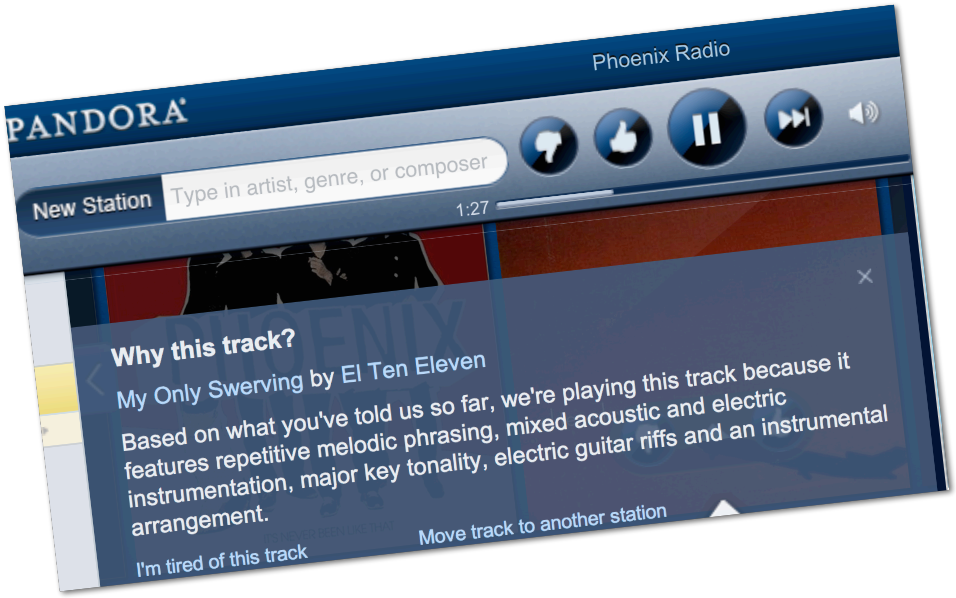
Classification based on item attributes

In the previous chapters we talked about making recommendations by collaborative filtering (also called *social filtering*). In collaborative filtering we harness the power of a community of people to help us make recommendations. You buy Wolfgang Amadeus Phoenix. We know that many of our customers who bought that album also bought Contra by Vampire Weekend. So we recommend that album to you. I watch an episode of Doctor Who and Netflix recommends Quantum Leap because many people who watched Doctor Who also watched Quantum Leap. In previous chapters we talked about some of the difficulties of collaborative filtering including problems with data sparsity and scalability. Another problem is that recommendation systems based on collaborative filtering tend to recommend already popular items—there is a bias toward popularity. As an extreme case, consider a debut album by a brand new band. Since that band and album have never been rated by anyone (or purchased by anyone since it is brand new), it will never be recommended.

"These recommenders can create a rich-get-richer effect for popular products and vice-versa for unpopular ones"

Daniel Fleder & Kartik Hosanagar. 2009. "Blockbusters Culture's Next Rise or Fall: The Impact of Recommender Systems on Sales Diversity" Management Science vol 55

In this chapter we look at a different approach. Consider the streaming music site, Pandora. In Pandora, as many of you know, you can set up different streaming radio stations. You seed each station with an artist and Pandora will play music that is similar to that artist. I can create a station seeded with the band Phoenix. It then plays bands it thinks are similar to Phoenix—for example, it plays a tune by El Ten Eleven. It doesn't do this with collaborative filtering—because people who listened to Phoenix also listened to the El Ten Eleven. It plays El Ten Eleven because the algorithm believes that El Ten Eleven is musically similar to Phoenix. In fact, we can ask Pandora why it played a tune by the group:

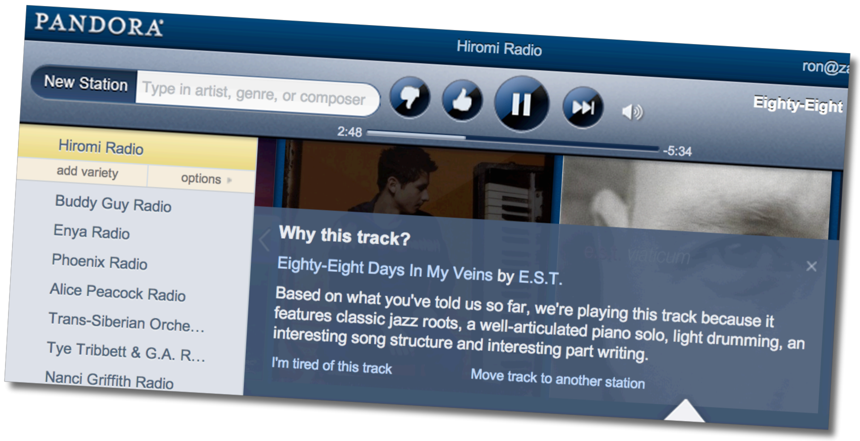

PANDORA
Phoenix Radio
New Station
Type in artist, genre, or composer
1:27
I'm tired of this track
Move track to another station

Why this track?

My Only Swerving by El Ten Eleven

Based on what you've told us so far, we're playing this track because it features repetitive melodic phrasing, mixed acoustic and electric instrumentation, major key tonality, electric guitar riffs and an instrumental arrangement.

It plays El Ten Eleven's tune *My Only Swerving* on the Phoenix station because "Based on what you told us so far, we're playing this track because it features repetitive melodic phrasing, mixed acoustic and electric instrumentation, major key tonality, electric guitar riffs and an instrumental arrangement." On my Hiromi station it plays a tune by E.S.T. because "it features classic jazz roots, a well-articulated piano solo, light drumming, an interesting song structure and interesting part writing."



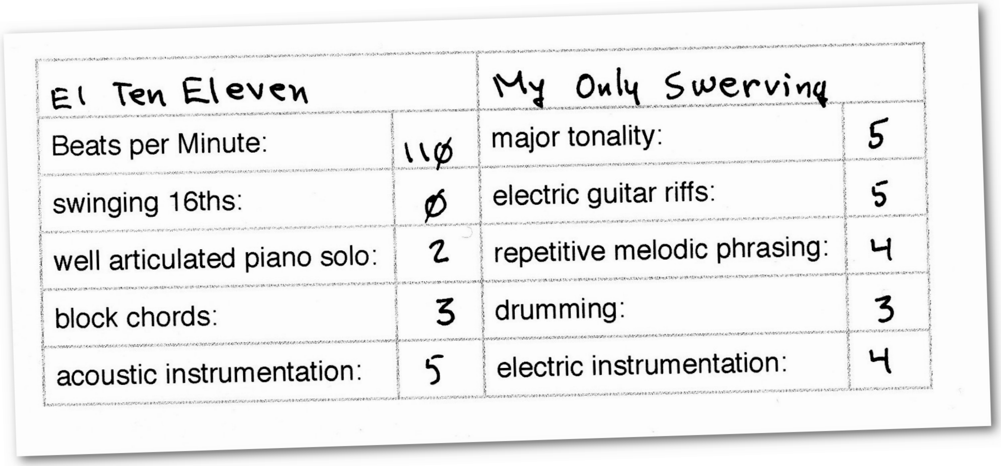
Why this track?

Eighty-Eight Days In My Veins by E.S.T.

Based on what you've told us so far, we're playing this track because it features classic jazz roots, a well-articulated piano solo, light drumming, an interesting song structure and interesting part writing.

I'm tired of this track Move track to another station

Pandora bases its recommendation on what it calls The Music Genome Project. They hire professional musicians with a solid background in music theory as analysts who determine the features (they call them 'genes') of a song. These analysts are given over 150 hours of training. Once trained they spend an average of 20-30 minutes analyzing a song to determine its genes/features. Many of these genes are technical



El Ten Eleven		My Only Swerving	
Beats per Minute:	110	major tonality:	5
swinging 16ths:	0	electric guitar riffs:	5
well articulated piano solo:	2	repetitive melodic phrasing:	4
block chords:	3	drumming:	3
acoustic instrumentation:	5	electric instrumentation:	4

The analyst provides values for over 400 genes. Its a very labor intensive process and approximately 15,000 new songs are added per month.

NOTE: The Pandora algorithms are proprietary and I have no knowledge as to how they work. What follows is not a description of how Pandora works but rather an explanation of how to construct a similar system.

