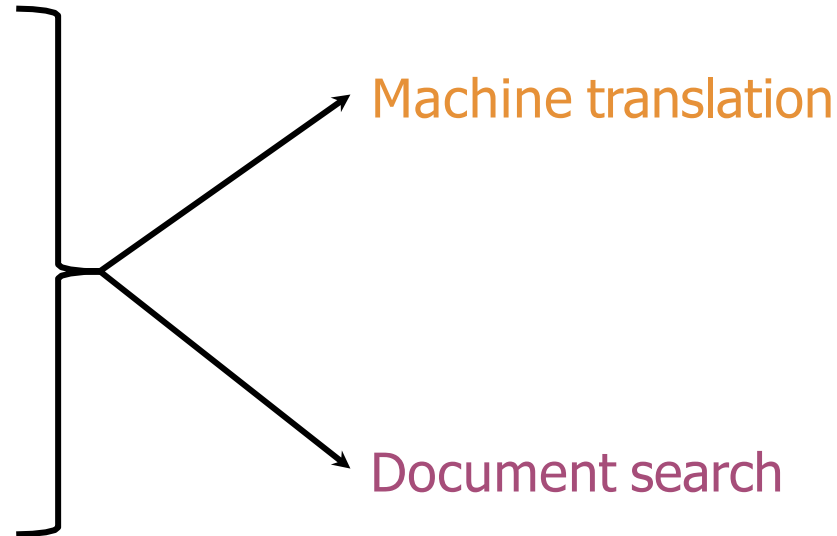


Machine Translation and Document Search

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



Overview-What you'll be able to do!

machine translation

"hello!"



"bonjour!"

document search

"Can I get a
refund?"



"What's your return
policy?"

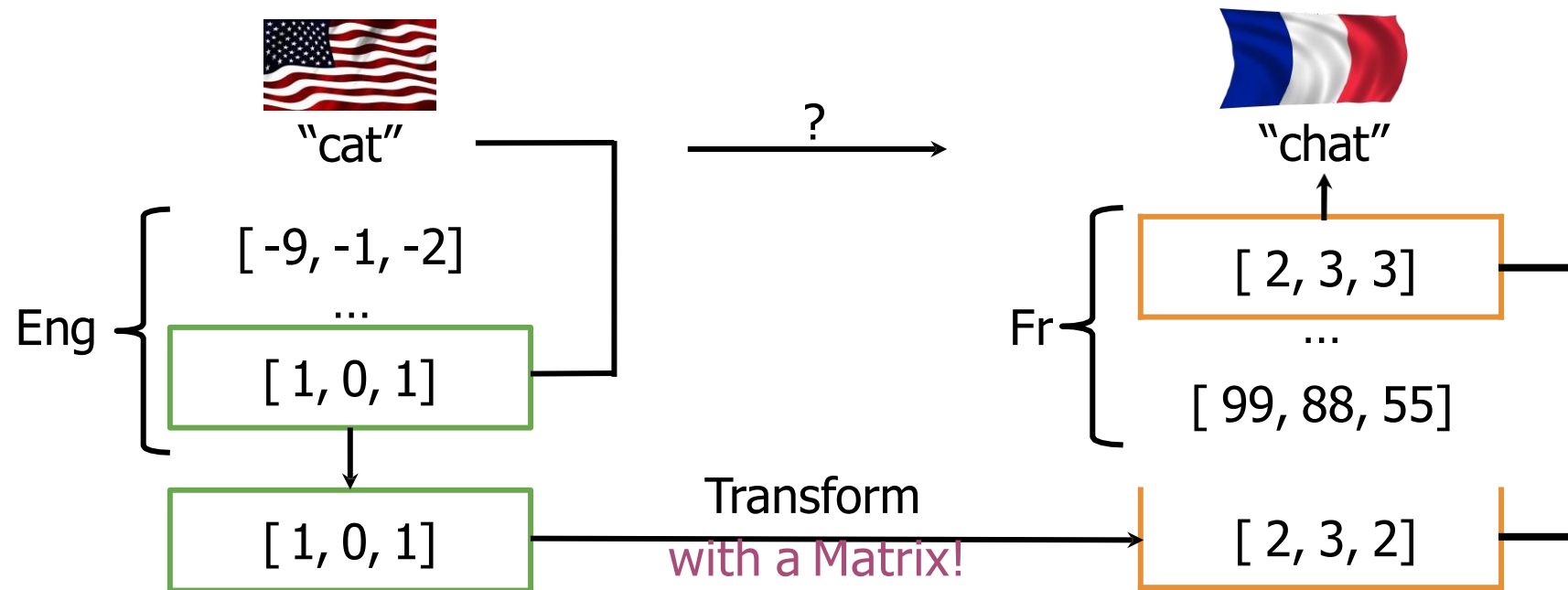
...

"May I get my money
back?"

