Instance-Based Classification

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Instance-Based Classification

Motivation

training data

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
1	0	1	0	1	0	0	1	1	0	positive
0	1	0	1	1	0	1	1	0	0	negative
0	1	0	1	1	0	1	0	0	0	negative
0	0	1	0	1	1	0	1	1	1	positive
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1	positive

test instance

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
1	0	1	0	1	0	0	1	1	0	?

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1	0	1	0	1	0	0	1	1	0	positive
0	1	0	1	1	0	1	1	0	0	negative
0	1	0	1	1	0	1	0	0	0	negative
0	0	1	0	1	1	0	1	1	1	positive
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1	positive

test instance

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
1	0	1	0	1	0	0	1	1	0	?

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0	1	0	1	1	0	1	1	0	0	negative
0	1	0	1	1	0	1	0	0	0	negative
0	0	1	0	1	1	0	1	1	1	positive
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1	positive

test instance

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
1	0	1	0	1	0	0	1	1	0	positive

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w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
1	0	1	0	1	0	0	1	1	0	positive
0	1	0	1	1	0	1	1	0	0	negative
0	1	0	1	1	0	1	0	0	0	negative
0	0	1	0	1	1	0	1	1	1	positive
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1	positive

test instance

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
1	0	1	0	1	0	0	1	0	0	?

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training data

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
1	0	1	0	1	0	0	1	1	0	positive
0	1	0	1	1	0	1	1	0	0	negative
0	1	0	1	1	0	1	0	0	0	negative
0	0	1	0	1	1	0	1	1	1	positive
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1	positive

test instance

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
1	0	1	0	1	0	0	1	1	0	positive

Typical Supervised Classification

training

w 1	w 2	w 3	w 4	w 5	w 6	w 7	w 8	w	w_ 10	sentiment
1	0	1	0	1	0	0	1	1	0	positive
0	1	0	1	1	0	1	1	0	0	negative
0	1	0	1	1	0	1	0	0	0	negative
0	0	1	0	1	1	0	1	1	1	positive
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1	positive

labeled examples

machine learning algorithm

model

testing

w 1	w 2	w 3	w 4	w 5	w 6	w 7	w 8	w	w_ 10	sentiment
1	0	1	0	1	0	0	1	1	0	???

new, unlabeled example

model

w 1	w 2	w 3	w 4	w 5	w 6	w 7	w 8	w	w_ 10	sentiment
1	0	1	0	1	0	0	1	1	0	positive

prediction

Instance-based Classification

w 1	w 2	w 3	w 4	w 5	w 6	w 7	w 8	w	w_ 10	sentiment
1	0	1	0	1	0	0	1	1	0	positive
0	1	0	1	1	0	1	1	0	0	negative
0	1	0	1	1	0	1	0	0	0	negative
0	0	1	0	1	1	0	1	1	1	positive
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1	positive

labeled examples

w 1	w 2	w 3	w 4	w 5	w 6	w 7	w 8	w	w_ 10	sentiment
1	0	1	0	1	0	0	1	1	0	???

new, unlabeled example

testing

instance-based algorithm

w 1	w 2	w 3	w 4	w 5	w 6	w 7	w 8	w	w_ 10	sentiment
1	0	1	0	1	0	0	1	1	0	positive

prediction

Instance-based Classification

- Assumption: instances with similar feature values should have the same target label

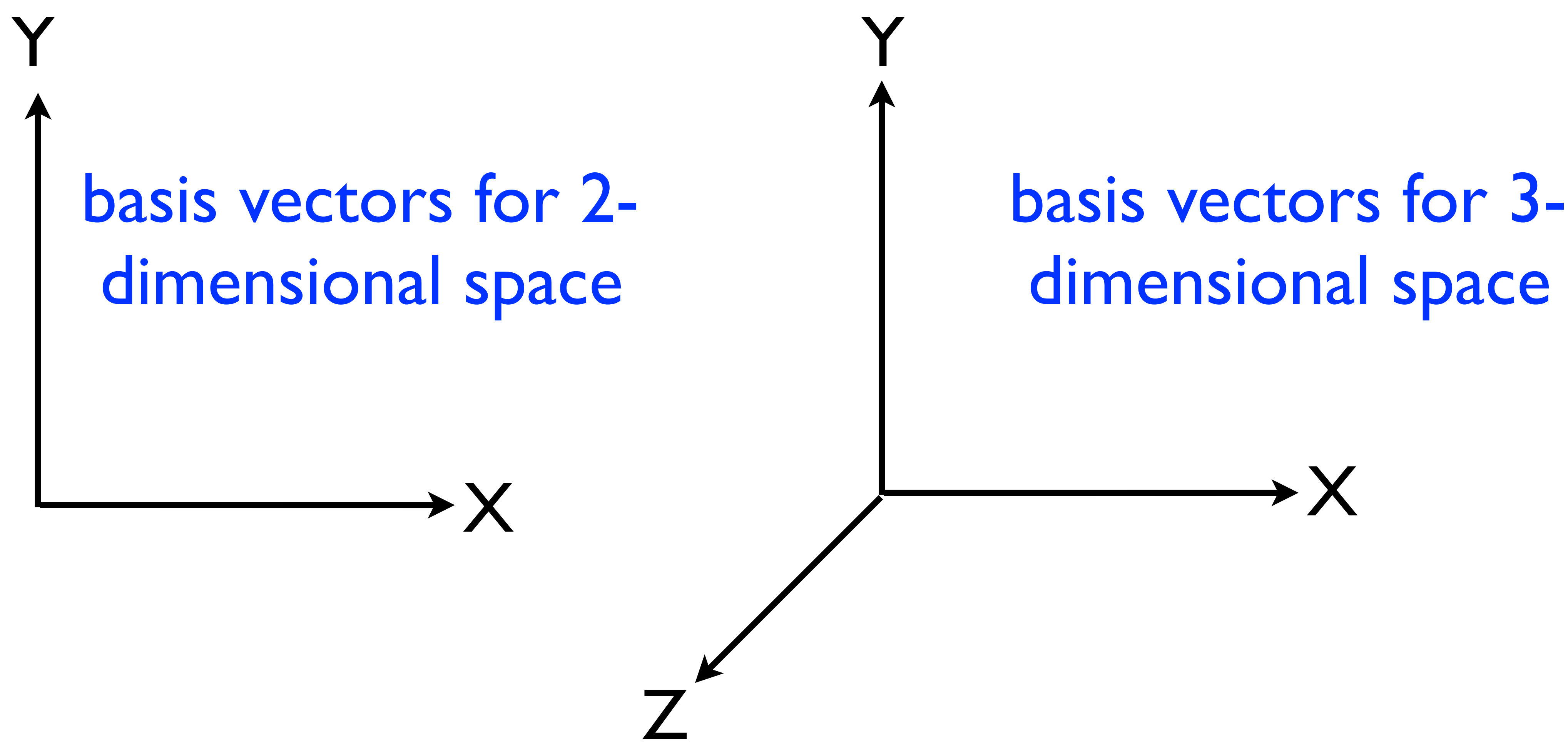
Instance-based Classification

- Assumption: instances with similar feature values should have the same target label
- Necessary Ingredients:
  - a similarity/distance metric: a measure of similarity between instances
  - an averaging technique: a way of combining the labels from the most similar training instances

Vector Space

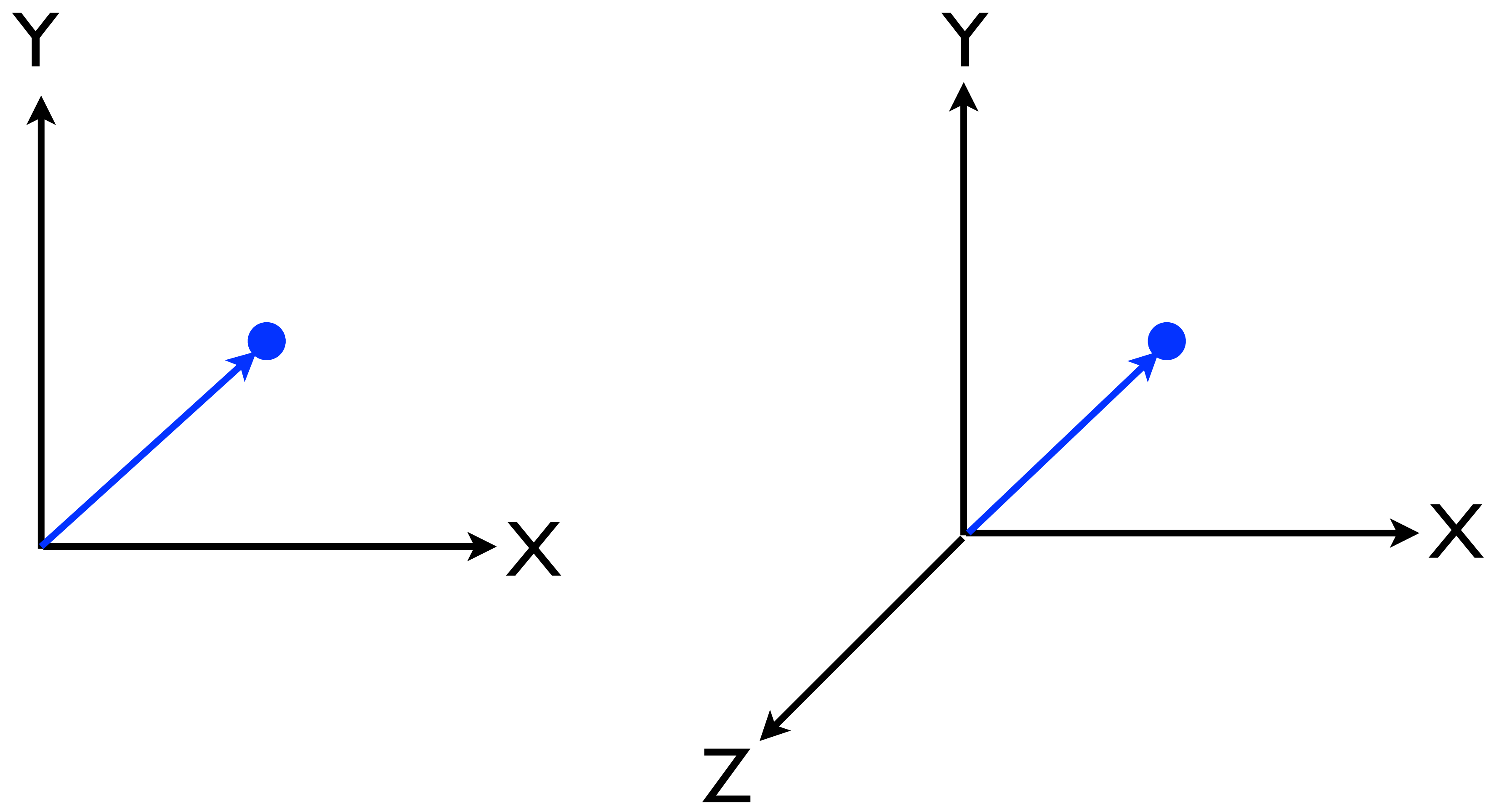
What is a Vector Space?

- Formally, a vector space is defined by a set of <u>linearly independent</u> basis vectors
- The basis vectors correspond to the dimensions or directions of the vector space



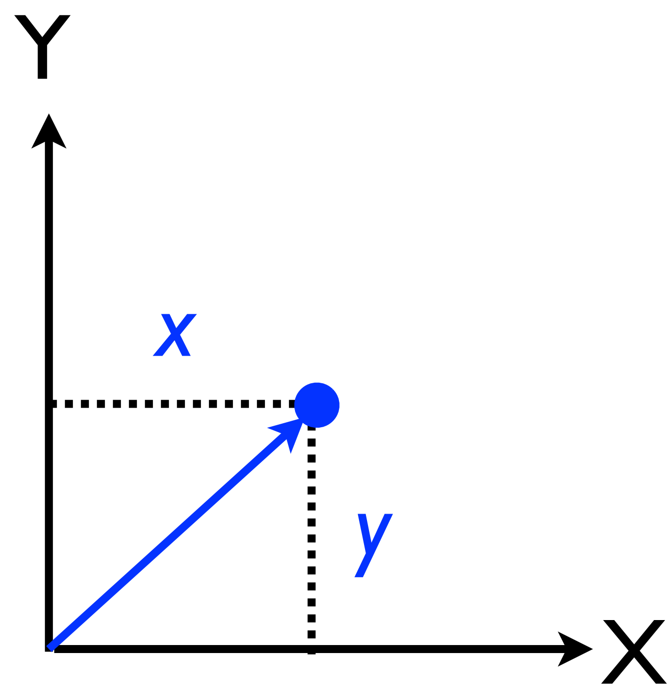
What is a Vector?