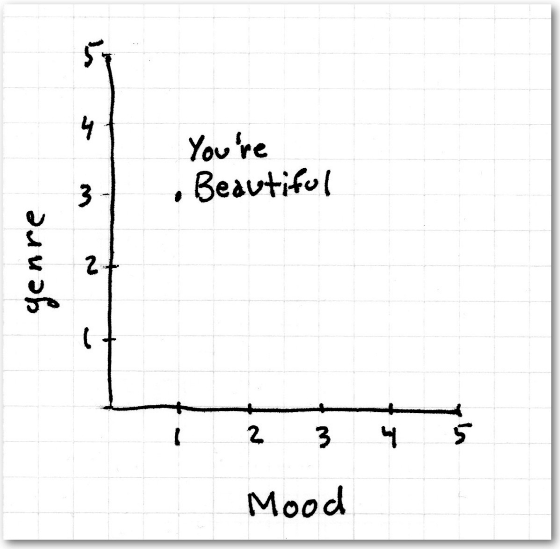
The importance of selecting appropriate values

Consider two genes that Pandora may have used: genre and mood. The values of these might look like this:

genre	
Country	1
Jazz	2
Rock	3
Soul	4
Rap	5

Mood	
Melancholy	1
joyful	2
passion	3
angry	4
unknown	5

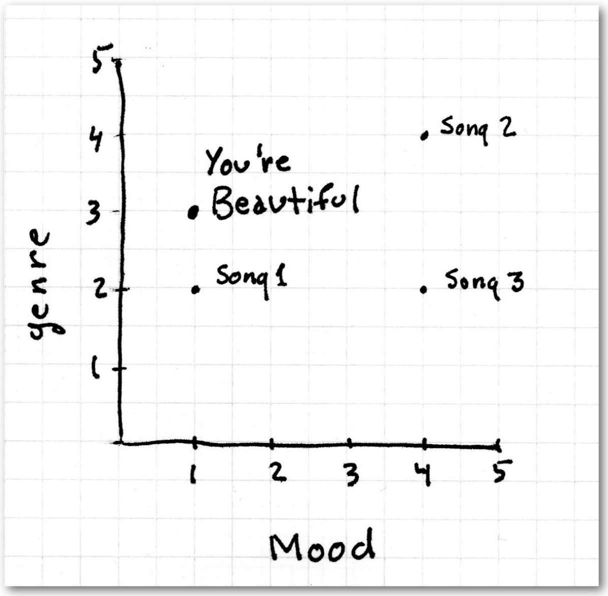
So a genre value of 4 means 'Soul' and a mood value of 3 means 'passion'. Suppose I have a rock song that is melancholy—for example the gag-inducing *You're Beautiful* by James Blunt. In 2D space, inked quickly on paper, that would look as follows:



FACT:
In a Rolling Stone poll on the Most Annoying Songs ever, You're Beautiful placed #7!

Let's say Tex just absolutely loves You're Beautiful and we would like to recommend a song to him.

Let me populate our dataset with more songs. Song 1 is a jazz song that is melancholy; Song 2 is a soul song that is angry and Song 3 is a jazz song that is angry. Which would you recommend to Tex?



Song 1 looks closest!

I hope you see that we have a fatal flaw in our scheme. Let's take a look at the possible values for our variables again:

Mood	
melancholy	1
joyful	2
passion	3
angry	4
unknown	5

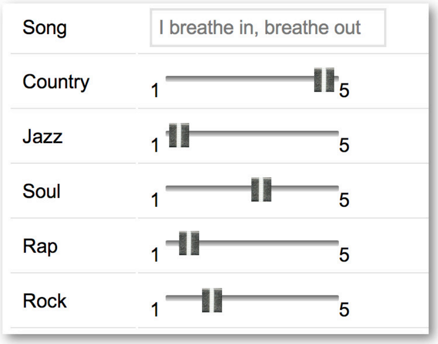
genre	
Country	1
Jazz	2
Rock	3
Soul	4
Rap	5

If we are trying to use any distance metrics with this scheme we are saying that jazz is closer to rock than it is to soul (the distance between jazz and rock is 1 and the distance between jazz and soul is 2). Or melancholy is closer to joyful than it is to angry. Even when we rearrange values the problem remains.

Mood	
melancholy	1
angry	2
passion	3
joyful	4
unknown	5

genre	
Country	1
Jazz	2
Soul	3
Rap	4
Rock	5

Re-ordering does not solve the problem. No matter how we rearrange the values this won't work. This shows us that we have chosen our features poorly. We want features where the values fall along a meaningful scale. We can easily fix our genre feature by dividing it into 5 separate features—one for country, another for jazz, etc.



Song: I breathe in, breathe out

They all can be on a 1-5 scale—how 'country' is the sound of this track—‘1’ means no hint of country to ‘5’ means this is a solid country sound. Now the scale does mean something. If we are trying to find a song similar to one that rated a country value of ‘5’, a song that rated a country of ‘4’ would be closer than one of a ‘1’.

This is exactly how Pandora constructs its gene set. The values of most genes are on a scale of 1-5 with ½ integer increments. Genes are arranged into categories. For example, there is a musical qualities category which contains genes for Blues Rock Qualities, Folk Rock Qualities, and Pop Rock Qualities among others. Another category is instruments with genes such as Accordion, Dirty Electric Guitar Riffs and Use of Dirty Sounding Organs. Using these genes, each of which has a well-defined set of values from 1 to 5, Pandora represents each song as a vector of 400 numeric values (each song is a point in a 400 dimensional space). Now Pandora can make recommendations (that is, decide to play a song on a user-defined radio station) based on standard distance functions like those we already have seen.

A simple example

Let us create a simple dataset so we can explore this approach. Suppose we have seven features each one ranging from 1-5 in ½ integer increments (I admit this isn't a very rational nor complete selection):

Amount of piano	1 indicates lack of piano; 5 indicates piano throughout and featured prominently
Amount of vocals	1 indicates lack of vocals; 5 indicates prominent vocals throughout song.
Driving beat	Combination of constant tempo, and how the drums & bass drive the beat.
Blues Influence	
Presence of dirty electric guitar	
Presence of backup vocals	
Rap Influence	

Now, using those features I rate ten tunes:

	Piano	Vocals	Driving beat	Blues infl.	Dirty elec. Guitar	Backup vocals	Rap infl.
Dr. Dog/ Fate	2.5	4	3.5	3	5	4	1
Phoenix/ Lisztomania	2	5	5	3	2	1	1
Heartless Bastards / Out at Sea	1	5	4	2	4	1	1
Todd Snider/ Don't Tempt Me	4	5	4	4	1	5	1
The Black Keys/ Magic Potion	1	4	5	3.5	5	1	1
Glee Cast/ Jessie's Girl	1	5	3.5	3	4	5	1
Black Eyed Peas/ Rock that Body	2	5	5	1	2	2	4
La Roux/ Bulletproof	5	5	4	2	1	1	1
Mike Posner/ Cooler than me	2.5	4	4	1	1	1	1
Lady Gaga/ Alejandro	1	5	3	2	1	2	1

Thus, each tune is represented as a list of numbers and we can use any distance function to compute the distance between tunes. For example, The Manhattan Distance between Dr. Dog's *Fate* and Phoenix's *Lisztomania* is:

Dr. Dog/ Fate	2.5	4	3.5	3	5	4	1
Phoenix/ Lisztomania	2	5	5	3	2	1	1
Distance	**0.5**	**1**	**1.5**	**0**	**3**	**3**	**0**

summing those distances gives us a Manhattan Distance of 9.

sharpen your pencil

I am trying to find out what tune is closest to Glee's rendition of Jessie's Girl using **Euclidean Distance.** Can you finish the following table and determine what group is closest?

	distance to Glee's Jessie's Girl
Dr. Dog/ Fate	??
Phoenix/ Lisztomania	4.822
Heartless Bastards / Out at Sea	4.153
Todd Snider/ Don't Tempt Me	4.387
The Black Keys/ Magic Potion	4.528
Glee Cast/ Jessie's Girl	0
Black Eyed Peas/ Rock that Body	5.408
La Roux/ Bulletproof	6.500
Mike Posner/ Cooler than me	5.701
Lady Gaga/ Alejandro	??

sharpen your pencil - solution

	distance to Glee's Jessie's Girl
Dr. Dog/ Fate	2.291
Lady Gaga/ Alejandro	4.387

Recall that the Euclidean Distance between any two objects, x and y, which have n attributes is:

$$d(x,y) = \sqrt{\sum_{k=1}^{n} (x_k - y_k)^2}$$

So the Euclidean Distance between Glee and Lady Gaga

	piano	vocals	beat	blues	guitar	backup	rap	SUM	SQRT
Glee	1	5	3.5	3	4	5	1		
Lady G	1	5	3	2	1	2	1		
(x-y)	0	0	0.5	1	3	3	0		
$(x-y)^2$	0	0	0.25	1	9	9	0	19.25	4.387

Doing it Python Style!