- Machine translation allows you to speak in one language and have your words translated into another
- It uses advanced algorithms and vast amounts of data to understand the nuances and subtleties of language, and
- It can even adapt to the unique way in which different individuals speak

Transforming word vectors

- Translation = Transformation
- How to get a good transformation
- Overview of Translation



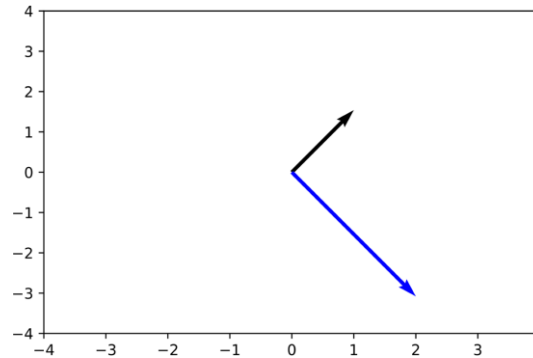
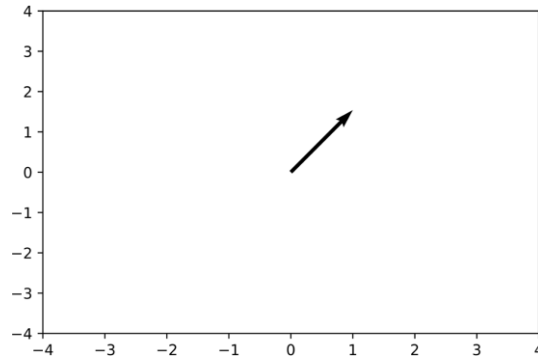
Transforming vectors

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

X

R

Y



```
R = np.array([[2,0],
```

```
x = np.array([[1,1]])
```

```
np.dot(x,R)
```

```
array([[2,-2]])
```

Try it yourself!

Align word vectors

$$\begin{pmatrix} [\text{"cat" vector}] \\ [\dots \text{vector}] \\ [\text{"zebra" vector}] \end{pmatrix} \mathbf{X} \mathbf{R} \approx \mathbf{Y} \begin{pmatrix} [\text{"chat" vecteur}] \\ [\dots \text{vecteur}] \\ [\text{"z bresse" vecteur}] \end{pmatrix} \mathbf{Y}$$

subsets of the full
vocabulary

Solving for R

initialize R

in a loop:

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

$$g = \frac{d}{dR} Loss$$

gradient

$$R = R - \alpha g$$

update

Frobenius norm

$$\| \mathbf{XR} - \mathbf{Y} \|_F$$

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

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

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

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

```
A = np.array([[2,2],[2,2]])  
A_squared = np.square(A)  
A_squared
```

```
array([[4,4],[4,4]])
```

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

```
4.0
```

Frobenius norm squared

$$\|\mathbf{XR} - \mathbf{Y}\|_F^2$$

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

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

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

Gradient

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

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

Summary

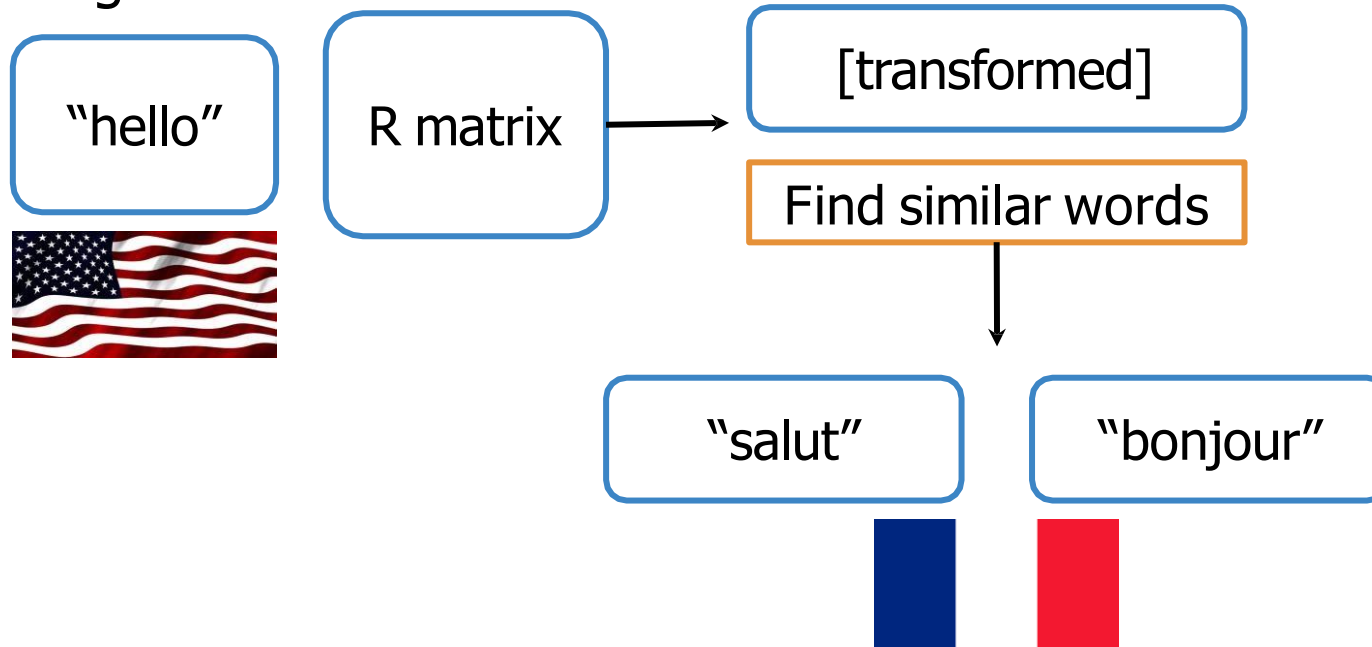
- $\mathbf{XR} \approx \mathbf{Y}$
- minimize $\|\mathbf{XR} - \mathbf{Y}\|_F^2$

