## 1. Document Representation

Suppose we have a small vocabulary:

We represent documents as **term-frequency vectors**.

- **Doc1**: "cat cat dog" → vector = (2, 1)
- **Doc2**: "cat dog" → vector = (1, 1)
- **Doc3**: "dog dog dog" → vector = (0, 4)

## 2. Euclidean Distance

$$d_E(A,B) = \sqrt{\sum (A_i - B_i)^2}$$

Distance(Doc1, Doc2)

$$\sqrt{(2-1)^2+(1-1)^2}=\sqrt{1}=1$$

Distance(Doc1, Doc3)

$$\sqrt{(2-0)^2+(1-4)^2}=\sqrt{4+9}=\sqrt{13}\approx 3.6$$

☐ Euclidean says **Doc1** is closer to **Doc2** (which is fine). But notice something important:

 If we just repeat Doc2 multiple times, its vector length increases, and Euclidean distance also increases—even though the content is the same!

Example: Doc2 = (1,1), Doc2 long = (10,10)

$$d_E((1,1),(10,10)) = \sqrt{(9^2+9^2)} = \sqrt{162} \approx 12.7$$

☐ This means the **same document but longer looks** "**far**" under Euclidean distance.

## 3. Cosine Similarity

Cosine measures angle, not length:

$$\cos(\theta) = \frac{A \cdot B}{||A||||B||}$$

Similarity(Doc1, Doc2):

$$\frac{1}{\sqrt{2^2+1^2}} \cdot \frac{(2)(1)+(1)(1)}{\sqrt{2^2+1^2}} = \frac{2+1}{\sqrt{5}} \cdot \sqrt{2} = \frac{3}{\sqrt{10}} \approx 0.95$$

Similarity(Doc1, Doc3):

$$\frac{1}{\sqrt{5}} \cdot \frac{(2)(0) + (1)(4)}{\sqrt{5} \cdot \sqrt{16}} = \frac{4}{\sqrt{80}} = \frac{4}{8.94} \approx 0.45$$

• Similarity(Doc2, Doc2\_long):

$$\dot{c} \frac{(1)(10)+(1)(10)}{\sqrt{2} \cdot \sqrt{200}} = \frac{20}{1.41 \cdot 14.14} = \frac{20}{20} = 1$$

☐ Cosine gives 1.0 (perfect match) for the same doc regardless of length.
☐ It correctly shows Doc1 is more similar to Doc2 (0.95) than to Doc3 (0.45).

## 4. Conclusion

- **Euclidean Distance** penalizes document length, so longer documents always look "farther," even if they have the same proportions of words.
- **Cosine Similarity** removes the effect of document length (normalizes vectors) and focuses only on word distribution.

That's why in **text mining, IR, and NLP**, we prefer **Cosine similarity/distance** over Euclidean.