Recall that our data for social filtering was of the format:

```
users = {"Angelica": {"Blues Traveler": 3.5, "Broken Bells": 2.0,
                      "Norah Jones": 4.5, "Phoenix": 5.0,
                      "Slightly Stoopid": 1.5, "The Strokes": 2.5,
                      "Vampire Weekend": 2.0},
         "Bill":     {"Blues Traveler": 2.0, "Broken Bells": 3.5,
                      "Deadmau5": 4.0, "Phoenix": 2.0,
                      "Slightly Stoopid": 3.5, "Vampire Weekend": 3.0}}
```

We can represent this current data in a similar way:

```
music = {"Dr Dog/Fate": {"piano": 2.5, "vocals": 4, "beat": 3.5,
                         "blues": 3, "guitar": 5, "backup vocals": 4,
                         "rap": 1},
         "Phoenix/Lisztomania": {"piano": 2, "vocals": 5, "beat": 5,
                                 "blues": 3, "guitar": 2,
                                 "backup vocals": 1, "rap": 1},
         "Heartless Bastards/Out at Sea": {"piano": 1, "vocals": 5,
                                           "beat": 4, "blues": 2,
                                           "guitar": 4,
                                           "backup vocals": 1,
                                           "rap": 1},
         "Todd Snider/Don't Tempt Me": {"piano": 4, "vocals": 5,
                                        "beat": 4, "blues": 4,
                                        "guitar": 1,
                                        "backup vocals": 5, "rap": 1},
         "The Black Keys/Magic Potion":{"piano": 1, "vocals": 4,
                                           "beat": 5, "blues": 3.5,
                                           "guitar": 5,
                                           "backup vocals": 1,
                                           "rap": 1},
         "Glee Cast/Jessie's Girl": {"piano": 1, "vocals": 5,
                                     "beat": 3.5, "blues": 3,
                                     "guitar":4, "backup vocals": 5,
                                     "rap": 1},
         "La Roux/Bulletproof": {"piano": 5, "vocals": 5, "beat": 4,
                                "blues": 2, "guitar": 1,
                                "backup vocals": 1, "rap": 1},
        "Mike Posner": {"piano": 2.5, "vocals": 4, "beat": 4,
                        "blues": 1, "guitar": 1, "backup vocals": 1,
                        "rap": 1},
        "Black Eyed Peas/Rock That Body": {"piano": 2, "vocals": 5,
                                           "beat": 5, "blues": 1,
                                           "guitar": 2,
                                           "backup vocals": 2,
                                           "rap": 4},
        "Lady Gaga/Alejandro": {"piano": 1, "vocals": 5, "beat": 3,
                                "blues": 2, "guitar": 1,
                                "backup vocals": 2, "rap": 1}}
```

Now suppose I have a friend who says he likes the Black Keys Magic Potion. I can plug that into my handy Manhattan distance function:

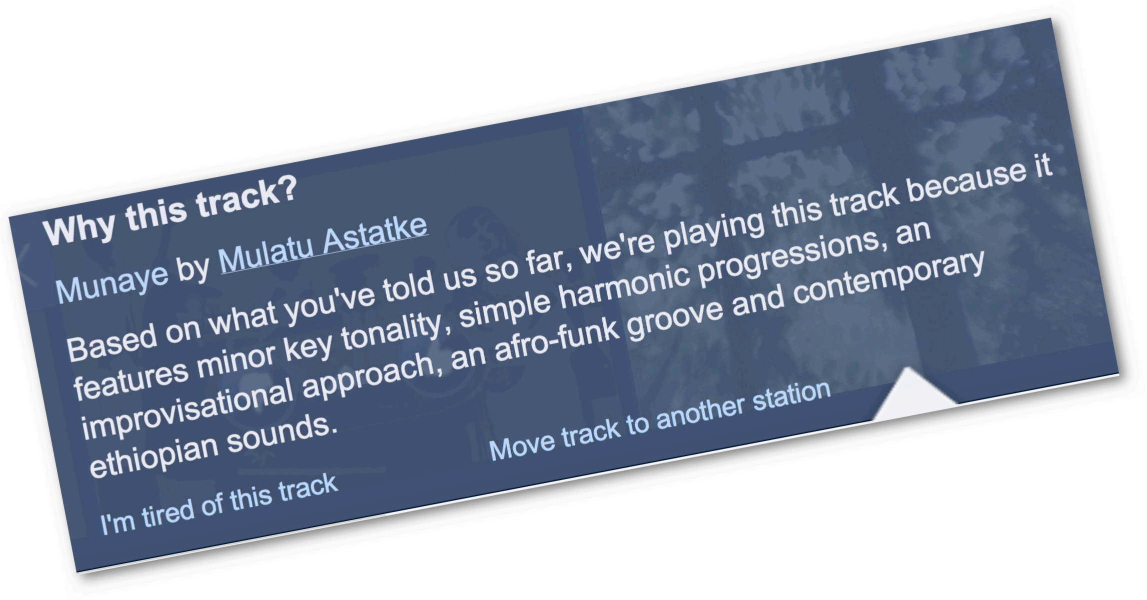
```
>>> computeNearestNeighbor('The Black Keys/Magic Potion', music)

[(4.5, 'Heartless Bastards/Out at Sea'), (5.5, 'Phoenix/Lisztomania'),
(6.5, 'Dr Dog/Fate'), (8.0, "Glee Cast/Jessie's Girl"), (9.0, 'Mike
Posner'), (9.5, 'Lady Gaga/Alejandro'), (11.5, 'Black Eyed Peas/Rock
That Body'), (11.5, 'La Roux/Bulletproof'), (13.5, "Todd Snider/Don't
Tempt Me")]
```

and I can recommend to him Heartless Bastard's Out at Sea. This is actually a pretty good recommendation.

NOTE:
The code for this example, as well as all examples in this book, is available on the book website
http://www.guidetodatamining.com

Answering the question "Why?"

When Pandora recommends something it explains why you might like it:



Why this track?

Munaye by Mulatu Astatke

Based on what you've told us so far, we're playing this track because it features minor key tonality, simple harmonic progressions, an improvisational approach, an afro-funk groove and contemporary ethiopian sounds.

We can do the same. Remember our friend who liked The Black Keys Magic Potion and we recommended Heartless Bastards Out at Sea. What features influenced that recommendation? We can compare the two feature vectors:

	Piano	Vocals	Driving beat	Blues infl.	Dirty elec. Guitar	Backup vocals	Rap infl.
Black Keys Magic Potion	1	5	4	2	4	1	1
Heartless Bastards Out at Sea	1	4	5	3.5	5	1	1
difference	0	1	1	1.5	1	0	0

The features that are closest between the two tunes are piano, presence of backup vocals, and rap influence—they all have a distance of zero. However, all are on the low end of the scale: no piano, no presence of backup vocals, and no rap influence and it probably would not be helpful to say "We think you would like this tune because it lacks backup vocals." Instead, we will focus on what the tunes have in common on the high end of the scale.

We think you might like Heartless Bastards Out at Sea because it has a driving beat and features vocals and dirty electric guitar.

Because our data set has few features, and is not well-balanced, the other recommendations are not as compelling:

```
>>> computeNearestNeighbor("Phoenix/Lisztomania", music)

[(5, 'Heartless Bastards/Out at Sea'), (5.5, 'Mike Posner'), (5.5, 'The
Black Keys/Magic Potion'), (6, 'Black Eyed Peas/Rock That Body'), (6,
'La Roux/Bulletproof'), (6, 'Lady Gaga/Alejandro'), (8.5, "Glee Cast/
Jessie's Girl"), (9.0, 'Dr Dog/Fate'), (9, "Todd Snider/Don't Tempt
Me")]

>>> computeNearestNeighbor("Lady Gaga/Alejandro", music)

[(5, 'Heartless Bastards/Out at Sea'), (5.5, 'Mike Posner'), (6, 'La
Roux/Bulletproof'), (6, 'Phoenix/Lisztomania'), (7.5, "Glee Cast/
Jessie's Girl"), (8, 'Black Eyed Peas/Rock That Body'), (9, "Todd
Snider/Don't Tempt Me"), (9.5, 'The Black Keys/Magic Potion'), (10.0,
'Dr Dog/Fate')]
```

That Lady Gaga recommendation is particularly bad.