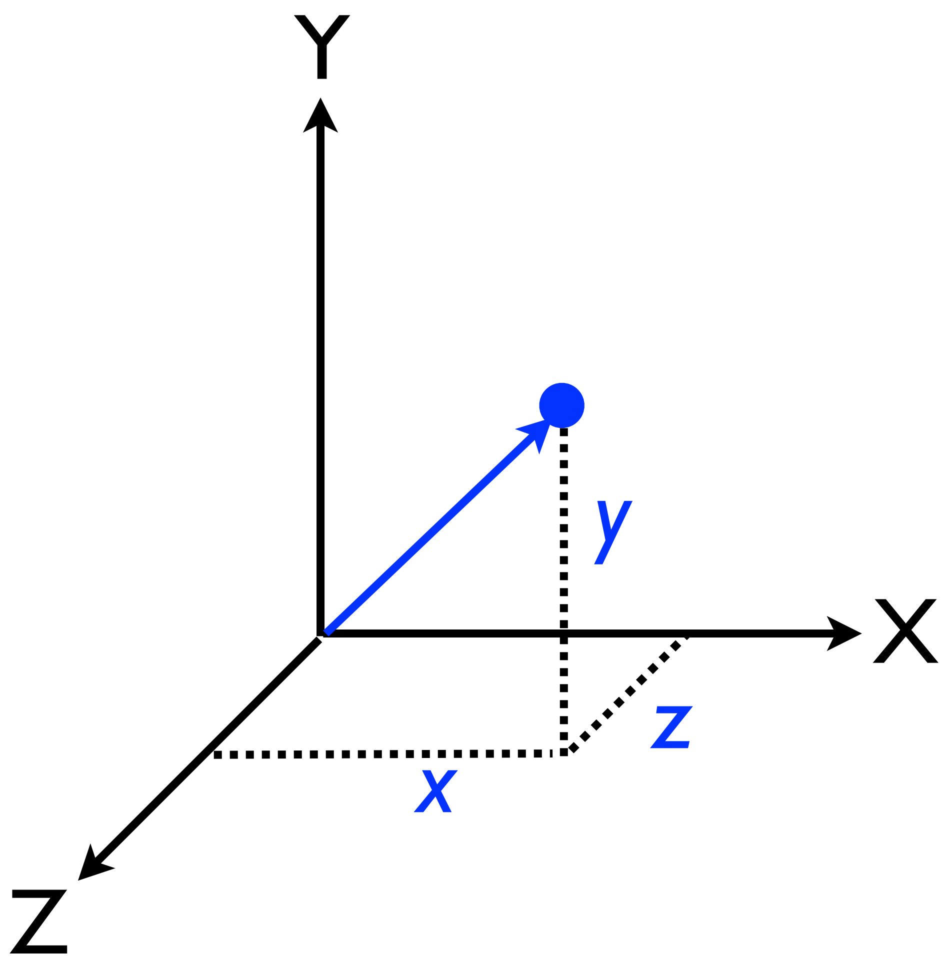
- A vector is a point in a vector space and has length (from the origin to the point) and direction



What is a Vector?

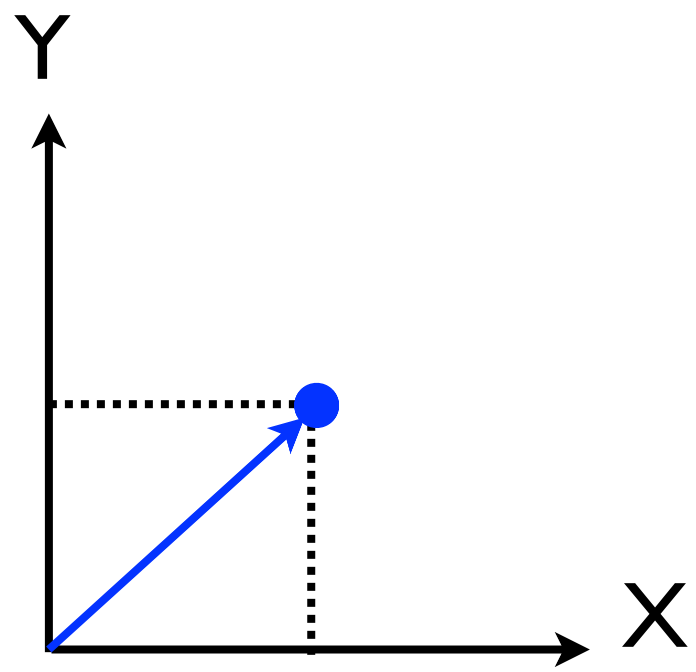
- A 2-dimensional vector can be written as **[*x*,*y*]**
- A 3-dimensional vector can be written as **[*x*,*y*,*z*]**



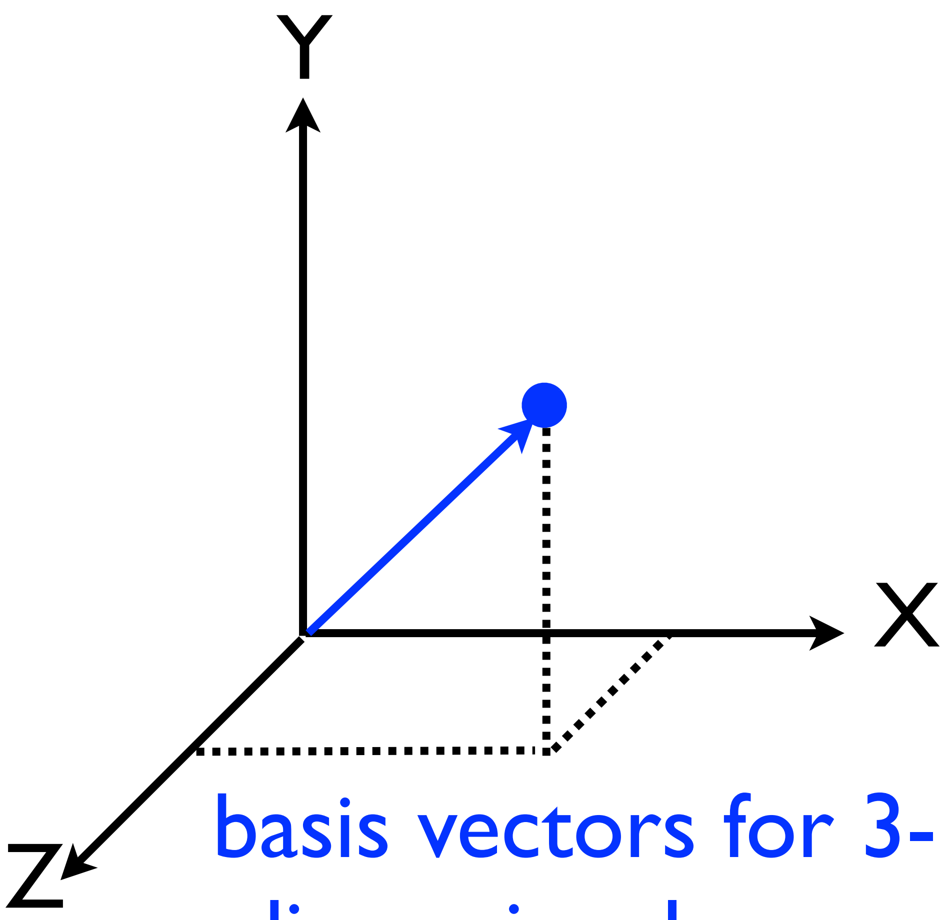


What is a Vector Space?

- The basis vectors are <u>linearly independent</u> because knowing a vector's value along one dimension doesn't say anything about its value along another dimension



basis vectors for 2-dimensional space



basis vectors for 3-dimensional space

Binary Text Representation

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
1	0	1	0	1	0	0	1	1	0	positive
0	1	0	1	1	0	1	1	0	0	negative
0	1	0	1	1	0	1	0	0	0	negative
0	0	1	0	1	1	0	1	1	1	positive
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1	positive

- Terms as features
- Bag of words representation: no word order
- 1 = the term appears in the text and 0 = the term does not appear in the text

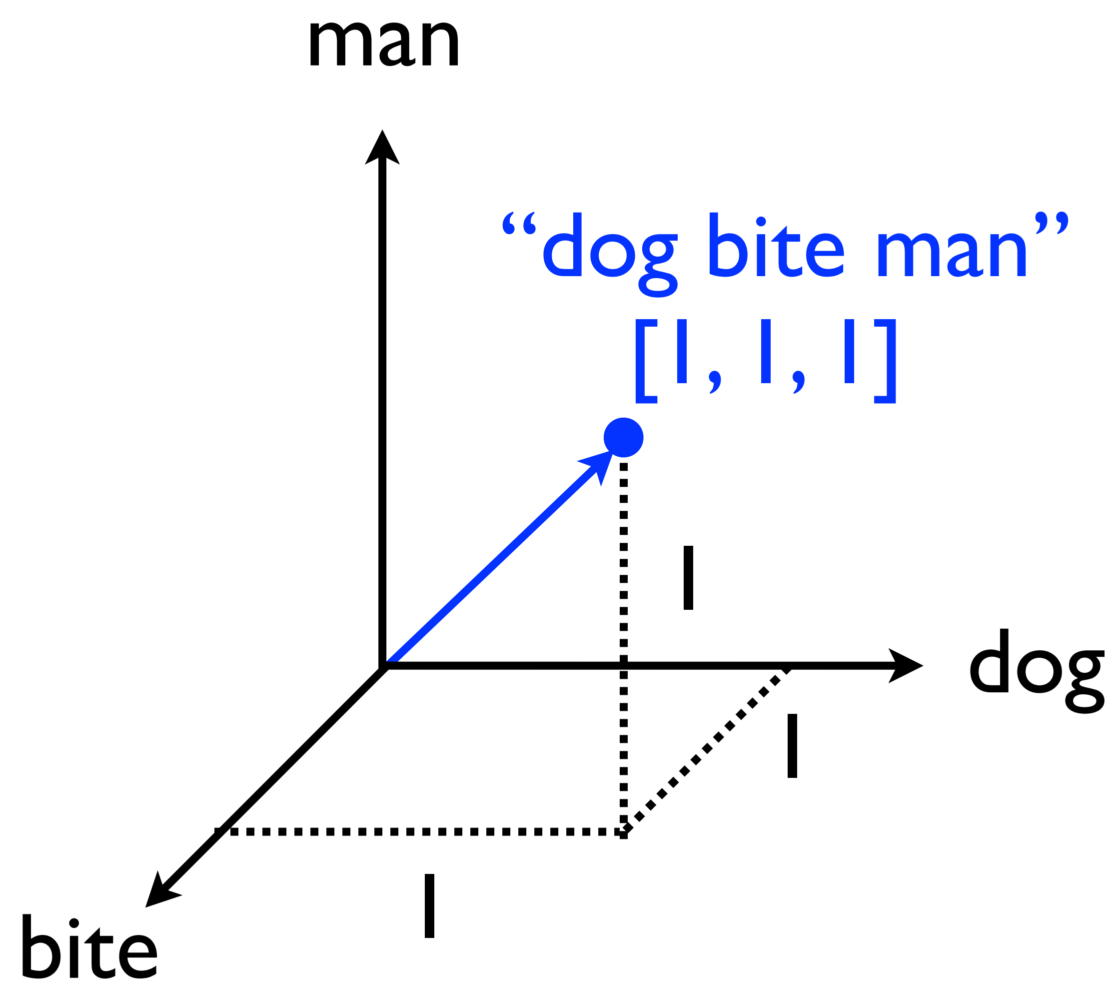
Vector Space Representation

- Let V denote the set of features in our feature representation
- Any arbitrary instance can be represented as a vector in |V|-dimensional space
- For simplicity, let's assume three features: dog, bite, man (i.e., |V| = 3)
- Why? Because it's easy to visualize 3-D space