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K-nearest neighbors

- K closest matches \longrightarrow K-nearest neighbors

- Finding the translation



Nearest neighbours

You

 San Francisco

Friend



Location

Shanghai

Nearest

2



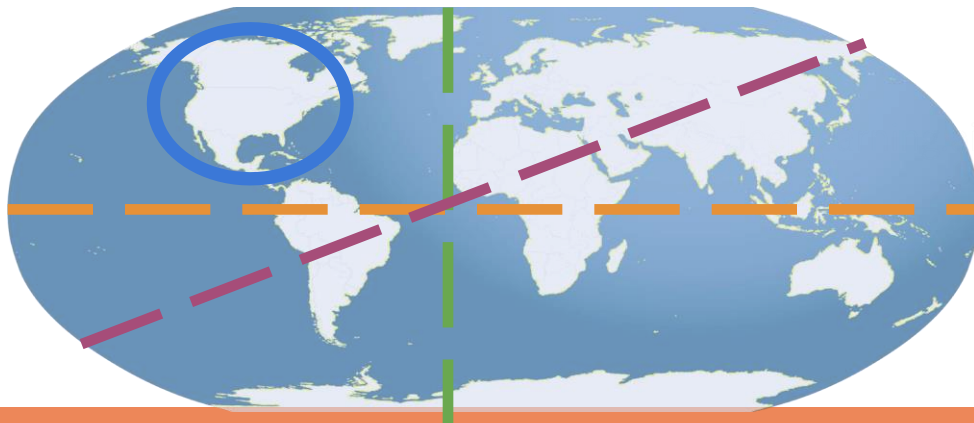
Bangalore

3



Los Angeles

1

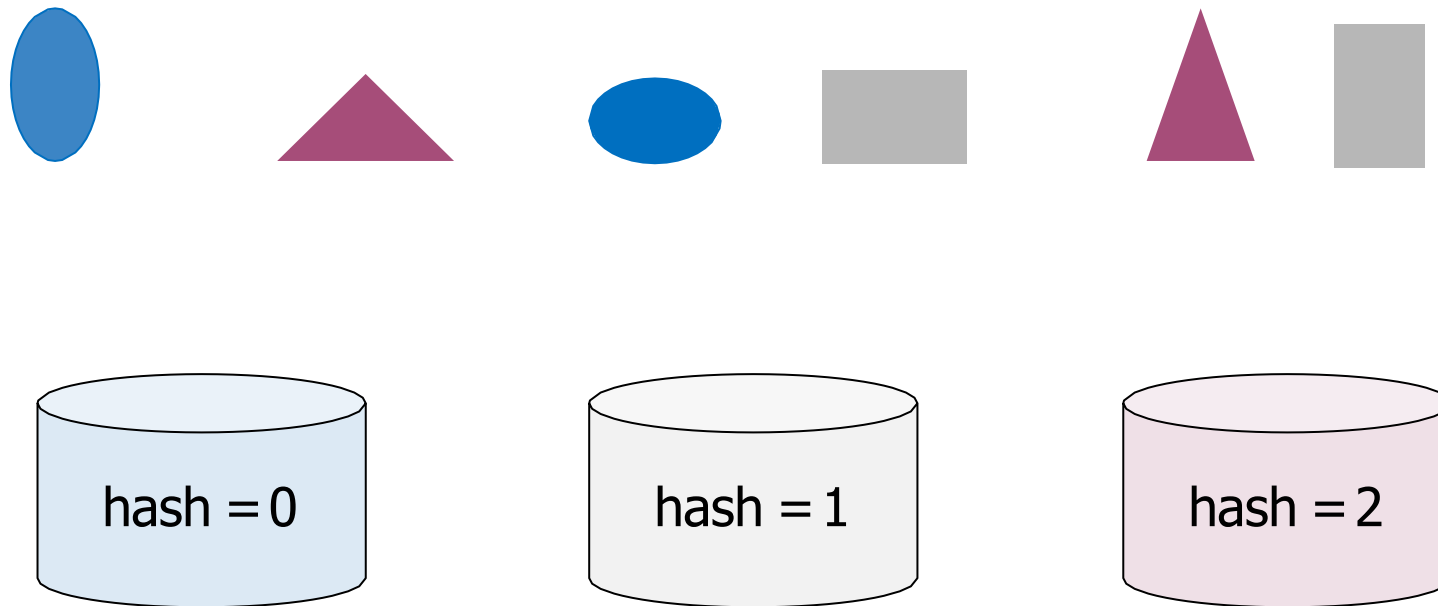


Hash tables!