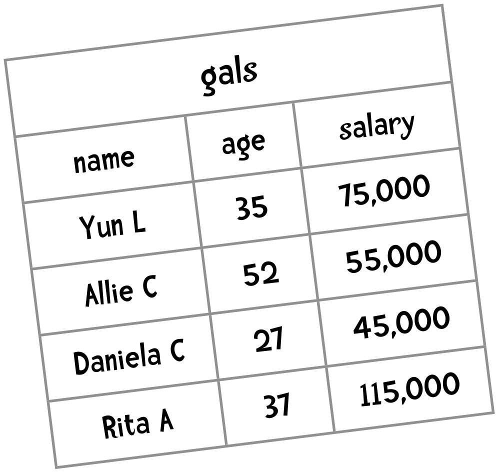
A problem of scale

Suppose I want to add another feature to my set. This time I will add beats per minute (or bpm). This makes some sense—I might like fast beat songs or slow ballads. Now my data would look like this:

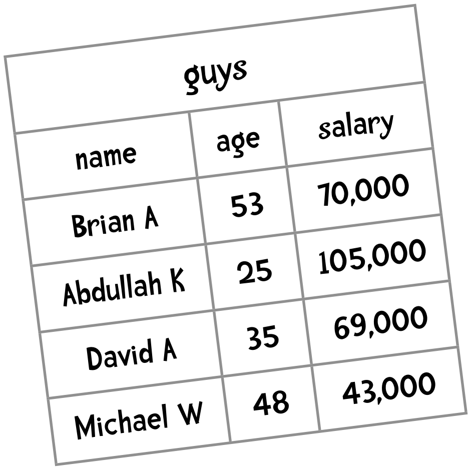
	Piano	Vocals	Driving beat	Blues infl.	Dirty elec. Guitar	Backup vocals	Rap infl.	bpm
Dr. Dog/ Fate	2.5	4	3.5	3	5	4	1	140
Phoenix/ Lisztomania	2	5	5	3	2	1	1	110
Heartless Bastards / Out at Sea	1	5	4	2	4	1	1	130
The Black Keys/ Magic Potion	1	4	5	3.5	5	1	1	88
Glee Cast/ Jessie's Girl	1	5	3.5	3	4	5	1	120
Bad Plus/ Smells like Teen Spirit	5	1	2	1	1	1	1	90

Without using beats per minute, the closest match to The Black Keys' Magic Potion is Heartless Bastards' Out to Sea and the tune furthest away is Bad Plus's version of Smells Like Teen Spirit. However, once we add beats per minute, it wrecks havoc with our distance function—bpm dominates the calculation. Now Bad Plus is closest to The Black Keys simply because the bpm of the two tunes are close.

Consider another example. Suppose I have a dating site and I have the weird idea that the best attributes to match people up by are salary and age.



gals		
name	age	salary
Yun L	35	75,000
Allie C	52	55,000
Daniela C	27	45,000
Rita A	37	115,000



guys		
name	age	salary
Brian A	53	70,000
Abdullah K	25	105,000
David A	35	69,000
Michael W	48	43,000

Here the scale for age ranges from 25 to 53 for a difference of 28 and the salary scale ranges from 43,000 to 115,000 for a difference of 72,000. Because these scales are so different, salary dominates any distance calculation. If we just tried to eyeball matches we might recommend David to Yun since they are the same age and their salaries are fairly close. However, if we went by any of the distance formulas we have covered, 53-year old Brian would be the person recommended to Yun. This does not look good for my fledgling dating site.

In fact, this difference in scale among attributes is a **big problem** for any recommendation system.

Arghhhh.

Normalization

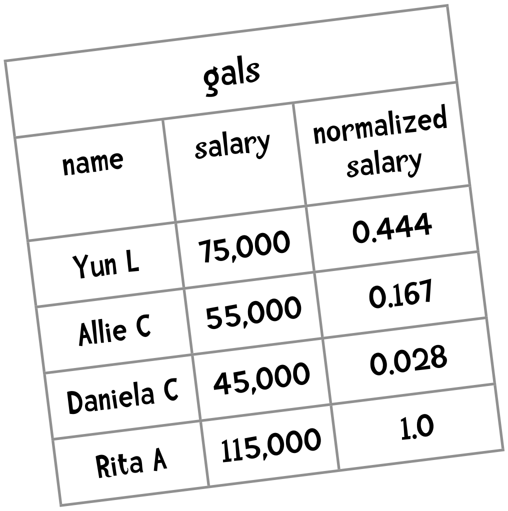
No need to panic.

Relax.

The solution is normalization!

To remove this bias we need to standardize or normalize the data. One common method of normalization involves having the values of each feature range from 0 to 1.

For example, consider the salary attribute in our dating example. The minimum salary was 43,000 and the max was 115,000. That makes the range from minimum to maximum 72,000. To convert each value to a value in the range 0 to 1 we subtract the minimum from the value and divide by the range.



gals		
name	salary	normalized salary
Yun L	75,000	0.444
Allie C	55,000	0.167
Daniela C	45,000	0.028
Rita A	115,000	1.0

So the normalized value for Yun is

(75,000 - 43,000) / 72,000 = 0.444

Depending on the dataset this rough method of normalization may work well.

If you have taken a statistics course you will be familiar with more accurate methods for standardizing data. For example, we can use what is called The Standard Score which can be computed as follows

We can standardize a value using the Standard Score (aka z-score) which tells us how many deviations the value is from the mean!

$$\frac{\text{(each value)} - \text{(mean)}}{\text{(standard deviation)}} = \text{Standard Score}$$

Standard Deviation is

$$sd = \sqrt{\frac{\sum_i (x_i - \bar{x})^2}{card(x)}}$$

card(x) is the cardinality of *x*—that is, how many values there are.

By the way, if you are rusty with statistics and like manga be sure to check out the awesome book "The Manga Guide to Statistics" by Shin Takahashi.

Consider the data from the dating site example a few pages back.

name	salary
Yun L	75,000
Allie C	55,000
Daniela C	45,000
Rita A	115,000
Brian A	70,000
Abdullah K	105,000
David A	69,000
Michael W	43,000

The sum of all the salaries is 577,000. Since there are 8 people, the mean is 72,125.

Now let us compute the standard deviation:

$$sd = \sqrt{\frac{\sum_i (x_i - \overline{x})^2}{card(x)}}$$

so that would be

$$\sqrt{\frac{(\overset{\text{Yun's salary}}{75{,}000} - 72{,}125)^2 + (\overset{\text{Allie's salary}}{55{,}000} - 72{,}125)^2 + (\overset{\text{Daniela's salary}}{45{,}000} - 72{,}125)^2 + \overset{\text{etc.}}{\ldots}}{8}}$$

$$= \sqrt{\frac{8{,}265{,}625 + 293{,}265{,}625 + 735{,}765{,}625 + \ldots}{8}} = \sqrt{602{,}395{,}375}$$

$$= 24{,}543.01$$

Again, the standard score is

$$\frac{\text{(each value) - (mean)}}{\text{(standard deviation)}}$$

So the Standard Score for Yun's salary is

$$\frac{75000 - 72125}{24543.01} = \frac{2875}{24543.01} = 0.117$$

sharpen your pencil

Can you compute the Standard Scores for the following people?

name	salary	Standard Score
Yun L	75,000	0.117
Allie C	55,000	
Daniela C	45,000	
Rita A	115,000	

sharpen your pencil – solution

Can you compute the Standard Scores for the following people?

name	salary	Standard Score
Yun L	75,000	0.117
Allie C	55,000	-0.698
Daniela C	45,000	-1.105
Rita A	115,000	1.747

Allie:
(55,000 - 72,125) / 24,543.01
= -0.698

Daniela:
(45,000 - 72,125) / 24,543.01
= -1.105

Rita:
(115,000 - 72,125) / 24,543.01
= 1.747

The problem with using Standard Score

The problem with the standard score is that it is greatly influenced by outliers. For example, if all the 100 employees of LargeMart make $10/hr but the CEO makes six million a year the mean hourly wage is

(100 * $10 + 6,000,000 / (40 * 52)) / 101

= (1000 + 2885) / 101 = $38/hr.