Vector Space Representation
with binary weights

- 1 = the term appears at least once
- 0 = the term does <u>not</u> appear

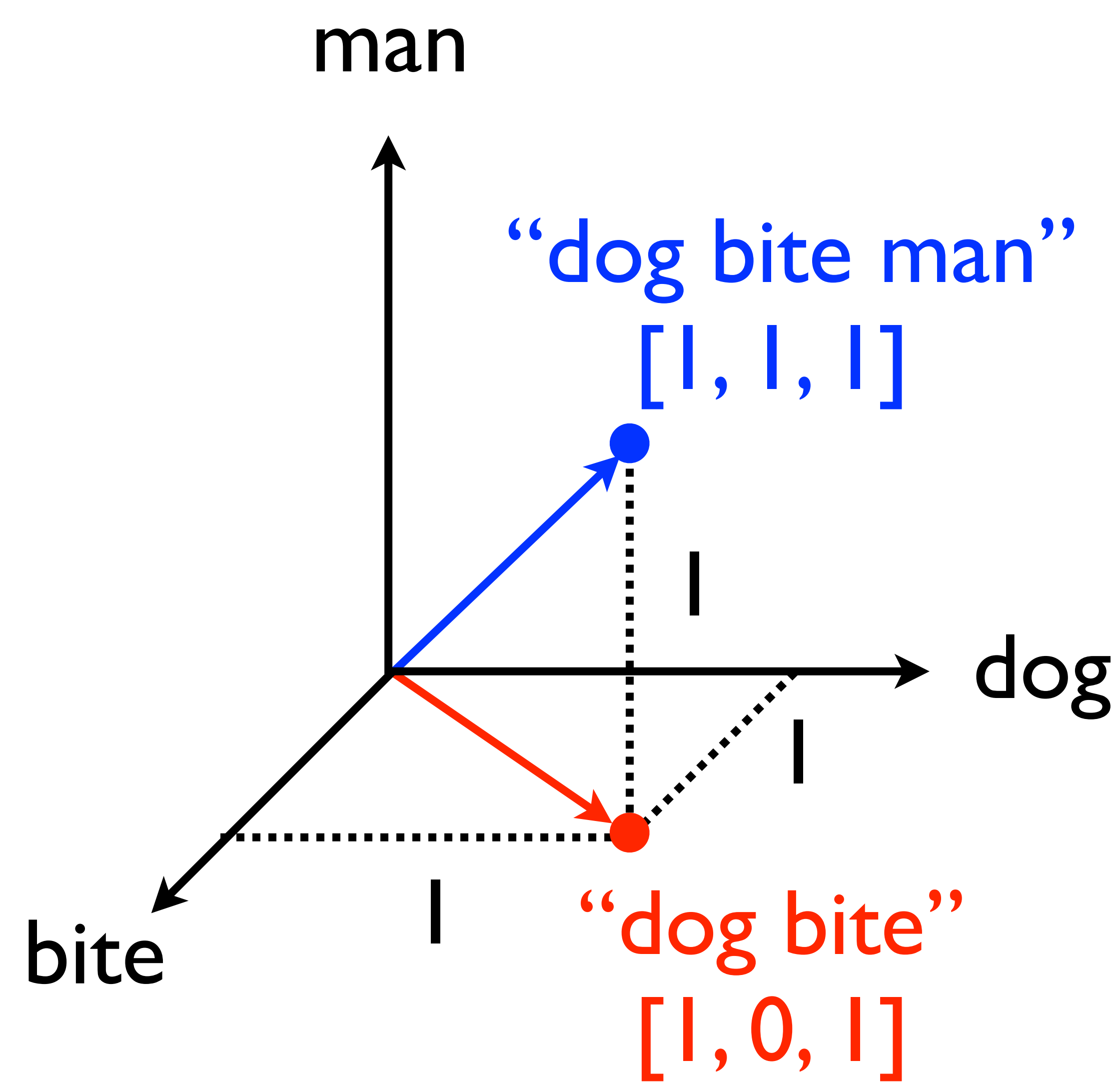
	dog	*man*	*bite*
i_1	1	1	1



Vector Space Representation
with binary weights

- 1 = the term appears at least once
- 0 = the term does <u>not</u> appear

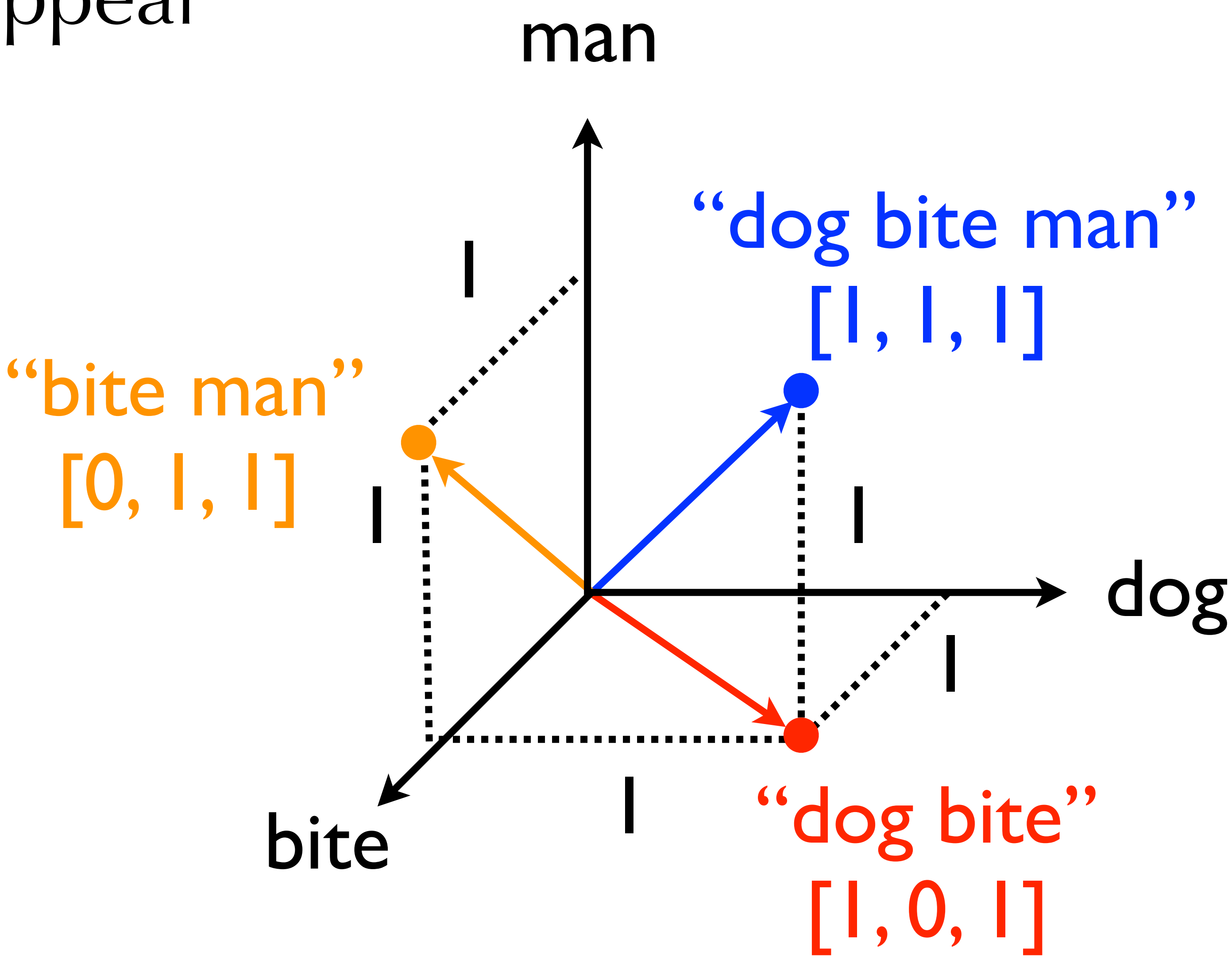
	dog	*man*	*bite*
i_1	1	1	1
i_2	1	0	1



Vector Space Representation
with binary weights

- 1 = the term appears at least once
- 0 = the term does not appear

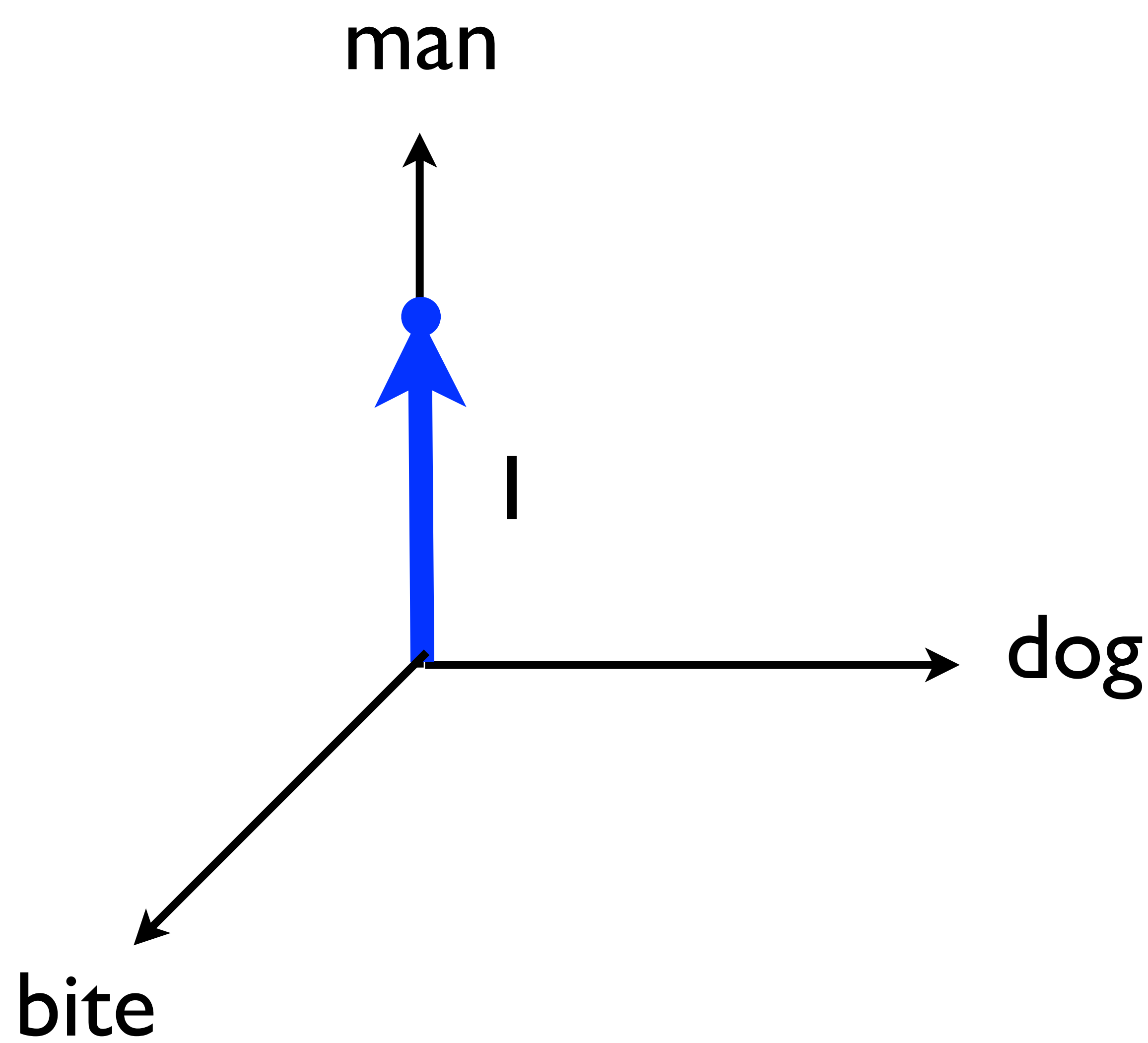
	dog	*man*	*bite*
i_1	1	1	1
i_2	1	0	1
i_3	0	1	1



Vector Space Representation

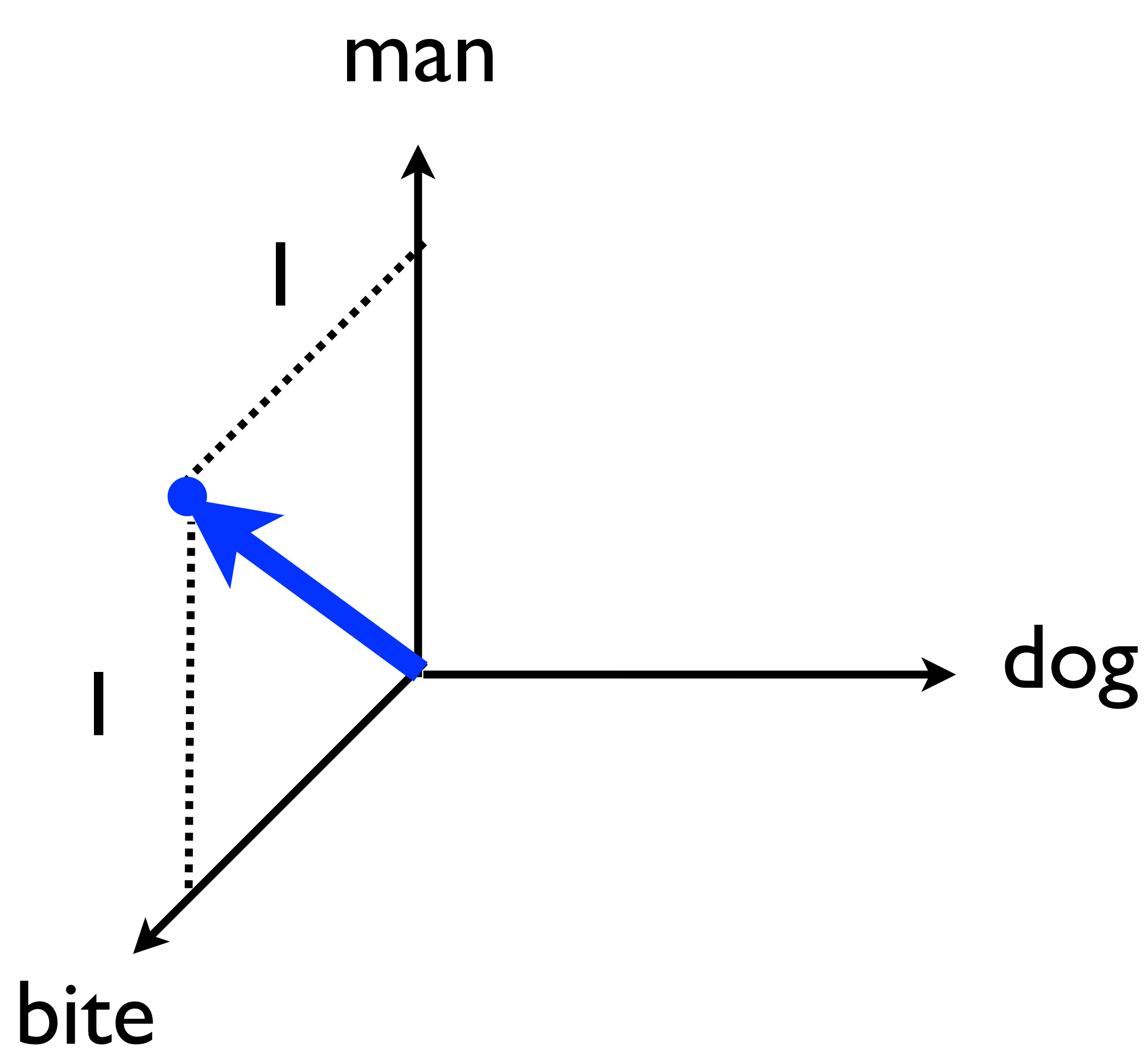
with binary weights

- What span(s) of text does this vector represent?