Hash tables and hash functions

- A hash function maps an object to a bucket in a hash table
- Hash tables



Hash function

- A simple hash function : Hash Value = vector % number of buckets

0	1	2	3	4	5	6	7	8	9
100				14			17		
10							97		

Hash function (vector) \longrightarrow Hash value

Hash value = vector % number of buckets

Create a basic hash table

```
def basic_hash_table(value_l, n_buckets):  
    def hash_function(value_l, n_buckets):  
        return int(value_l) % n_buckets  
    hash_table = {i: [] for i in range(n_buckets)}  
    for value in value_l:  
        hash_value =  
hash_function(value, n_buckets)  
        return hash_table
```

Hash function

0	1	2	3	4	5	6	7	8	9
100				14			17		
10							97		

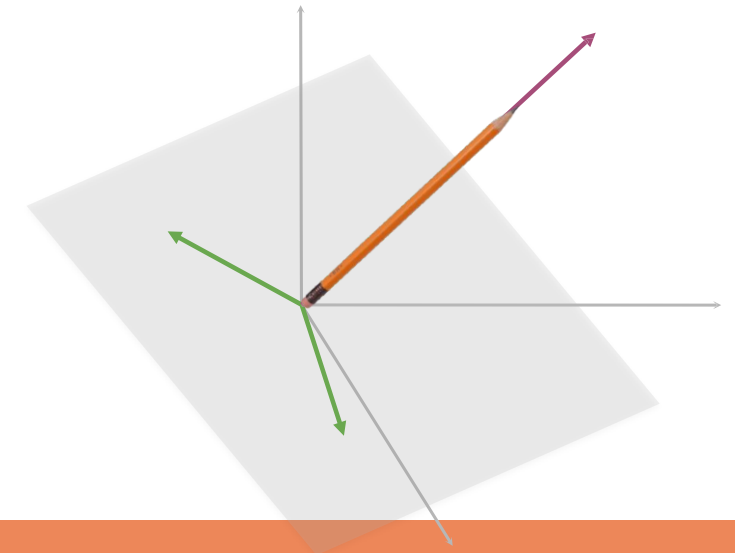
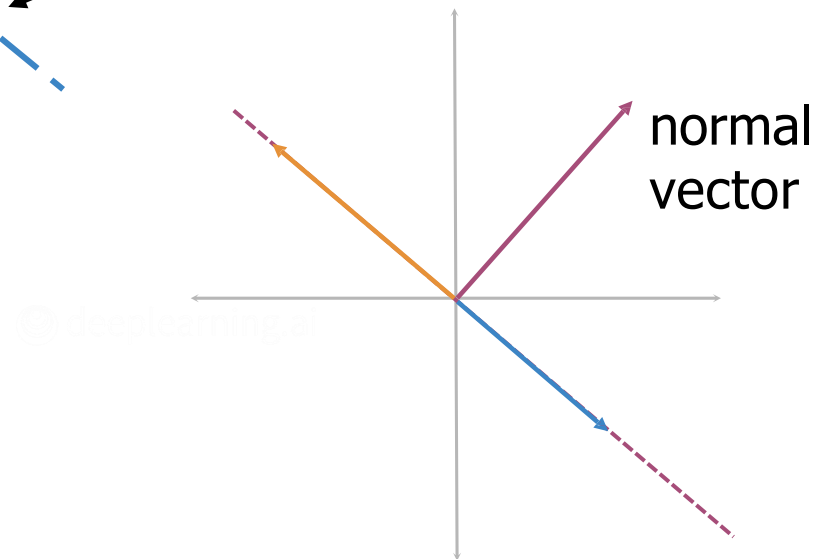
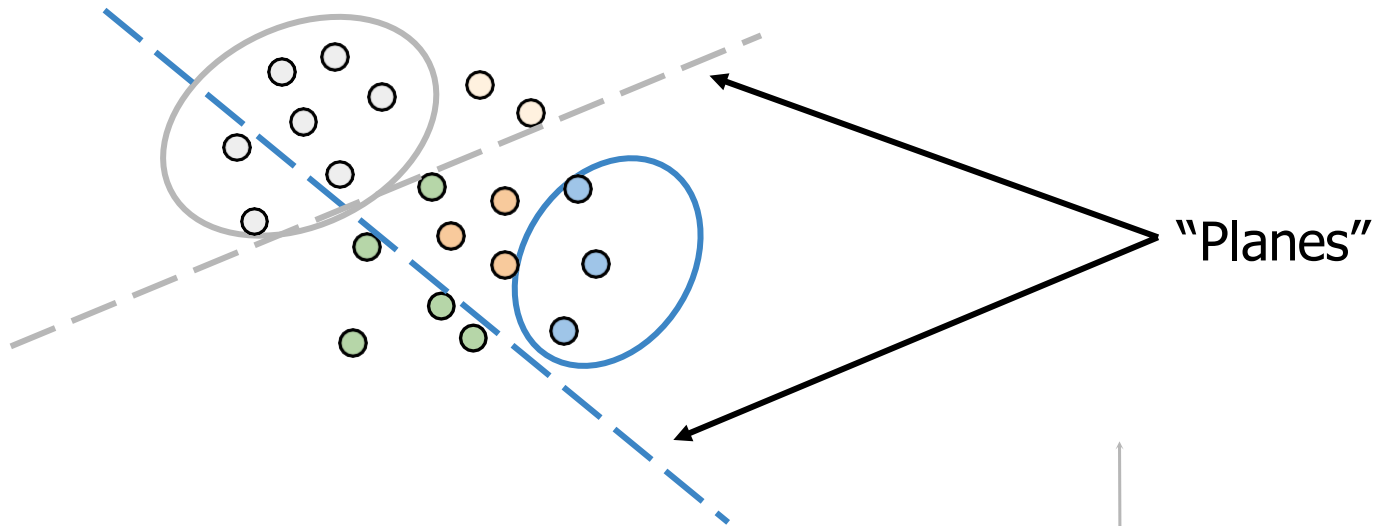
Hash function by location?