Not a bad average wage at LargeMart. As you can see, the mean is greatly influenced by outliers.

Because of this problem with the mean, the standard score formula is often modified.

Modified Standard Score

To compute the Modified Standard Score you replace the mean in the above formula by the median (the middle value) and replace the standard deviation by what is called the absolute standard deviation:

$$asd = \frac{1}{card(x)} \sum_i |x_i - \mu|$$

where μ is the median.

Modified Standard Score:

$$\frac{\text{(each value) - (median)}}{\text{(absolute standard deviation)}}$$

To compute the median you arrange the values from lowest to highest and pick the middle value. If there are an even number of values the median is the average of the two middle values.

Okay, let's give this a try. In the table on the right I've arranged our salaries from lowest to highest. Since there are an equal number of values, the median is the average of the two middle values:

Name	Salary
Michael W	43,000
Daniela C	45,000
Allie C	55,000
David A	69,000
Brian A	70,000
Yun L	75,000
Abdullah K	105,000
Rita A	115,000

$$median = \frac{(69{,}000 + 70{,}000)}{2} = 69{,}500$$

The absolute standard deviation is

$$asd = \frac{1}{card(x)} \sum_i |x_i - \mu|$$

$$asd = \frac{1}{8}(|43{,}000 - 69{,}500| + |45{,}000 - 69{,}500| + |55{,}000 - 69{,}500)| + ...)$$

$$= \frac{1}{8}(26{,}500 + 24{,}500 + 14{,}500 + 500 + ...)$$

$$= \frac{1}{8}(153{,}000) = 19{,}125$$

Now let us compute the Modified Standard Score for Yun.

$$\boxed{\text{Modified Standard Score: } \frac{\text{(each value) - (median)}}{\text{(absolute standard deviation)}}}$$

$$mss = \frac{(75{,}000 - 69{,}500)}{19{,}125} = \frac{5{,}500}{19{,}125} = 0.2876$$

sharpen your pencil

The following table shows the play count of various tracks I played. Can you standardize the values using the Modified Standard Score?

track	play count	modified standard score
Power/Marcus Miller	21	
I Breathe In, I Breathe Out/ Chris Cagle	15	
Blessed / Jill Scott	12	
Europa/Santana	3	
Santa Fe/ Beirut	7	

sharpen your pencil – solution

The following table shows the play count of various tracks I played. Can you standardize the values using the Modified Standard Score?

Step 1. Computing the median.

I put the values in order (3, 7, 12, 15, 21) and select the middle value, 12.
The median μ is 12.

Step 2. Computing the Absolute Standard Deviation.

$$asd = \frac{1}{5}(|3-12| + |7-12| + |12-12| + |15-12| + |21-12|)$$

$$= \frac{1}{5}(9+5+0+3+9) = \frac{1}{5}(26) = 5.2$$

Step 3. Computing the Modified Standard Scores.

Power / Marcus Miller: (21 - 12) / 5.2 = 9/5.2 = 1.7307692

I Breathe In, I Breathe Out / Chris Cagle: (15 - 12) / 5.2 = 3/5.2 = 0.5769231

Blessed / Jill Scott: (12 - 12) / 5.2 = 0

Europa / Santana: (3 - 12) / 5.2 = -9 / 5.2 = -1.7307692

Santa Fe / Beirut: (7 - 12) / 5.2 = - 5 / 5.2 = -0.961538

To normalize or not.

Normalization makes sense when the scale of the features—the scales of the different dimensions—significantly varies. In the music example earlier in the chapter there were a number of features that ranged from one to five and then beats-per-minute that could potentially range from 60 to 180. In the dating example, there was also a mismatch of scale between the features of age and salary.

Suppose I am dreaming of being rich and looking at homes in the Santa Fe, New Mexico area.

asking price	bedrooms	bathrooms	sq. ft.
$1,045,000	2	2.0	1,860
$1,895,000	3	4.0	2,907
$3,300,000	6	7.0	10,180
$6,800,000	5	6.0	8,653
$2,250,000	3	2.0	1,030

The table on the left shows a few recent homes on the market.

Here we see the problem again. Because the scale of one feature (in this case asking price) is so much larger than others it will dominate any distance calculation. Having two bedrooms or twenty will not have much of an effect on the total distance between two homes.

We should normalize when

1. **our data mining method calculates the distance between two entries based on the values of their features.**

2. **the scale of the different features is different (especially when it is drastically different—for ex., the scale of asking price compared to the scale of the number of bedrooms).**

Consider a person giving thumbs up and thumbs down ratings to news articles on a news site. Here a list representing a user's ratings consists of binary values (1 = thumbs up; 0 = thumbs down):

Bill = {0, 0, 0, 1, 1, 1, 1, 0, 1, 0 ... }

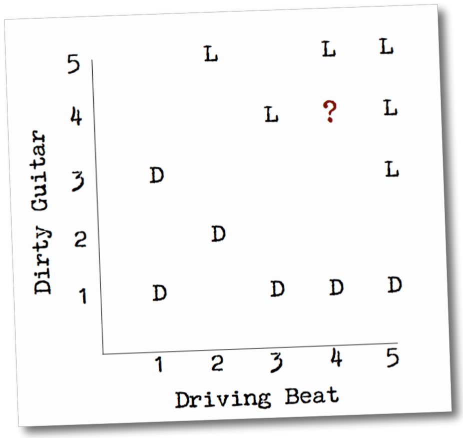
Obviously there is no need to normalize this data. What about the Pandora case: all variables lie on a scale from 1 to 5 inclusive. Should we normalize or not? It probably wouldn't hurt the accuracy of the algorithm if we normalized, but keep in mind that there is a computational cost involved with normalizing. In this case, we might empirically compare results between using the regular and normalized data and select the best performing approach. Later in this chapter we will see a case where normalization reduces accuracy.

Back to Pandora

In the Pandora inspired example, we had each song represented by a number of attributes. If a user creates a radio station for Green Day we decide what to play based on a nearest neighbor approach. Pandora allows a user to give a particular tune a thumbs up or thumbs down rating. How do we use the information that a user gives a thumbs up for a particular song.?

Suppose I use 2 attributes for songs: the amount of dirty guitar and the presence of a driving beat both rated on a 1-5 scale. A user has given the thumbs up to 5 songs indicating he liked the song (and indicated on the following chart with a 'L'); and a thumbs down to 5 songs indicating he disliked the song (indicated by a 'D').

Do you think the user will like or dislike the song indicated by the '?' in this chart?



I am guessing you said he would like the song. We base this on the fact that the ‘?’ is closer to the Ls in the chart than the Ds. We will spend the rest of this chapter and the next describing computational approaches to this idea. The most obvious approach is to find the nearest neighbor of the “?” and predict that it will share the class of the nearest neighbor. The question mark’s nearest neighbor is an L so we would predict that the ‘? tune’ is something the user would like.

The Python nearest neighbor classifier code

Let's use the example dataset I used earlier—ten tunes rated on 7 attributes (amount of piano, vocals, driving beat, blues influence, dirty electric guitar, backup vocals, rap influence).