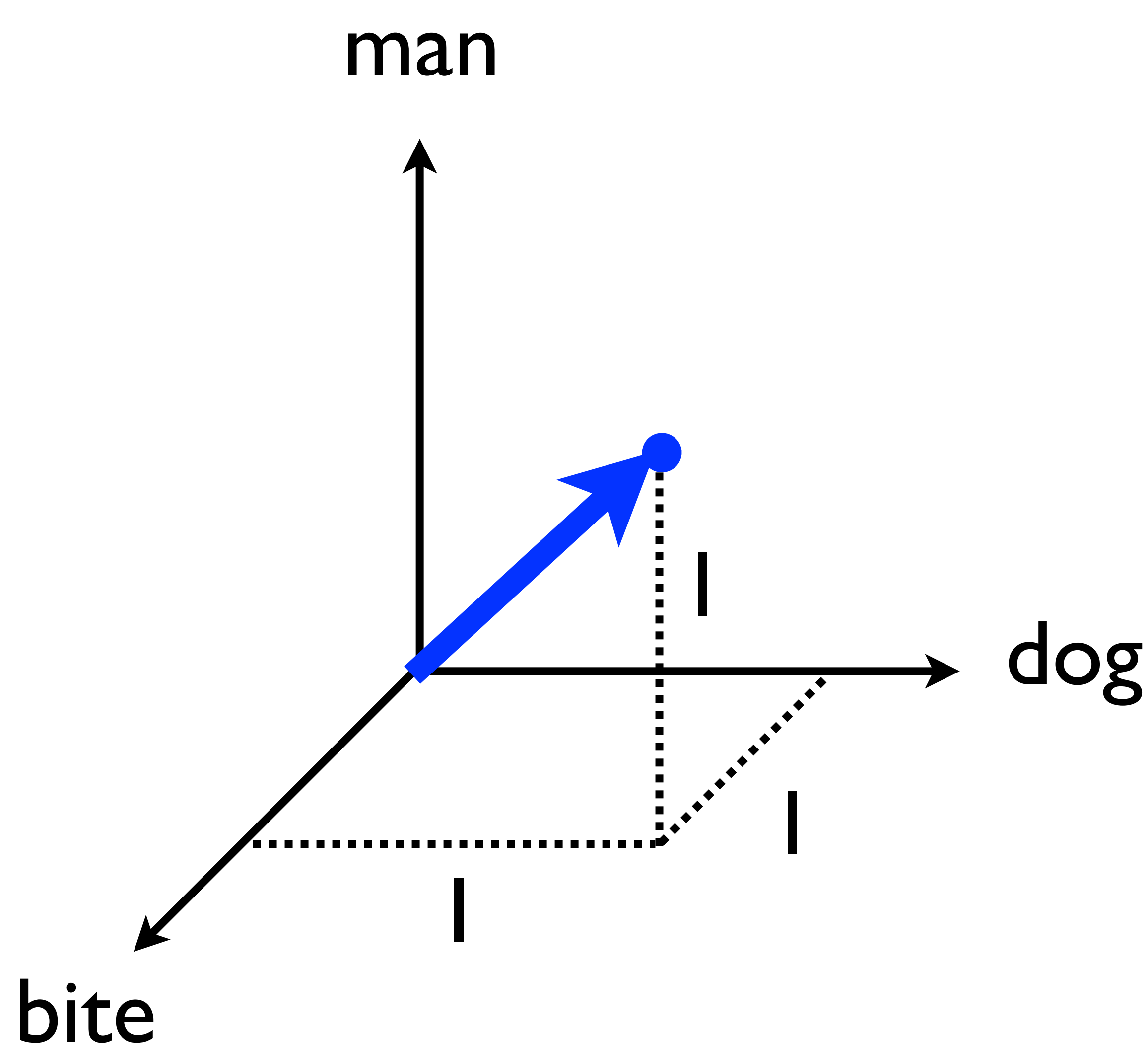
Vector Space Representation
with binary weights

- What span(s) of text does this vector represent?



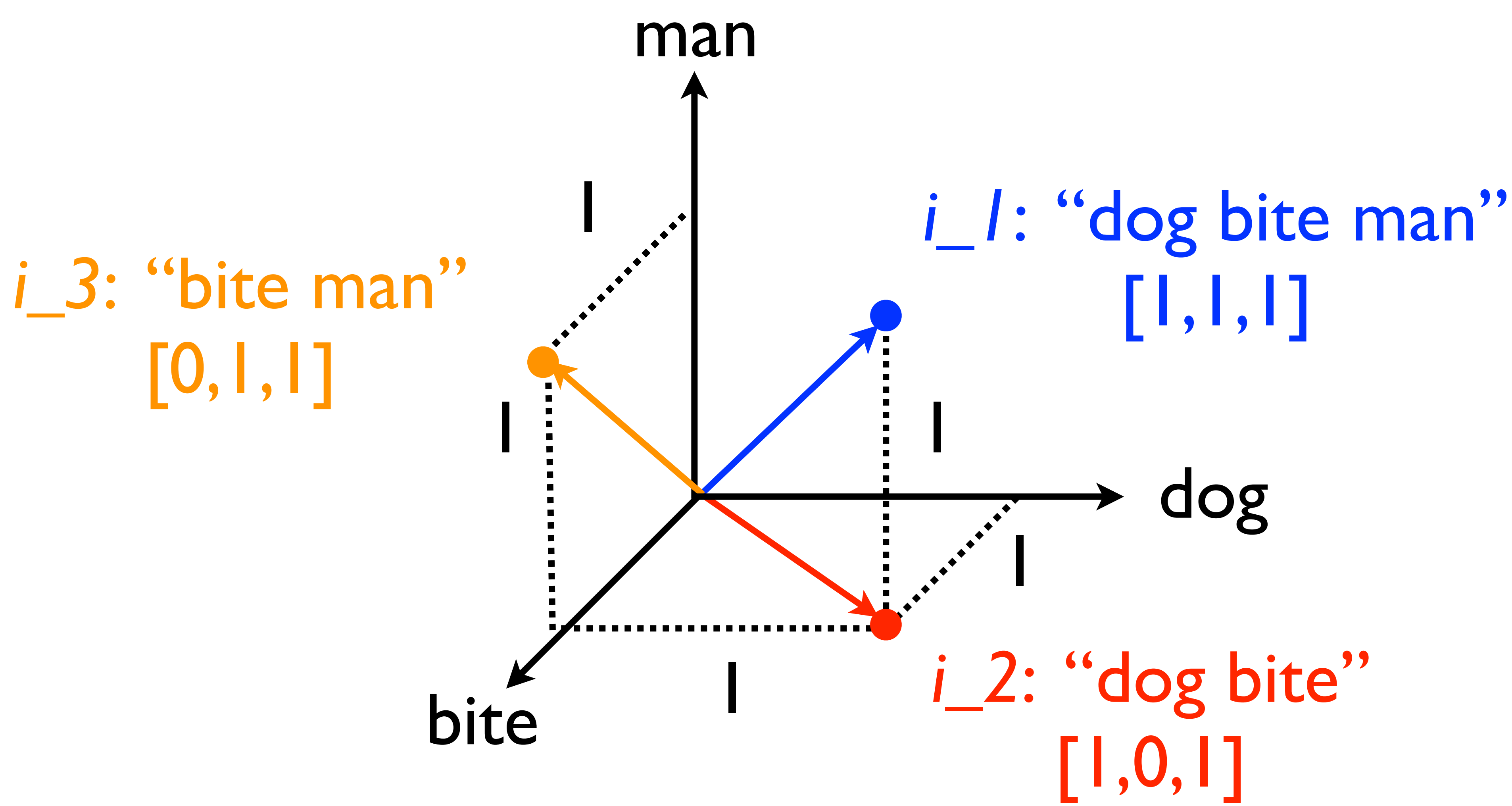
Vector Space Representation
with binary weights

- What span(s) of text does this vector represent?



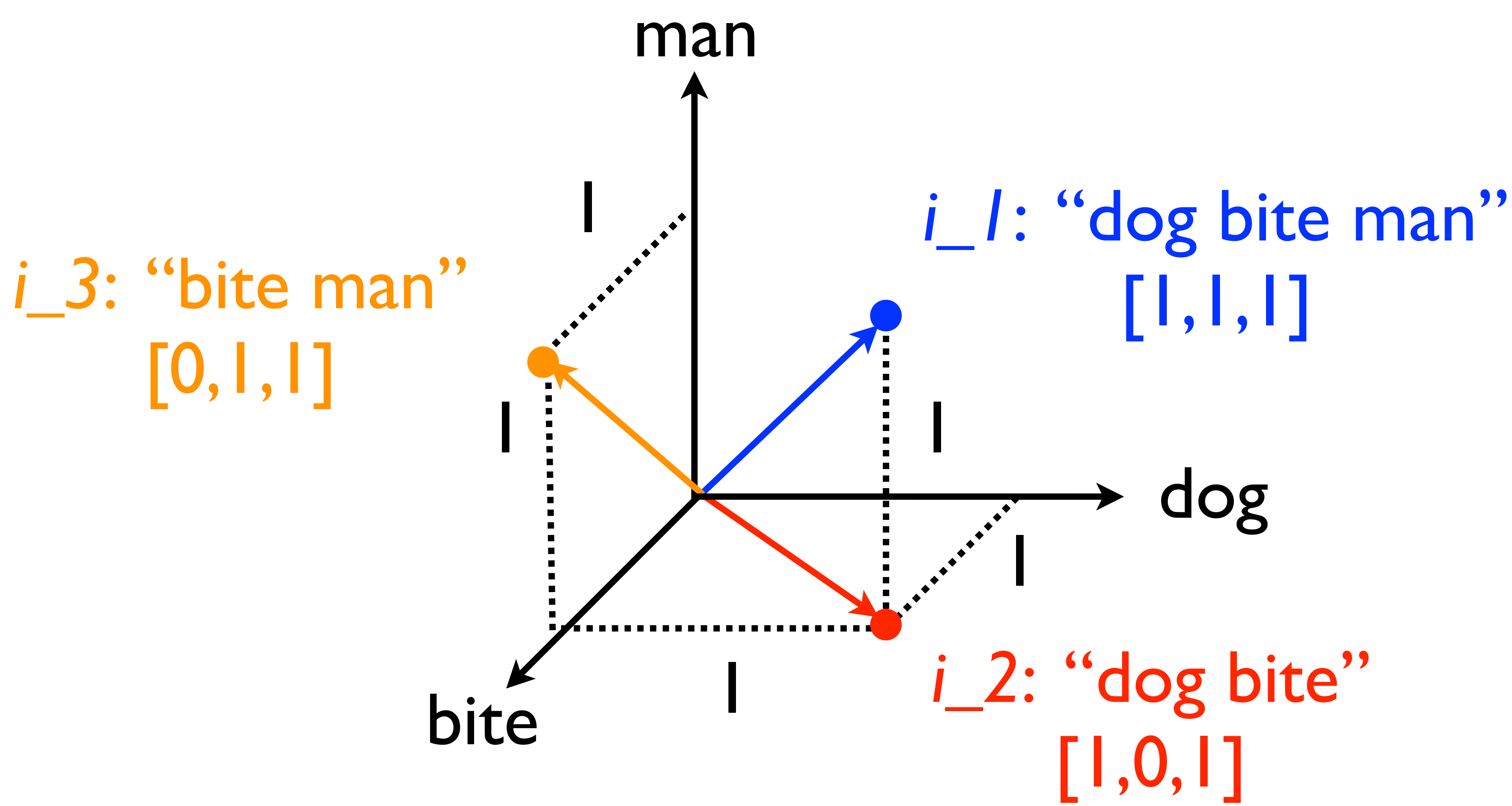
Vector Space Representation
with binary weights

- Any arbitrary span of text can be represented as a vector in |V|-dimensional space



Vector Space Representation
with binary weights

- How can we use a vector-space representation to compute similarity or distance?



Vector Space Representation
with binary weights

- How can we use a vector-space representation to compute similarity or distance?

- Euclidean distance:

$$D(x,y) = \sqrt{\left(\sum_{i=1}^{|\mathcal{V}|}(x_i - y_i)^2\right)}$$

Euclidean Distance

	x	y	$(x_i - y_i)^2$
dog	1	1	0
bite	1	1	0
man	1	1	0
$$D(x,y) = \sqrt{\left(\sum_{i=1}^{\lvert\mathcal{V}\rvert}(x_i - y_i)^2\right)}$$			**0**

"dog bite man" vs. "dog bite man"

Euclidean Distance

	x	y	$(x_i - y_i)^2$
dog	1	1	0
bite	1	1	0
man	1	0	1
$D(x,y) = \sqrt{\left(\sum_{i=1}^{\lvert\mathcal{V}\rvert}(x_i - y_i)^2\right)}$			1

"dog bite man" vs. "dog bite"

Euclidean Distance

	x	y	$(x_i - y_i)^2$
dog	1	0	1
bite	1	1	0
man	1	0	1
$D(x,y) = \sqrt{\left(\sum_{i=1}^{\lvert\mathcal{V}\rvert}(x_i - y_i)^2\right)}$			**1.41**

"dog bite man" vs. "bite"

Binary Text Representation

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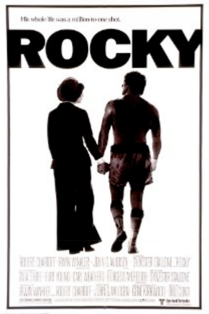
1	0	1	0	1	0	0	1	1	0	positive
0	1	0	1	1	0	1	1	0	0	negative
0	1	0	1	1	0	1	0	0	0	negative
0	0	1	0	1	1	0	1	1	1	positive
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1	positive

- Is this a good (bag of words) representation?
- Can we do better?

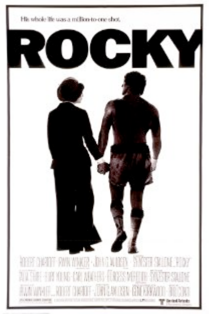


Term-Weighting

what are the most important terms?

