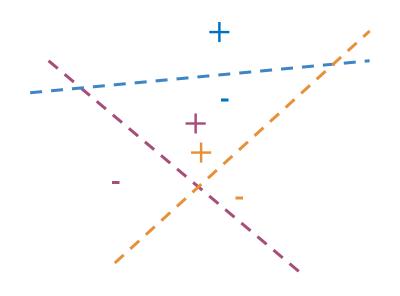
Outline

Multiple planes — Dot products — Hash values

Multiple planes



Multiple planes, single hash value?



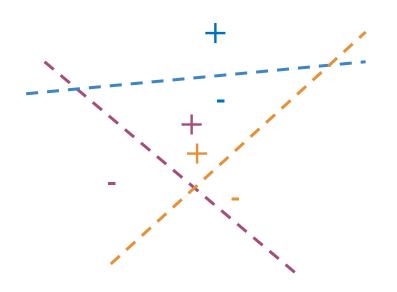
$$\mathbf{P}_1 \mathbf{v}^T = 3, sign_1 = +1, h_1 = 1$$

$$\mathbf{P}_2 \mathbf{v}^T = 5, sign_2 = +1, h_2 = 1$$

$$\mathbf{P}_3 \mathbf{v}^T = -2, sign_3 = -1, h_3 = 0$$

$$hash = 2^{0} \times h_{1} + 2^{1} \times h_{2} + 2^{2} \times h_{3}$$
$$= 1 \times 1 + 2 \times 1 + 4 \times 0$$

Multiple planes, single hash value!



$$sign_i \ge 0, \rightarrow h_i = 1$$

 $sign_i < 0, \rightarrow h_i = 0$

$$hash = \sum_{i}^{H} 2^{i} \times h_{i}$$

Multiple planes, single hash value!!

```
def hash_multiple_plane(P_1,v):
   hash value = 0
   for i, P in enumerate(P 1):
      sign = side_of_plane(P,v)
      hash i = 1 if sign >=0 else 0
      hash value += 2**i * hash i
   return hash value
```

Try it!

Summary

◆ Planes → Sign of dot product → Hash values



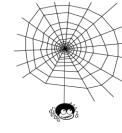
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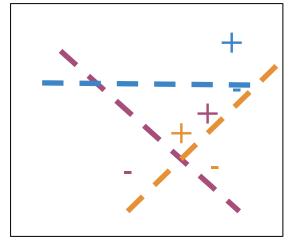
Approximate nearest neighbors

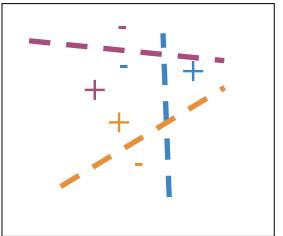
Outline

Multiple sets of planes for approximate K-nearest neighbors

Random planes

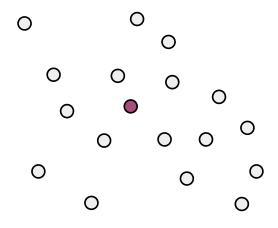


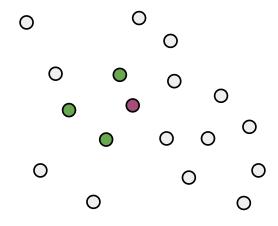


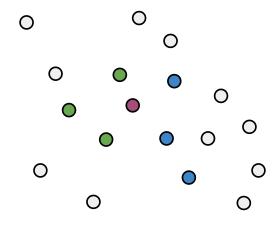


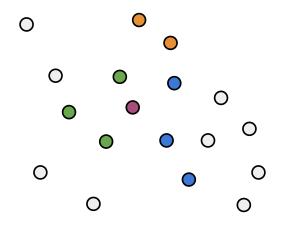


Cultural reference: Spider-Man: Into the Spider-Verse









Approximate nearest (friendly) neighbors

Make one set of random planes

See notebook for calculating the hash value!

Summary

Multiple universes — Locality sensitive — A. K-NN hashing



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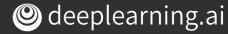
Searching documents

Outline

- Representation for documents
- Document search with K-nearest neighbors

Document representation

I love learning! [?, ?, ?] [1, 0, 1]**Document Search** love [-1, 0, 1]K-NN! learning [1, 0, 1]I love learning! [1, 0, 3]



Document vectors

```
word embedding = \{"I": np.array([1,0,1]),
                  "love": np.array([-1,0,1]),
                  "learning": np.array([1,0,1])}
words in document = ['I', 'love', 'learning']
document embedding = np.array([0,0,0])
for word in words in document:
        document embedding +=
print(document embedding)
array([1 0 3])
```

Try it!

Revisit Learning Objectives

- Transform vector
- "K nearest neighbors"
- Hash tables
- Divide vector space into regions
- Locality sensitive hashing
- Approximated nearest neighbors