0	1	2	3	4	5	6	7	8	9
14									100
10									97
17									

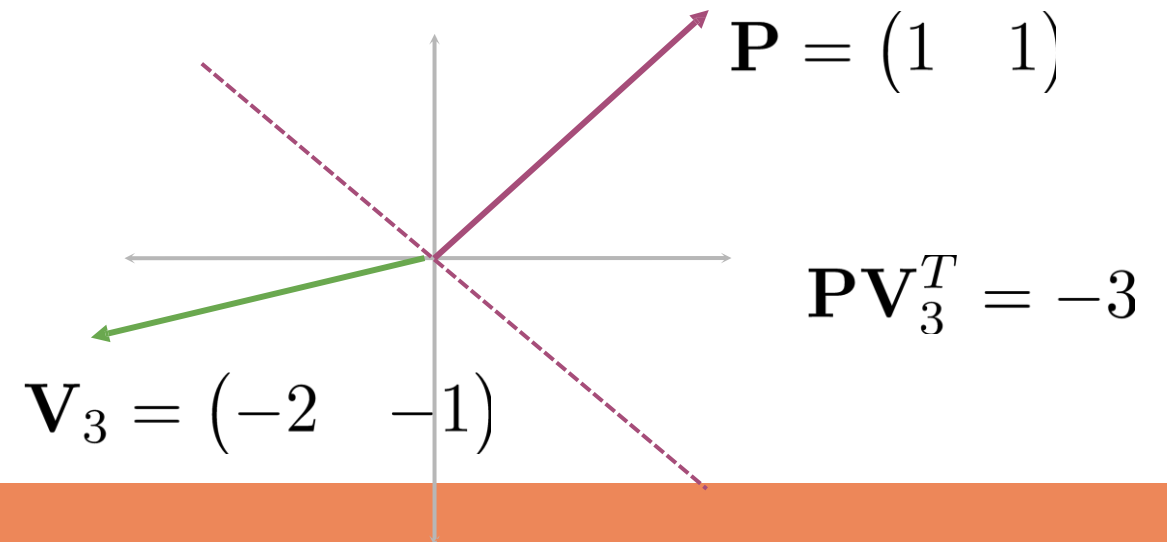
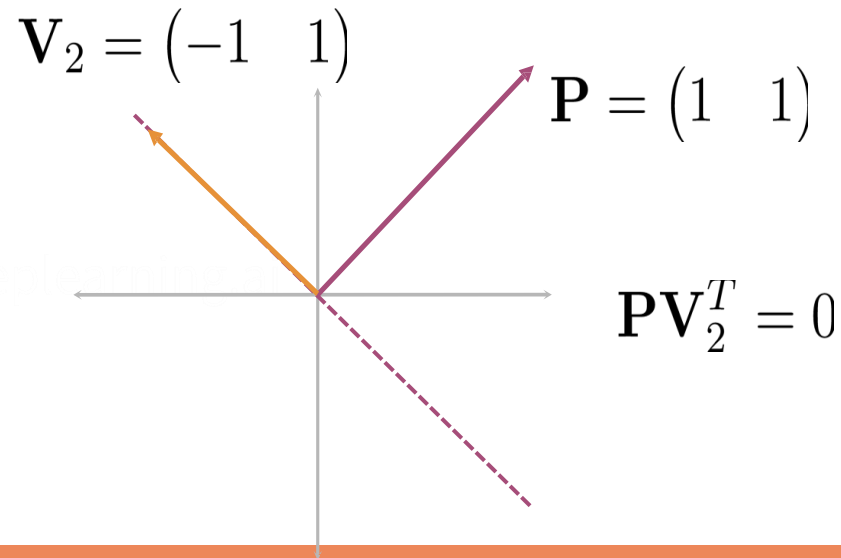
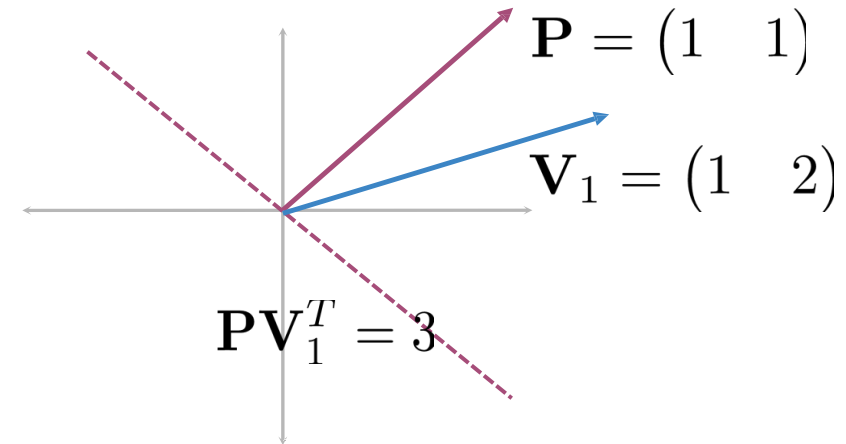
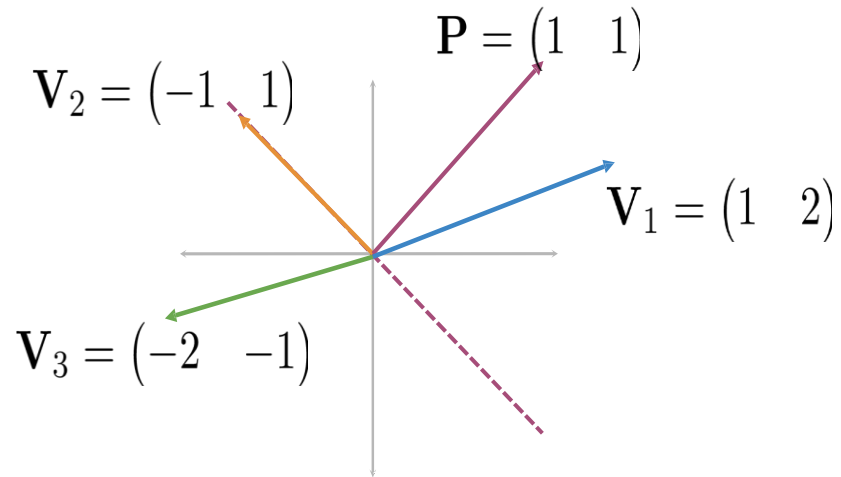
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Locality sensitive hashing, next!