- Movie: Rocky (1976)
- Plot:

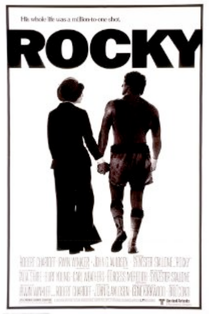
Rocky Balboa is a struggling boxer trying to make the big time. Working in a meat factory in Philadelphia for a pittance, he also earns extra cash as a debt collector. When heavyweight champion Apollo Creed visits Philadelphia, his managers want to set up an exhibition match between Creed and a struggling boxer, touting the fight as a chance for a "nobody" to become a "somebody". The match is supposed to be easily won by Creed, but someone forgot to tell Rocky, who sees this as his only shot at the big time. Rocky Balboa is a small-time boxer who lives in an apartment in Philadelphia, Pennsylvania, and his career has so far not gotten off the canvas. Rocky earns a living by collecting debts for a loan shark named Gazzo, but Gazzo doesn't think Rocky has the viciousness it takes to beat up deadbeats. Rocky still boxes every once in a while to keep his boxing skills sharp, and his ex-trainer, Mickey, believes he could've made it to the top if he was willing to work for it. Rocky, goes to a pet store that sells pet supplies, and this is where he meets a young woman named Adrian, who is extremely shy, with no ability to talk to men. Rocky befriends her. Adrain later surprised Rocky with a dog from the pet shop that Rocky had befriended. Adrian's brother Paulie, who works for a meat packing company, is thrilled that someone has become interested in Adrian, and Adrian spends Thanksgiving with Rocky. Later, they go to Rocky's apartment, where Adrian explains that she has never been in a man's apartment before. Rocky sets her mind at ease, and they become lovers. Current world heavyweight boxing champion Apollo Creed comes up with the idea of giving an unknown a shot at the title. Apollo checks out the Philadelphia boxing scene, and chooses Rocky. Fight promoter Jergens gets things in gear, and Rocky starts training with Mickey. After a lot of training, Rocky is ready for the match, and he wants to prove that he can go the distance with Apollo. The 'Italian Stallion', Rocky Balboa, is an aspiring boxer in downtown Philadelphia. His one chance to make a better life for himself is through his boxing and Adrian, a girl who works in the local pet store. Through a publicity stunt, Rocky is set up to fight Apollo Creed, the current heavyweight champion who is already set to win. But Rocky really needs to triumph, against all the odds...



Term-Frequency

how important is a term?

rank	term	freq.	rank	term	freq.
1	a	22	16	creed	5
2	rocky	19	17	philadelphia	5
3	to	18	18	has	4
4	the	17	19	pet	4
5	is	11	20	boxing	4
6	and	10	21	up	4
7	in	10	22	an	4
8	for	7	23	boxer	4
9	his	7	24	s	3
10	he	6	25	balboa	3
11	adrian	6	26	it	3
12	with	6	27	heavyweigh	3
13	who	6	28	champion	3
14	that	5	29	fight	3
15	apollo	5	30	become	3



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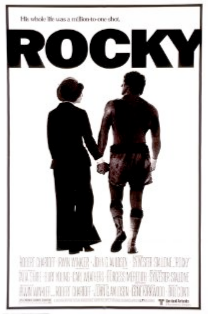
4	the	17	19	pet	4
5	is	11	20	boxing	4
6	and	10	21	up	4
7	in	10	22	an	4
8	for	7	23	boxer	4
9	his	7	24	s	3
10	he	6	25	balboa	3
11	adrian	6	26	it	3
12	with	6	27	heavyweigh	3
13	who	6	28	champion	3
14	that	5	29	fight	3
15	apollo	5	30	become	3

Inverse Document Frequency (IDF)

how important is a term?

$$idf_t = \log(\frac{N}{df_t})$$

- N = number of training set instances
- df_t = number of training set instances where term t appears



Inverse Document Frequency (IDF)

how important is a term?

rank	term	idf	rank	term	idf
1	doesn	11.66	16	creed	6.84
2	adrain	10.96	17	paulie	6.82
3	viciousness	9.95	18	packing	6.81
4	deadbeats	9.86	19	boxes	6.75
5	touting	9.64	20	forgot	6.72
6	jergens	9.35	21	ease	6.53
7	gazzo	9.21	22	thanksgivin	6.52
8	pittance	9.05	23	earns	6.51
9	balboa	8.61	24	pennsylvani	6.50
10	heavyweigh	7.18	25	promoter	6.43
11	stallion	7.17	26	befriended	6.38
12	canvas	7.10	27	exhibition	6.31
13	ve	6.96	28	collecting	6.23
14	managers	6.88	29	philadelphia	6.19
15	apollo	6.84	30	gear	6.18

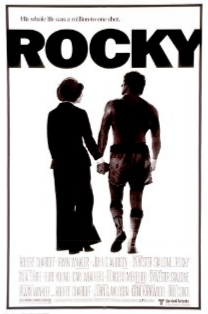
TF.IDF

how important is a term?

$$tf_t \times idf_t$$

greater when the term is frequent in the instance

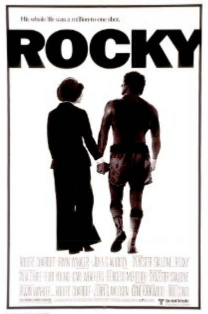
greater when the term is rare in the training set



TF.IDF

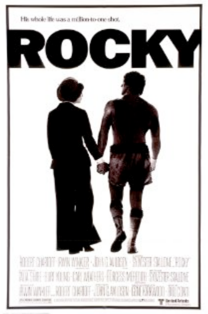
how important is a term?

rank	term	tf.idf	rank	term	tf.idf
1	rocky	96.72	16	meat	11.76
2	apollo	34.20	17	doesn	11.66
3	creed	34.18	18	adrain	10.96
4	philadelphia	30.95	19	fight	10.02
5	adrian	26.44	20	viciousness	9.95
6	balboa	25.83	21	deadbeats	9.86
7	boxing	22.37	22	touting	9.64
8	boxer	22.19	23	current	9.57
9	heavyweigh	21.54	24	jergens	9.35
10	pet	21.17	25	s	9.29
11	gazzo	18.43	26	struggling	9.21
12	champion	15.08	27	training	9.17
13	match	13.96	28	pittance	9.05
14	earns	13.01	29	become	8.96
15	apartment	11.82	30	mickey	8.96



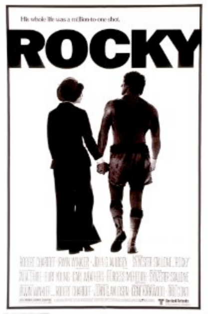
TF, IDF, or TF.IDF?

adrain adrian all already also an and apartment apollo as aspiring at
balboa become better big boxer boxing but by can career champion
chance creed current debt doesn earns every exhibition extra far fight for gazzo gets girl
go has he heavyweight her himself his if in is it keep later life living loan lovers
make man match meat men mickey named nobody of paulie pet philadelphia
rocky set she shot small somebody someone still store struggling supplies surprised
that the they think this through time title to trainer training up want when where
who willing with woman won works



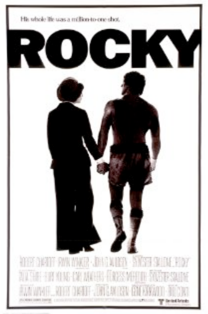
TF, IDF, or TF.IDF?

ability adrain adrian already apartment apollo aspiring balboa become befriended befriends big boxer boxes boxing canvas champion chance checks chooses collecting collector creed current deadbeats debt debts distance doesn downtown earns ease easily exhibition extra extremely factory fight forgot gazzo gear gotten heavyweight his is jergens later loan lot lovers managers match meat mickey named nobody odds packing paulie pennsylvania pet philadelphia pittance promoter publicity ready rocky sells set shark sharp shot shy somebody someone stallion store struggling stunt supplies supposed surprised thanksgiving think thrilled time title touting trainer training triumph up ve viciousness visits where who willing won works



TF, IDF, or TF.IDF?

ability adrain adrian already apollo aspiring balboa beat befriended befriends better boxer boxes boxing canvas cash champion checks chooses collecting collector creed current deadbeats debt debts distance doesn downtown earns ease easily exhibition explains extra extremely factory far forgot gazzo gear giving gotten heavyweight idea interested italian jergens keep living loan lot lovers managers match meat mickey nobody odds packing paulie pennsylvania pet philadelphia pittance promoter prove publicity ready rocky sells shark sharp shop shy skills somebody spends stallion struggling stunt supplies supposed surprised thanksgiving think thrilled title touting trainer training triumph unknown ve viciousness visits want willing win won



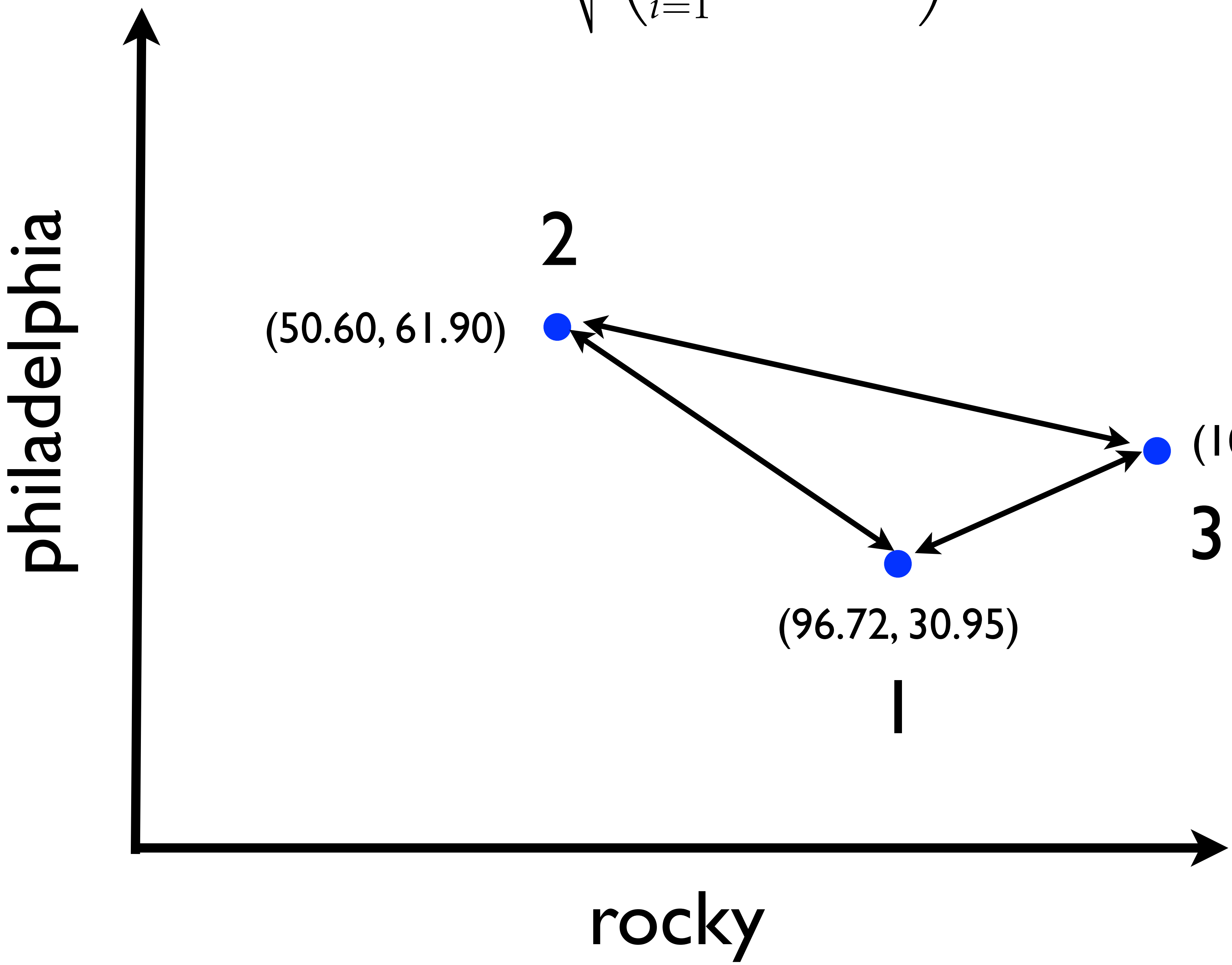
Calculating TF.IDF Weights

$$tf_t \times log\left(\frac{N}{df_t}\right)$$

term	tf	N	df	idf	tf.idf
rocky	19	230721	1420	5.09	96.72
philadelphia	5	230721	473	6.19	30.95
boxer	4	230721	900	5.55	22.19
fight	3	230721	8170	3.34	10.02
mickey	2	230721	2621	4.48	8.96
for	7	230721	117137	0.68	4.75