	Piano	Vocals	Driving beat	Blues infl.	Dirty elec. Guitar	Backup vocals	Rap infl.
Dr. Dog/ Fate	2.5	4	3.5	3	5	4	1
Phoenix/ Lisztomania	2	5	5	3	2	1	1
Heartless Bastards / Out at Sea	1	5	4	2	4	1	1
Todd Snider/ Don't Tempt Me	4	5	4	4	1	5	1
The Black Keys/ Magic Potion	1	4	5	3.5	5	1	1
Glee Cast/ Jessie's Girl	1	5	3.5	3	4	5	1
Black Eyed Peas/ Rock that Body	2	5	5	1	2	2	4
La Roux/ Bulletproof	5	5	4	2	1	1	1
Mike Posner/ Cooler than me	2.5	4	4	1	1	1	1
Lady Gaga/ Alejandro	1	5	3	2	1	2	1

Earlier in this chapter we developed a Python representation of this data:

```
music = {"Dr Dog/Fate": {"piano": 2.5, "vocals": 4, "beat": 3.5,
                         "blues": 3, "guitar": 5, "backup vocals": 4,
                         "rap": 1},
         "Phoenix/Lisztomania": {"piano": 2, "vocals": 5, "beat": 5,
                                 "blues": 3, "guitar": 2,
                                 "backup vocals": 1, "rap": 1},
         "Heartless Bastards/Out at Sea": {"piano": 1, "vocals": 5,
                                           "beat": 4, "blues": 2,
                                           "guitar": 4,
                                           "backup vocals": 1,
                                           "rap": 1},
         "Todd Snider/Don't Tempt Me": {"piano": 4, "vocals": 5,
                                        "beat": 4, "blues": 4,
                                        "guitar": 1,
                                        "backup vocals": 5, "rap": 1},
```

Here the strings *piano, vocals, beat, blues, guitar, backup vocals*, and *rap* occur multiple times; if I have a 100,000 tunes those strings are repeated 100,000 times. I'm going to remove those strings from the representation of our data and simply use vectors:

```
#
#  the item vector represents the attributes: piano, vocals,
#  beat, blues, guitar, backup vocals, rap
#
items = {"Dr Dog/Fate": [2.5, 4, 3.5, 3, 5, 4, 1],
         "Phoenix/Lisztomania": [2, 5, 5, 3, 2, 1, 1],
         "Heartless Bastards/Out at Sea": [1, 5, 4, 2, 4, 1, 1],
         "Todd Snider/Don't Tempt Me": [4, 5, 4, 4, 1, 5, 1],
         "The Black Keys/Magic Potion": [1, 4, 5, 3.5, 5, 1, 1],
         "Glee Cast/Jessie's Girl": [1, 5, 3.5, 3, 4, 5, 1],
         "La Roux/Bulletproof": [5, 5, 4, 2, 1, 1, 1],
         "Mike Posner": [2.5, 4, 4, 1, 1, 1, 1],
         "Black Eyed Peas/Rock That Body": [2, 5, 5, 1, 2, 2, 4],
         "Lady Gaga/Alejandro": [1, 5, 3, 2, 1, 2, 1]}
```

In linear algebra, a vector is a quantity that has magnitude and direction.
Various well defined operators can be performed on vectors including adding and subtracting vectors and scalar multiplication.

In data mining, a vector is simply a list of numbers that represent the attributes of an object. The example on the previous page represented attributes of a song as a list of numbers. Another example, would be representing a text document as a vector—each position of the vector would represent a particular word and the number at that position would represent how many times that word occurred in the text.

Plus, using the word "vector" instead of "list of attributes" is cool!

Once we define attributes this way, we can perform vector operations (from linear algebra) on them.

In addition to representing the attributes of a song as a vector, I need to represent the thumbs up/ thumbs down ratings that users gives to songs. Because each user doesn't rate all songs (sparse data) I will go with the dictionary of dictionaries approach:

```
users = {"Angelica": {"Dr Dog/Fate": "L", "Phoenix/Lisztomania": "L",
                      "Heartless Bastards/Out at Sea": "D",
                      "Todd Snider/Don't Tempt Me": "D",
                      "The Black Keys/Magic Potion": "D",
                      "Glee Cast/Jessie's Girl": "L",
                      "La Roux/Bulletproof": "D",
                      "Mike Posner": "D",
                      "Black Eyed Peas/Rock That Body": "D",
                      "Lady Gaga/Alejandro": "L"},
         "Bill":  {"Dr Dog/Fate": "L", "Phoenix/Lisztomania": "L",
                   "Heartless Bastards/Out at Sea": "L",
                   "Todd Snider/Don't Tempt Me": "D",
                   "The Black Keys/Magic Potion": "L",
                   "Glee Cast/Jessie's Girl": "D",
                   "La Roux/Bulletproof": "D", "Mike Posner": "D",
                   "Black Eyed Peas/Rock That Body": "D",
                   "Lady Gaga/Alejandro": "D"}             }
```

My way of representing ‘thumbs up’ as *L* for *like* and ‘thumbs down’ as *D* is arbitrary. You could use 0 and 1, *like* and *dislike*.

In order to use the new vector format for songs I need to revise the Manhattan Distance and the computeNearestNeighbor functions.

```
def manhattan(vector1, vector2):
   """Computes the Manhattan distance."""
   distance = 0
   total = 0
   n = len(vector1)
   for i in range(n):
      distance += abs(vector1[i] - vector2[i])
   return distance
```

```
def computeNearestNeighbor(itemName, itemVector, items):
   """creates a sorted list of items based on their distance to item"""
   distances = []
   for otherItem in items:
      if otherItem != itemName:
         distance = manhattan(itemVector, items[otherItem])
         distances.append((distance, otherItem))
   # sort based on distance -- closest first
   distances.sort()
   return distances
```

Finally, I need to create a classify function. I want to predict how a particular user would rate an item represented by itemName and itemVector. For example:

```
"Chris Cagle/ I Breathe In. I Breathe Out"  [1, 5, 2.5, 1, 1, 5, 1]
```

(NOTE: To better format the Python example below, I will use the string *Cagle* to represent that singer and song pair.)

The first thing the function needs to do is find the nearest neighbor of this Chris Cagle tune. Then it needs to see how the user rated that nearest neighbor and predict that the user will rate Chris Cagle the same. Here's my rudimentary classify function:

```
def classify(user, itemName, itemVector):
   """Classify the itemName based on user ratings
   Should really have items and users as parameters"""
   # first find nearest neighbor
   nearest = computeNearestNeighbor(itemName, itemVector, items)[0][1]
   rating = users[user][nearest]
   return rating
```

Ok. Let's give this a try. I wonder if Angelica will like Chris Cagle's I Breathe In, I Breathe Out?

```
classify('Angelica', 'Cagle', [1, 5, 2.5, 1, 1, 5, 1])
"L"
```

We are predicting she will like it! Why are we predicting that?

```
computeNearestNeighbor('Angelica', 'Cagle', [1, 5, 2.5, 1, 1, 5, 1])

[(4.5, 'Lady Gaga/Alejandro'), (6.0, "Glee Cast/Jessie's Girl"), (7.5,
"Todd Snider/Don't Tempt Me"), (8.0, 'Mike Posner'), (9.5, 'Heartless
Bastards/Out at Sea'), (10.5, 'Black Eyed Peas/Rock That Body'), (10.5,
'Dr Dog/Fate'), (10.5, 'La Roux/Bulletproof'), (10.5, 'Phoenix/
Lisztomania'), (14.0, 'The Black Keys/Magic Potion')]
```

We are predicting that Angelica will like Chris Cagle's *I Breathe In, I Breathe Out* because that tune's nearest neighbor is Lady Gaga’s *Alejandro* and Angelica liked that tune.

What we have done here is build a classifier—in this case, our task was to classify tunes as belonging to one of two groups—the like group and the dislike group.

A classifier is a program that uses an object's attributes to determine what group or class it belongs to!

A classifier uses a set of objects that are already labeled with the class they belong to. It uses that set to classify new, unlabeled objects. So in our example, we knew about songs that Angelica liked (labeled 'liked') and songs she did not like. We wanted to predict whether Angelica would like a Chris Cagle tune.

First we found a song Angelica rated that was most similar to the Chris Cagle tune.

It was Lady Gaga's *Alejandro*

Next, we checked whether Angelica liked or disliked the *Alejandro*—she liked it. So we predict that Angelica will also like the Chris Cagle tune, *I Breathe In, I Breathe Out*.

I like Phoenix, Lady Gaga and Dr. Dog. I don't like The Black Keys and Mike Posner!

Classifiers can be used in a wide range of applications. The following page lists just a few.

Twitter Sentiment Classification

A number of people are working on classifying the sentiment (a positive or negative opinion) in tweets. This can be used in a variety of ways. For example, if Axe releases a new underarm deodorant, they can check whether people like it or not. The attributes are the words in the tweet.

Classification for Targeted Political Ads

This is called microtargeting. People are classified into such groups as “Barn Raisers”, “Inner Compass”, and “Hearth Keepers.” Hearth Keepers, for example, focus on their family and keep to themselves.

Health and the Quantified Self

It’s the start of the quanitifed self explosion. We can now buy simple devices like the Fitbit, and the Nike Fuelband. Intel and other companies are working on intelligent homes that have floors that can weigh us, keep track of our movements and alert someone if we deviate from normal. Experts are predicting that in a few years we will be wearing tiny compu-patches that can monitor dozens of factors in real time and make instant classifications.