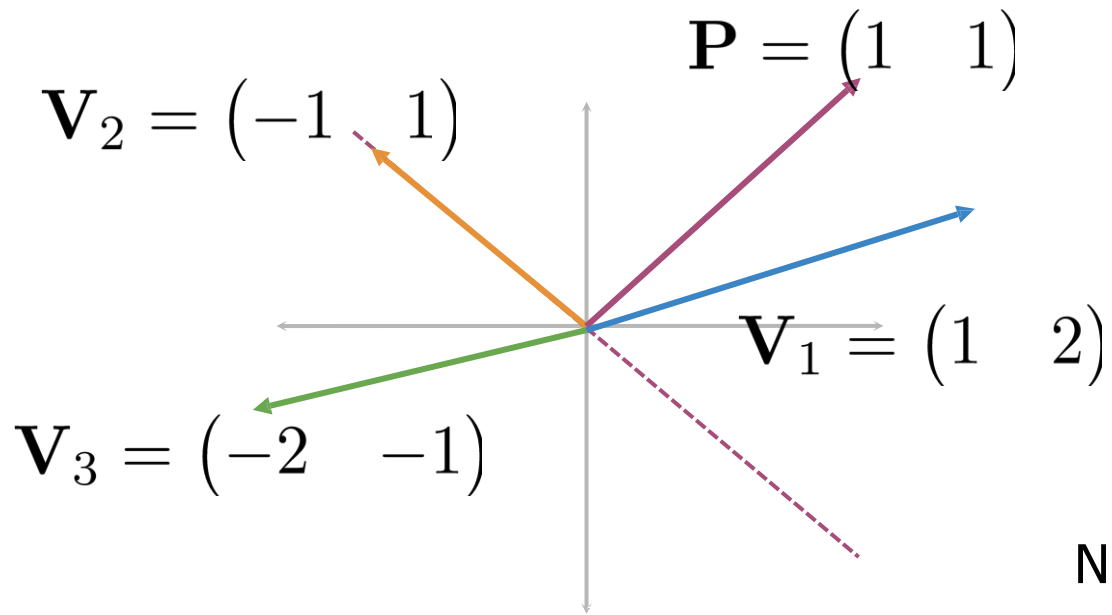
Locality Sensitive Hashing



Which side of the plane?