Putting Everything Together

$$D(x,y) = \sqrt{\left(\sum_{i=1}^{|\mathcal{V}|}(x_i - y_i)^2\right)}$$



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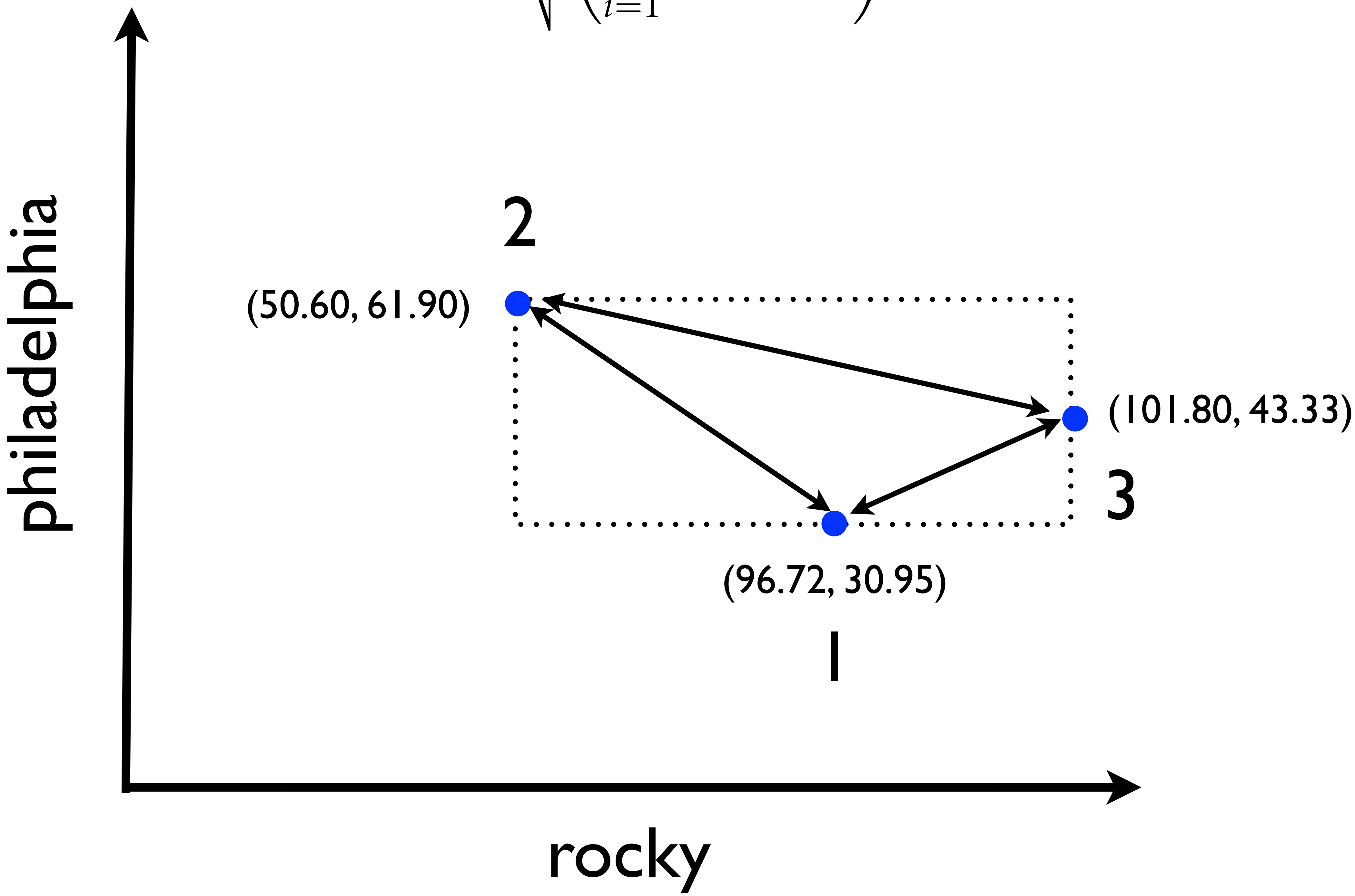
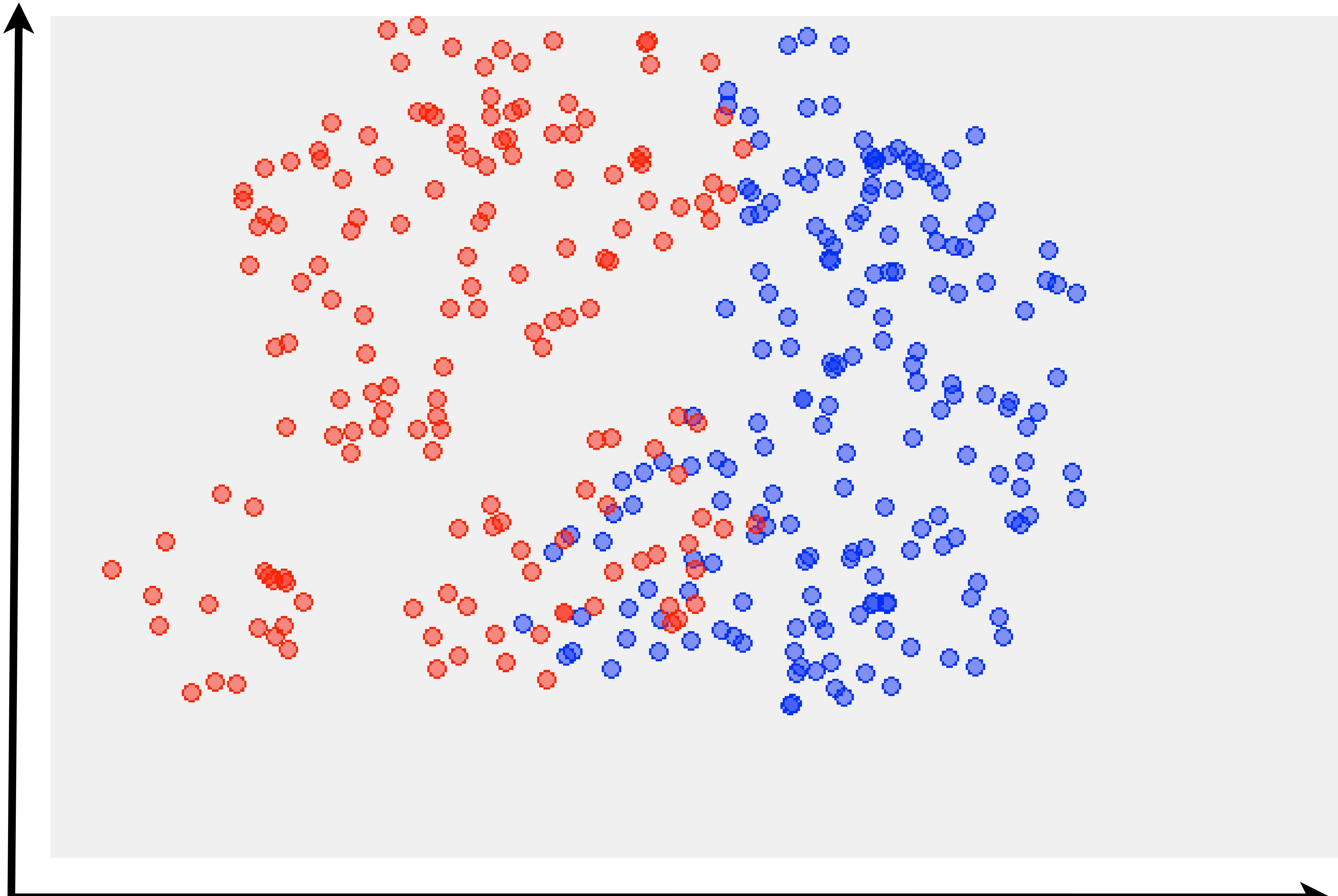
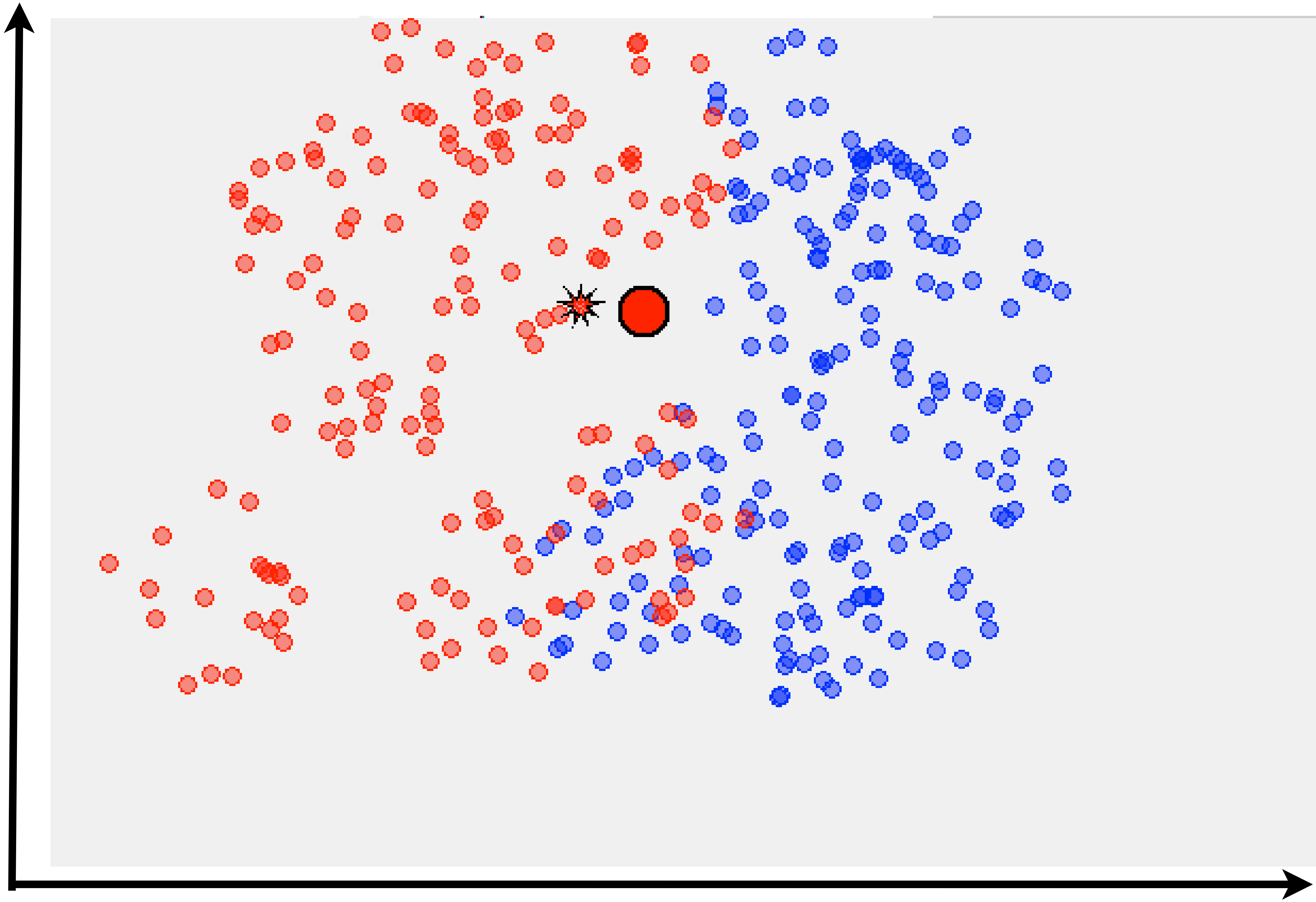