Automatic identification of people in photos.

There are apps now that can identify and tag your friends in photographs. (And the same techniques apply to identifying people walking down the street using public video cams.) Techniques vary but some of them use attributes like the relative position and size of a person’s eyes, nose, jaw, etc.

Targeted Marketing

Similar to political microtargeting. Instead of a broad advertising campaign to sell my expensive Vegas time share luxury condos, can I identify likely buyers and market just to them? Even better if I can identify subgroups of likely buyers and I can really tailor my ads to specific groups.

The list is endless

- classifying people as terrorist or nonterrorist
- automatic classification of email (hey, this email looks pretty important; this is regular email; this looks like spam)
- predicting medical clinical outcomes
- identifying financial fraud (for ex., credit card fraud)

What sport?

To give you a preview of what we will be working on in the next few chapters let us work with an easier example than those given on the previous page—classifying what sport various world-class women athletes play based solely on their height and weight. In the following table I have a small sample dataset drawn from a variety of web sources.

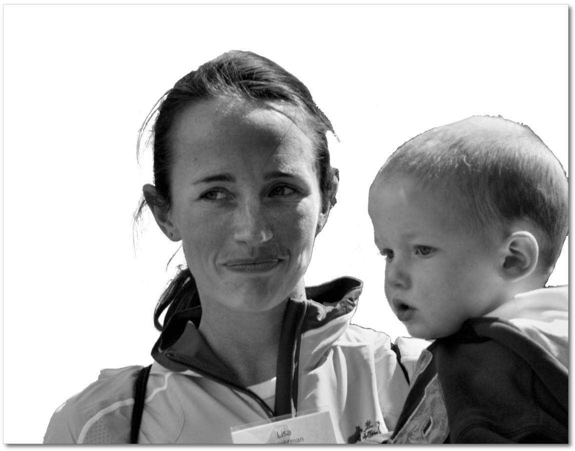
Name	Sport	Age	Height	Weight
Asuka Teramoto	Gymnastics	16	54	66
Brittainey Raven	Basketball	22	72	162
Chen Nan	Basketball	30	78	204
Gabby Douglas	Gymnastics	16	49	90
Helalia Johannes	Track	32	65	99
Irina Miketenko	Track	40	63	106
Jennifer Lacy	Basketball	27	75	175
Kara Goucher	Track	34	67	123
Linlin Deng	Gymnastics	16	54	68
Nakia Sanford	Basketball	34	76	200
Nikki Blue	Basketball	26	68	163
Qiushuang Huang	Gymnastics	20	61	95
Rebecca Tunney	Gymnastics	16	58	77
Rene Kalmer	Track	32	70	108
Shanna Crossley	Basketball	26	70	155
Shavonte Zellous	Basketball	24	70	155
Tatyana Petrova	Track	29	63	108
Tiki Gelana	Track	25	65	106
Valeria Straneo	Track	36	66	97
Viktoria Komova	Gymnastics	17	61	76

The gymnastic data lists some of the top participants in the 2012 and 2008 Olympics. The basketball players play for teams in the WNBA. The women track stars were finishers in the 2012 Olympic marathon . Granted this is a trivial example but it will allow us to apply some of the techniques we have learned.

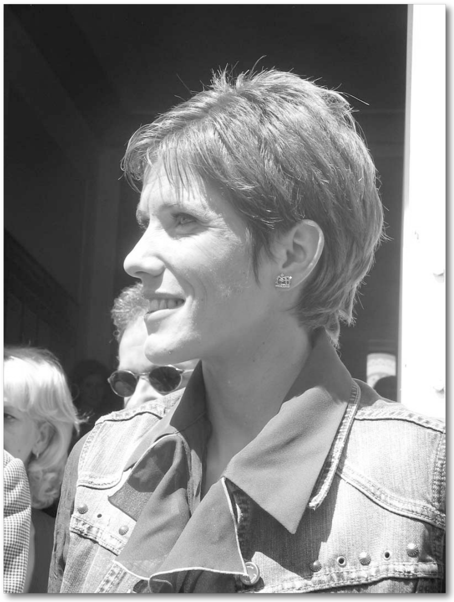
As you can see, I've included age in the table. Just scanning the data you can see that age alone is a moderately good predictor. Try to guess the sports of these athletes.

Candace Parker; Age 26

McKayla Maroney; Age 16



Lisa Jane Weightman; Age 34



Olivera Jevtić: Age 35

The answers

Candace Parker plays basketball for the WNBA's Los Angeles Sparks and Russia's UMMC Ekaterinburg. McKayla Maroney was a member of the U.S. Women's Gymnastic Team and won a Gold and a Silver. Olivera Jevtić is a Serbian long-distance runner who competed in the 2008 and 2012 Olympics. Lisa Jane Weightman is an Australian long-distance runner who also competed in the 2008 and 2012 Olympics.

You just performed classification—you predicted the class of objects based on their attributes. (In this case, predicting the sport of athletes based on a single attribute, age.)

brain calisthenics

Suppose I want to guess what sport a person plays based on their height and weight. My database is small—only two people. Nakia Sanford, the center for the Women's National Basketball Association team Phoenix Mercury, is 6'4" and weighs 200 pounds. Sarah Beale, a forward on England's National Rugby Team, is 5'10" and weighs 190.
Based on that database, I want to classify Catherine Spencer as either a basketball player or rugby player. She is 5'10" and weighs 200 pounds. What sport do you think she plays?

brain calisthenics - cont'd

If you said rugby, you would be correct. Catherine Spencer is a forward on England's national team. However, if we based our guess on a distance formula like Manhattan Distance we would be wrong. The Manhattan Distance between Catherine and Basketball player Nakia is 6 (they weigh the same and have a six inch difference in height). The distance between Catherine and Rugby player Sarah is 10 (their height is the same and they differ in weight by 10 pounds). So we would pick the closest person, Nakia, and predict Catherine plays the same sport.

Is there anything we learned that could help us make more accurate classifications?

Hmmm. This rings a bell. I think there was something related to this earlier in the chapter...

brain calisthenics - cont'd

We can use the Modified Standard Score!!!

$$\frac{\text{(each value) - (median)}}{\text{(absolute standard deviation)}}$$

Test Data.

Let us remove age from the picture. Here is a group of individuals I would like to classify:

Name	Sport	Height	Weight
Crystal Langhorne		74	190
Li Shanshan		64	101
Kerri Strug		57	87
Jaycie Phelps	`	60	97
Kelly Miller		70	140
Zhu Xiaolin		67	123
Lindsay Whalen		69	169
Koko Tsurumi		55	75
Paula Radcliffe		68	120
Erin Thorn		69	144

Let's build a classifier!

Python Coding

Instead of hard-coding the data in the Python code, I decided to put the data for this example into two files: athletesTrainingSet.txt and athletesTestSet.txt.

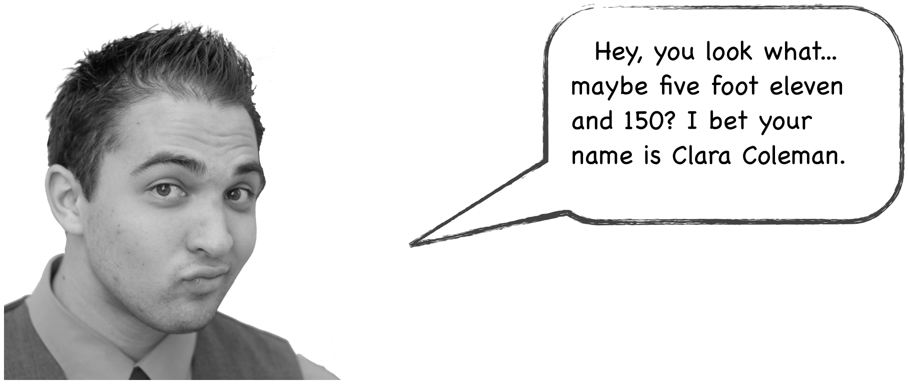
I am going to use the data in the athletesTrainingSet.txt file to build the classifier. The data in the athletesTestSet.txt file will be used to evaluate this classifier. In other words, each entry in the test set will be classified by using all the entries in the training set.

The data files and the Python code are on the book's website, guidetodatamining.com.