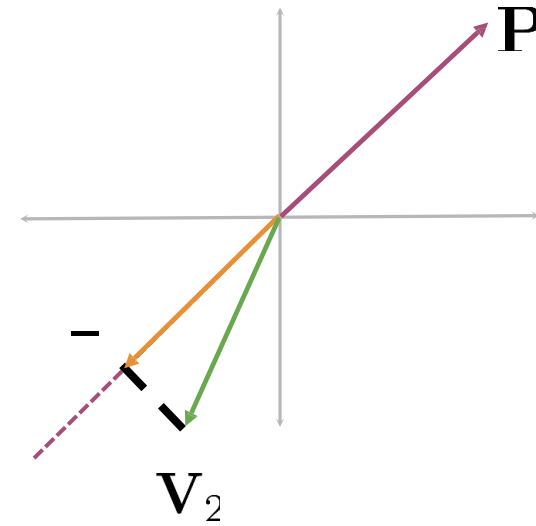
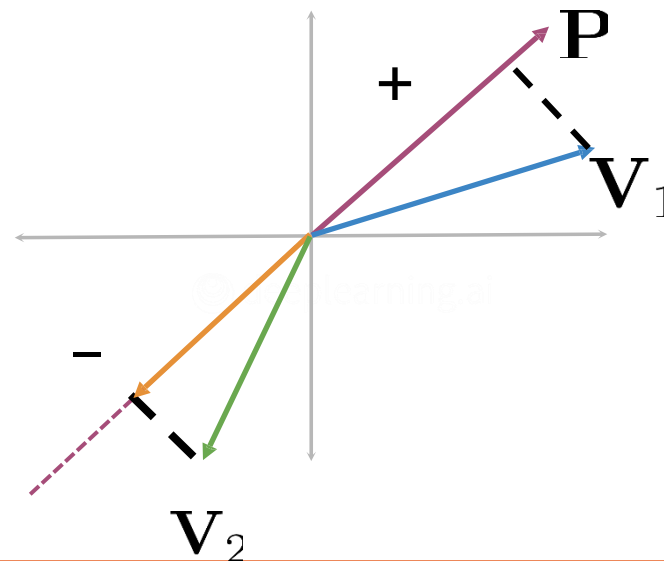
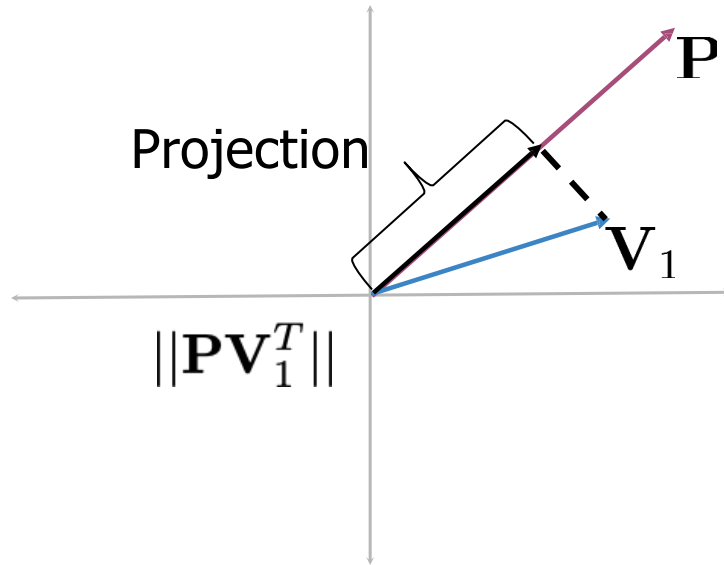
Which side of the plane?



$$\begin{aligned}\mathbf{P}\mathbf{V}_1^T &= 3 \\ \mathbf{P}\mathbf{V}_2^T &= 0 \\ \mathbf{P}\mathbf{V}_3^T &= -3\end{aligned}$$

Notice the signs?

Visualizing a dot product



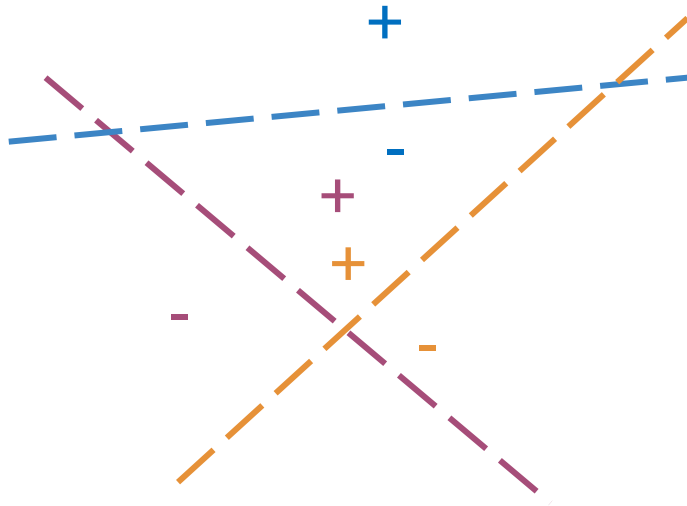
Sign indicates direction

Which side of the plane?

```
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
```

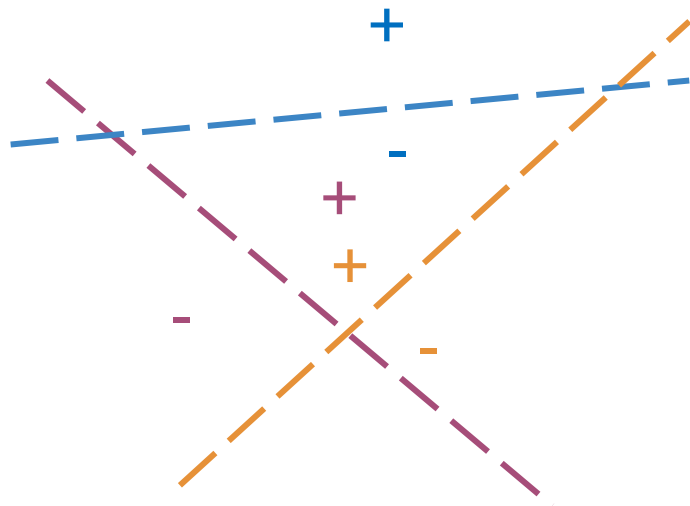
Try it!

Multiple planes



single hash value?

Multiple planes, single hash value?