Nearest-Neighbor Classification



source: http://www.math.le.ac.uk/people/ag153/homepage/KNN/

Nearest-Neighbor Classification



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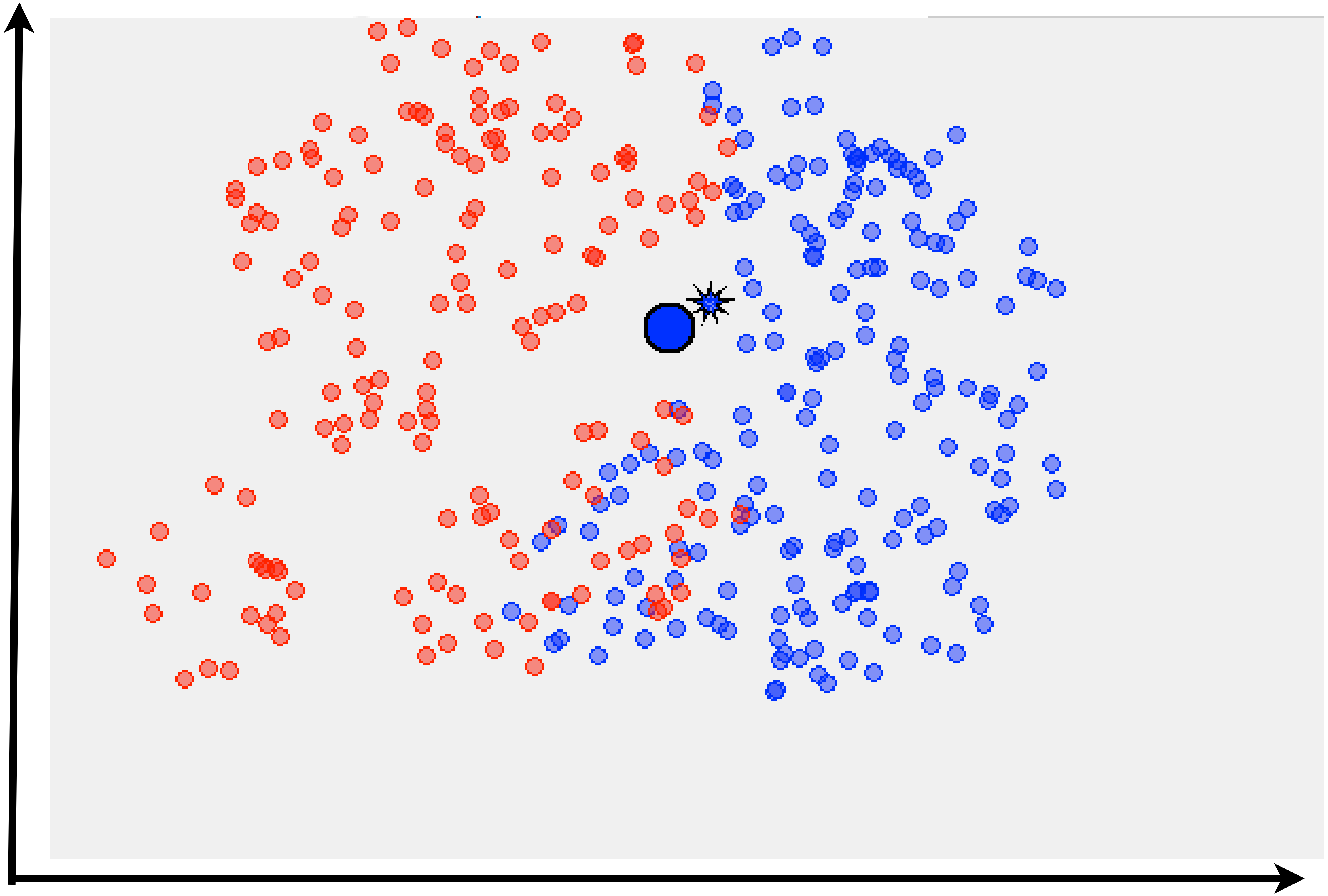
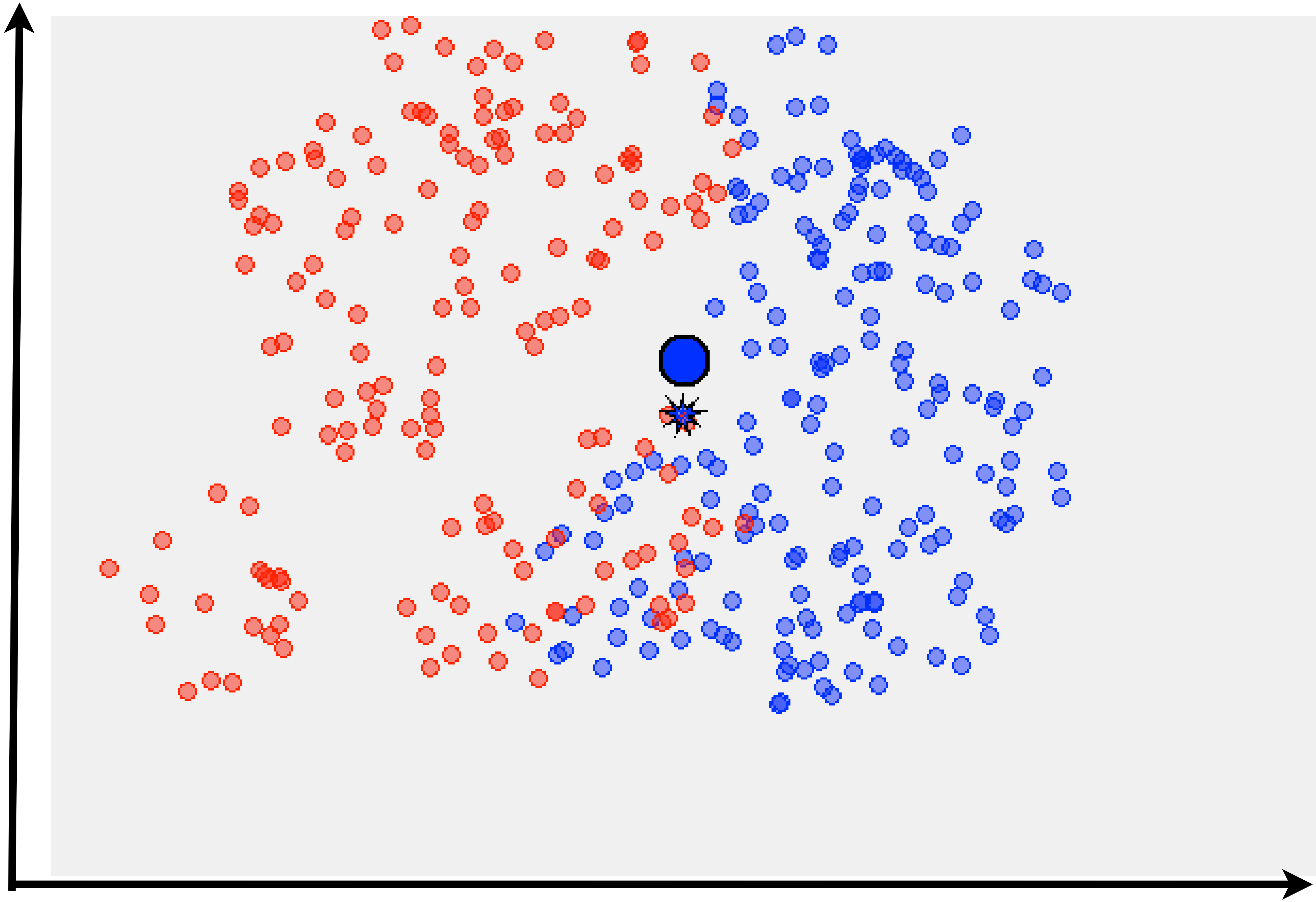


Nearest-Neighbor Classification



Nearest-Neighbor Classification

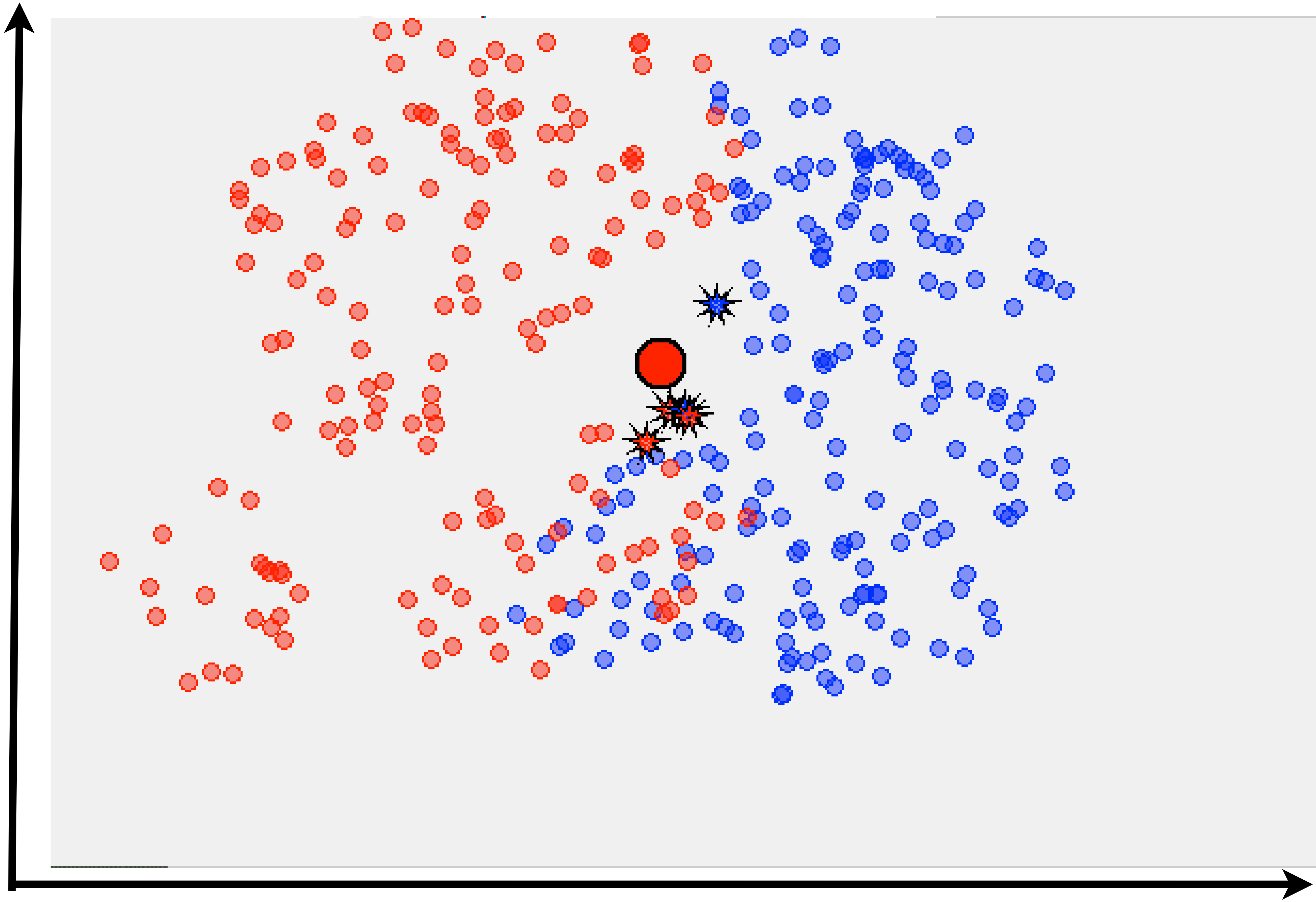
- Given a test instance, assign the label associated with the nearest training set instance
- What is a potential limitation of this approach?

Nearest-Neighbor Classification

- Given a test instance, assign the label associated with the nearest training set instance
- What is a potential limitation of this approach?
- The nearest neighbor may be an outlier
- For example: a positive movie review with lots of negative words
- Solution: use the majority class associated with the K nearest neighbors

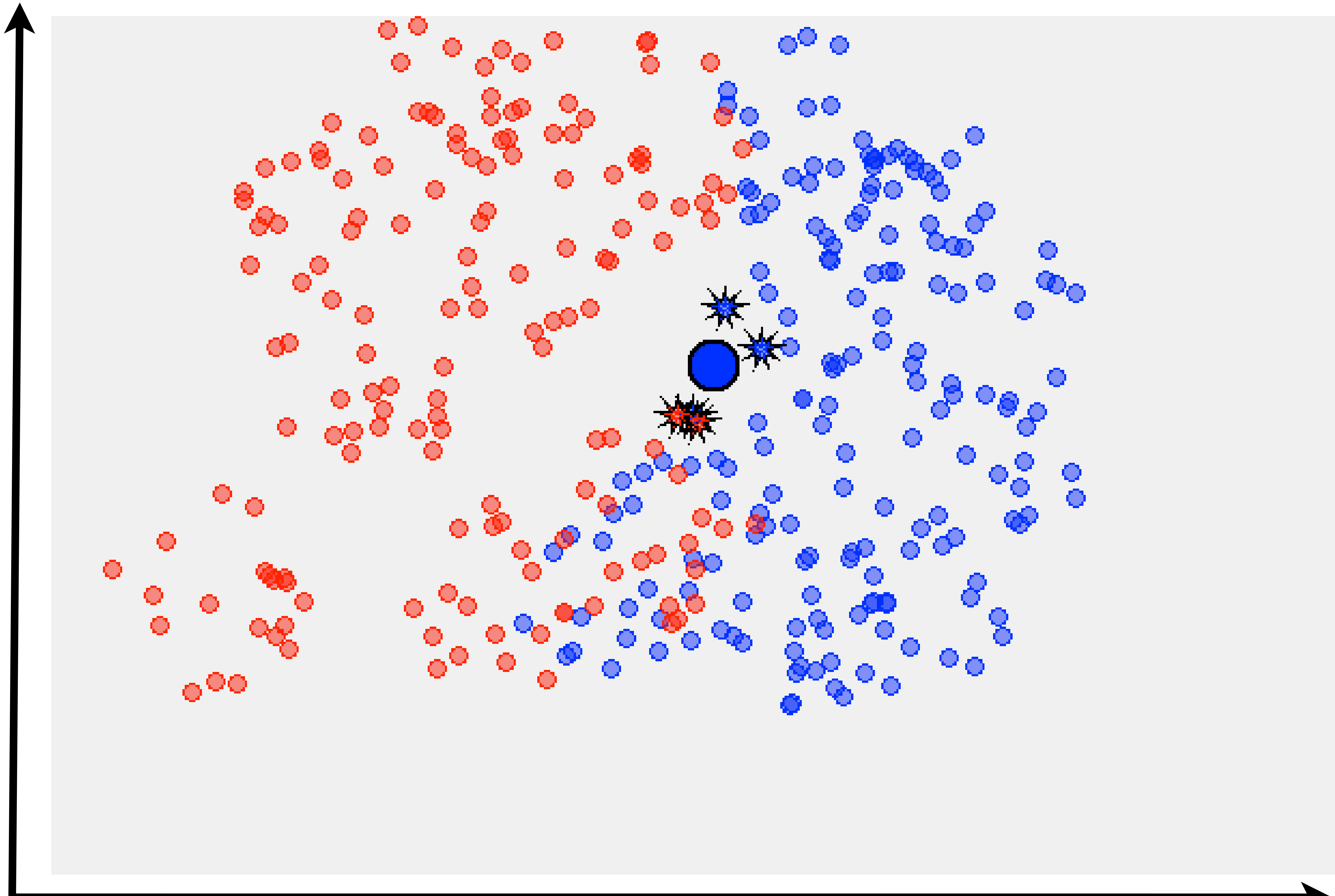
K Nearest-Neighbor (KNN)

(K = 5)



K Nearest-Neighbor (KNN)

(K = 5)



K Nearest-Neighbor Classification

- Given a test instance, assign the majority label associated with the K nearest training set instances
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K Nearest-Neighbor Classification

- Given a test instance, assign the majority label associated with the K nearest training set instances
- What is a potential limitation of this approach?
- Nearest-neighbors that are far away have the same influence as nearest-neighbors that are close
- Solution: use some kind of weighted voting
- There are many, many variants
- Including one that does weighted voting using the entire training set

K Nearest-Neighbor (KNN)
practical matters

- Feature normalization
- Feature weighting
- Computational complexity

K Nearest-Neighbor (KNN)
practical matters: feature normalization

- KNN assumes that feature values (and differences in feature value) are comparable between features
- This can be tricky if feature values are not comparable

$$D(x,y) = \sqrt{\left(\sum_{i=1}^{|\mathcal{V}|}(x_i - y_i)^2\right)}$$

K Nearest-Neighbor (KNN)

practical matters: feature normalization

f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_10	sentiment
10.5	1.2	100.4	4.54	33.4	503.4	76.8	0.54	2.31	145.6	positive
13.5	1.5	101.4	5.65	34.5	400.3	79.7	0.36	5.35	353.3	negative
20.4	1.6	143.5	7.47	24.5	323.2	74.3	0.75	10.54	550.5	negative
12.4	1.4	164.2	5.76	65.6	543.2	43.4	0.23	1.65	365.2	positive
12.5	3.2	156.4	4.54	67.5	234.5	45.3	0.54	1.67	543.2	negative
15.7	1.8	154.6	8.67	65.7	156.5	55.5	0.45	5.64	300.4	positive

- Features that capture different types of evidence may have very different ranges
- What can we do so that they have roughly equal contribution?

K Nearest-Neighbor (KNN)

min/max normalization

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
0	0	0	0	0.21	0.9	0.92	0.6	0.07	0	positive
0.3	0.15	0.02	0.27	0.23	0.63	1	0.25	0.42	0.51	negative
1	0.2	0.68	0.71	0	0.43	0.85	1	1	1	negative
0.19	0.1	1	0.3	0.96	1	0	0	0	0.54	positive
0.2	1	0.88	0	1	0.2	0.05	0.6	0	0.98	negative
0.53	0.3	0.85	1	0.96	0	0.33	0.42	0.45	0.38	positive

$$w_{i,j}^{\text{norm}} = \frac{w_{i,j} - \min(w_{i,*})}{\max(w_{i,*}) - \min(w_{i,*})}$$

K Nearest-Neighbor (KNN)
practical matters: feature weighting

- In some cases, some features are more important than others
- TF.IDF assumption: the most important features are the rare ones
  - A feature that distinguishes between instances will also distinguish between the target class values
- Alternative: learn feature weights from the training data

K Nearest-Neighbor (KNN)
practical matters: feature weighting

- Weighted Euclidean Distance:

$$D(x,y)\sqrt{\left(\sum_{i=1}^{|\mathcal{V}|} w_i(x_i - y_i)^2\right)}$$

K Nearest-Neighbor (KNN)
practical matters: feature weighting

- Split the data into two sets
- Make predictions on the second set using the first set
- For each second-set instance that is misclassified based on its first-set nearest neighbor:
  - Find the features where the instances are the most similar
  - Increase their weights (i.e. accentuate their differences)

K Nearest-Neighbor (KNN)

practical matters: making predictions

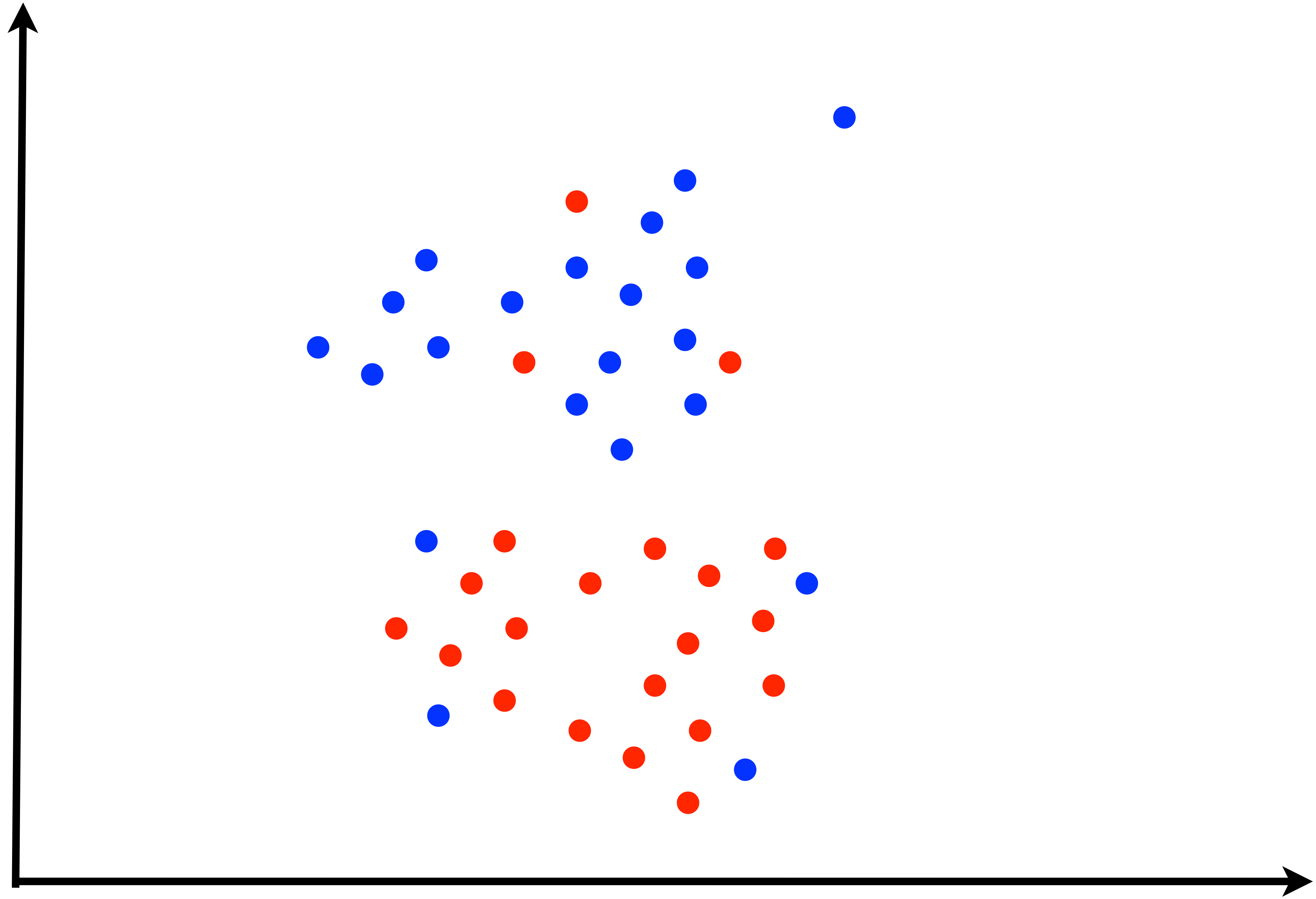
- How fast/slow is KNN is making predictions?

K Nearest-Neighbor (KNN)
practical matters: making predictions

- How fast/slow is KNN is making predictions?
- KNN can be very slow
- It needs to compute the similarity/distance between the test instance and <u>every</u> training instance
- Is there anything we can do to speed the process?

K Nearest-Neighbor (KNN)

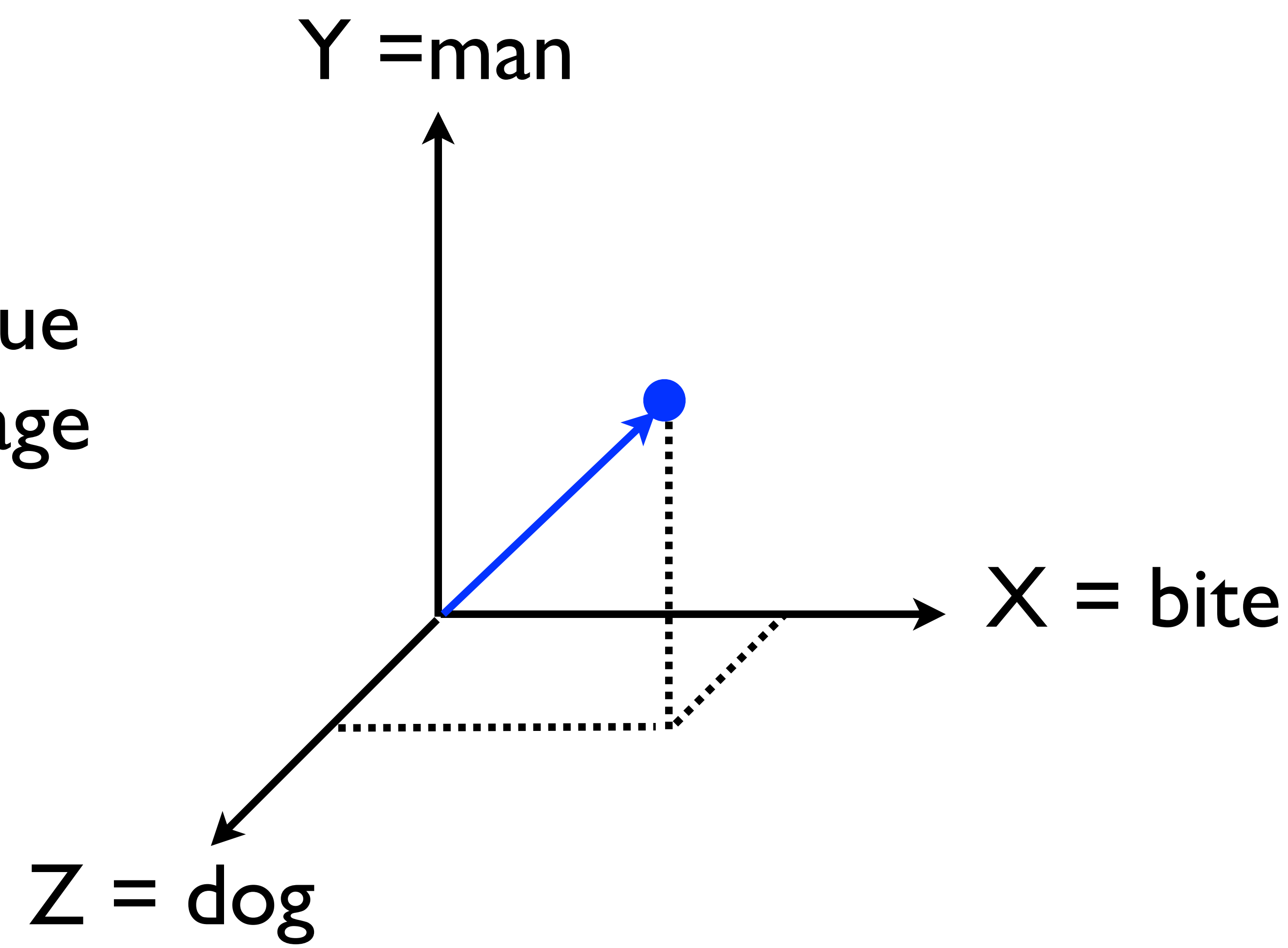
practical matters: making predictions



Independence Assumption

- The basis vectors (X, Y, Z) are <u>linearly independent</u> because knowing a vector's value on one dimension doesn't say anything about its value along another dimension

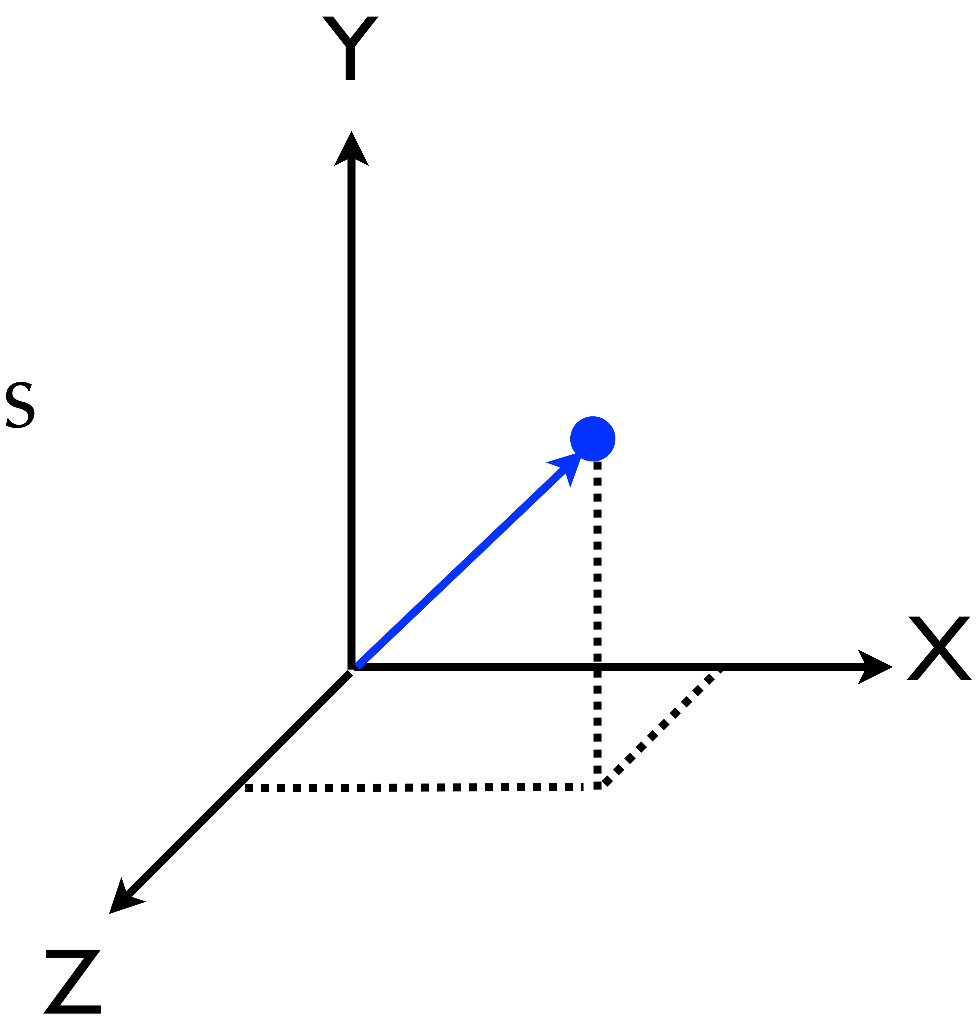
does this hold true for natural language text?



basis vectors for 3-dimensional space

Independence Assumption

- Representing texts as vectors assumes that terms are independent
- The fact that one occurs says nothing about another one occurring
- This is viewed as a limitation
- However, the implications of this limitation are still debated
- A very popular solution



Summary

- Instance-based classification relies on one assumption:
  - similar instances should have the same label
- Ingredients:
  - similarity metric: to find the nearest neighbors
  - averaging technique: to combine their true labels into a final prediction
- K-NN: use the geometric distance to find the K nearest neighbors and take the majority label