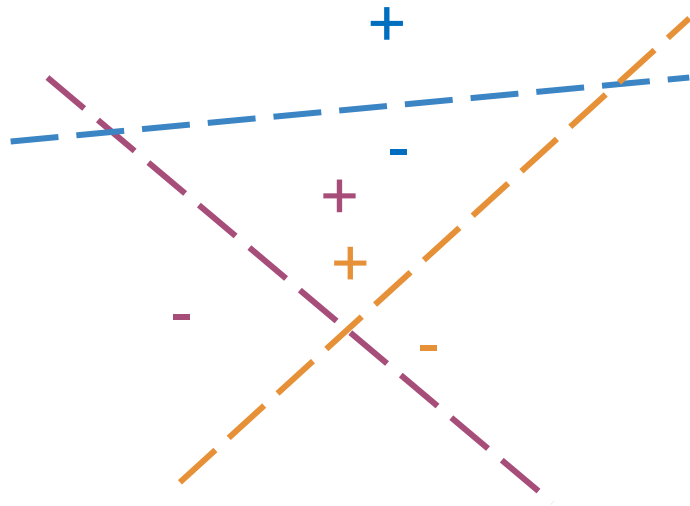
$$\mathbf{P}_1 \mathbf{v}^T = 3, \text{sign}_1 = +1, h_1 = 1$$

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

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

$$\begin{aligned} \text{hash} &= 2^0 \times h_1 + 2^1 \times h_2 + 2^2 \times h_3 \\ &= 1 \times 1 + 2 \times 1 + 4 \times 0 \\ &= 3 \end{aligned}$$

Multiple planes, single hash value!



$$\text{sign}_i \geq 0, \rightarrow h_i = 1$$

$$\text{sign}_i < 0, \rightarrow h_i = 0$$

$$\text{hash} = \sum_i^H 2^i \times h_i$$

Multiple planes, single hash value!!

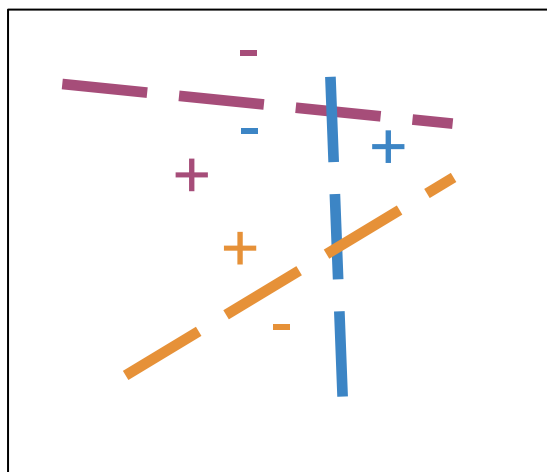
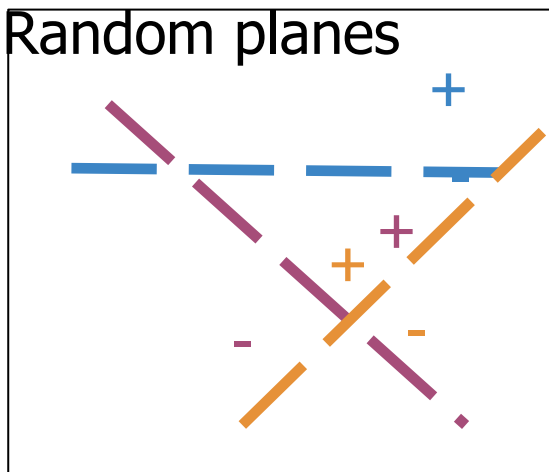
```
def hash_multiple_plane(P_l,v):  
    hash_value = 0  
  
    for i, P in enumerate(P_l):  
        sign = side_of_plane(P,v)  
        hash_i = 1 if sign >=0 else 0  
        hash_value += 2**i * hash_i  
  
    return hash_value
```

Try it!

Approximate nearest neighbors

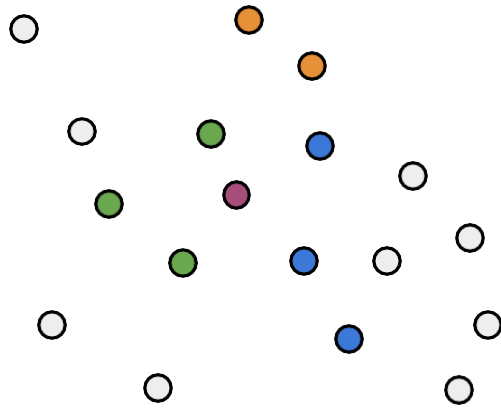
- Multiple sets of planes for approximate K-nearest neighbors

- Random planes



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

Multiple sets of random planes



Approximate nearest
(friendly) neighbors

Make one set of random planes

```
num_dimensions = 2 #300 in assignment
num_planes = 3 #10 in assignment

random_planes_matrix = np.random.normal(
    size=(num_planes,
          num_dimensions))
```

```
array([[ 1.76405235  0.40015721]
       [ 0.97873798  2.2408932 ]
       [ 1.86755799 -0.97727788]])
```

```
v = np.array([[2,2]])
```

```
def side_of_plane_matrix(P,v):
    dotproduct = np.dot(P,v.T)
    sign_of_dot_product =
np.sign(dotproduct)
num_planes_matrix = side_of_plane_matrix(
    random_planes_matrix,v)
```

```
array([[1.]
       [1.]
       [1.]])
```

See notebook for calculating the hash value!

Searching documents

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

I love learning!

[?, ?, ?]

I

[1, 0, 1]

+

love

[-1, 0, 1]

+

learning

[1, 0, 1]

=

I love learning!

[1, 0, 3]

Document Search

K-NN!

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 += word_embedding[word]

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