The format of these files looks like this:

Asuka Teramoto	Gymnastics	54	66
Brittainey Raven	Basketball	72	162
Chen Nan	Basketball	78	204
Gabby Douglas	Gymnastics	49	90

Each line of the text represents an object described as a tab-separated list of values. I want my classifier to use a person's height and weight to predict what sport that person plays. So the last two columns are the numerical attributes I will use in the classifier and the second column represents the class that object is in. The athlete's name is not used by the classifier. I don't try to predict what sport a person plays based on their name and I am not trying to predict the name from some attributes.


Hey, you look what... maybe five foot eleven and 150? I bet your name is Clara Coleman.

However, keeping the name might be useful as a means of explaining the classifier's decision to users: "We think Amelia Pond is a gymnast because she is closest in height and weight to Gabby Douglas who is a gymnast."

As I said, I am going to write my Python code to not be so hard coded to a particular example (for example, to only work for the athlete example). To help meet this goal I am going to add an initial header line to the athlete training set file that will indicate the function of each column. Here are the first few lines of that file:

comment	class	num	num
Asuka Teramoto	Gymnastics	54	66
Brittainey Raven	Basketball	72	162

Any column labeled *comment* will be ignored by the classifier; a column labeled *class* represents the class of the object, and columns labeled *num* indicate numerical attributes of that object.

brain calisthenics -

How do you think we should represent this data in Python? Here are some possibilities (or come up with your own representation).

a dictionary of the form:

```
{'Asuka Termoto': ('Gymnastics', [54, 66]),
 'Brittainey Raven': ('Basketball', [72, 162]), ...
```

a list of lists of the form:

```
[['Asuka Termoto', 'Gymnastics', 54, 66],
 ['Brittainey Raven', 'Basketball', 72, 162], ...
```

a list of tuples of the form:

```
[('Gymnastics', [54, 66], ['Asuka Termoto']),
 ('Basketball', [72, 162], ['Brittainey Raven'],...
```

brain calisthenics - answer

a dictionary of the form:

```
{'Asuka Termoto': ('Gymnastics', [54, 66]),
 'Brittainey Raven': ('Basketball', [72, 162]), ...
```

This is not a very good representation of our data. The key for the dictionary is the athlete's name, which we do not even use in the calculations.

a list of lists of the form:

```
[['Asuka Termoto', 'Gymnastics', 54, 66],
 ['Brittainey Raven', 'Basketball', 72, 162], ...
```

This is not a bad representation. It mirrors the input file and since the nearest neighbor algorithm requires us to iterate through the list of objects, a list makes sense.

a list of tuples of the form:

```
[('Gymnastics', [54, 66], ['Asuka Termoto']),
 ('Basketball', [72, 162], ['Brittainey Raven'],...
```

I like this representation better than the above since it separates the attributes into their own list and makes the division between class, attributes, and comments precise. I made the comment (the name in this case) a list since there could be multiple columns that are comments.

My python code that reads in a file and converts it to the format

```
[('Gymnastics', [54, 66], ['Asuka Termoto']),
 ('Basketball', [72, 162], ['Brittainey Raven'],...
```

looks like this:

```
class Classifier:

    def __init__(self, filename):

        self.medianAndDeviation = []

        # reading the data in from the file
        f = open(filename)
        lines = f.readlines()
        f.close()
        self.format = lines[0].strip().split('\t')
        self.data = []
        for line in lines[1:]:
            fields = line.strip().split('\t')
            ignore = []
            vector = []
            for i in range(len(fields)):
                if self.format[i] == 'num':
                    vector.append(int(fields[i]))
                elif self.format[i] == 'comment':
                    ignore.append(fields[i])
                elif self.format[i] == 'class':
                    classification = fields[i]
            self.data.append((classification, vector, ignore))
```

code it

Before we can standardize the data using the Modified Standard Score we need methods that will compute the median and absolute standard deviation of numbers in a list:

```
>>> heights = [54, 72, 78, 49, 65, 63, 75, 67, 54]
>>> median = classifier.getMedian(heights)
>>> median
65
>>> asd = classifier.getAbsoluteStandardDeviation(heights, median)
>>> asd
8.0
```

Can you write these methods?

AssertionError?

See next page

Download the template testMedianAndASD.py to write and test these methods at guidetodatamining.com

Assertion Errors and the Assert statement.

It is important that each component of a solution to a problem be turned into a piece of code that implements it and a piece of code that tests it. In fact, it is good practice to write the test code before you write the implementation. The code template I have provided contains a test function called `unitTest.` A simplified version of that function, showing only one test, is shown here:

```
def unitTest():
    list1 = [54, 72, 78, 49, 65, 63, 75, 67, 54]
    classifier = Classifier('athletesTrainingSet.txt')
    m1 = classifier.getMedian(list1)
    assert(round(m1, 3) == 65)
    print("getMedian and getAbsoluteStandardDeviation work correctly")
```

The getMedian function you are to complete initially looks like this:

```
def getMedian(self, alist):
        """return median of alist"""

        """TO BE DONE"""
        return 0
```

So initially, `getMedian` returns 0 as the median for any list. You are to complete getMedian so it returns the correct value. In the `unitTest` procedure, I call getMedian with the list

```
[54, 72, 78, 49, 65, 63, 75, 67, 54]
```

The assert statement in `unitTest` says the value returned by `getMedian` should equal 65. If it does, execution continues to the next line and

```
getMedian and getAbsoluteStandardDeviation work correctly
```

is printed. If they are not equal the program terminates with an error:

```
File "testMedianAndASD.py", line 78, in unitTest

    assert(round(m1, 3) == 65)

AssertionError
```

If you download the code from the book's website and run it without making any changes, you will get this error. Once you have correctly implemented `getMedian` and `getAbsoluteStandardDeviation` this error will disappear.

This use of assert as a means of testing software components is a common technique among software developers.

"it is important that each part of the specification be turned into a piece of code that implements it and a test that tests it. If you don't have tests like these then you don't know when you are done, you don't know if you got it right, and you don't know that any future changes might be breaking something." - Peter Norvig

Solution

Here is one way of writing these algorithms:

```
  def getMedian(self, alist):
        """return median of alist"""
        if alist == []:
            return []
        blist = sorted(alist)
        length = len(alist)
        if length % 2 == 1:
            # length of list is odd so return middle element
            return blist[int(((length + 1) / 2) -  1)]
        else:
            # length of list is even so compute midpoint
            v1 = blist[int(length / 2)]
            v2 =blist[(int(length / 2) - 1)]
            return (v1 + v2) / 2.0


    def getAbsoluteStandardDeviation(self, alist, median):
        """given alist and median return absolute standard deviation"""
        sum = 0
        for item in alist:
            sum += abs(item - median)
        return sum / len(alist)
```

As you can see my getMedian method first sorts the list before finding the median. Because I am not working with huge data sets I think this is a fine solution. If I wanted to optimize my code, I might replace this with a selection algorithm.

Right now, the data is read from the file athletesTrainingSet.txt and stored in the list `data` in the classifier with the following format:

```
[('Gymnastics', [54, 66], ['Asuka Teramoto']),
 ('Basketball', [72, 162], ['Brittainey Raven']),
 ('Basketball', [78, 204], ['Chen Nan']),
 ('Gymnastics', [49, 90], ['Gabby Douglas']), ...
```

Now I would like to normalize the vector so the list `data` in the classifier contains normalized values. For example,

```
[('Gymnastics', [-1.93277, -1.21842], ['Asuka Teramoto']),
 ('Basketball', [1.09243, 1.63447], ['Brittainey Raven']),
 ('Basketball', [2.10084, 2.88261], ['Chen Nan']),
 ('Gymnastics', [-2.77311, -0.50520], ['Gabby Douglas']),
 ('Track', [-0.08403, -0.23774], ['Helalia Johannes']),
 ('Track', [-0.42017, -0.02972], ['Irina Miketenko']),
```

To do this I am going to add the following lines to my init method:

```
        # get length of instance vector
        self.vlen = len(self.data[0][1])
        # now normalize the data
        for i in range(self.vlen):
            self.normalizeColumn(i)
```

In the for loop we want to normalize the data, column by column. So the first time through the loop we will normalize the height column, and the next time through, the weight column.

code it

Can you write the normalizeColumn method?

Download the template normalizeColumnTemplate.py to write and test this method at guidetodatamining.com

Solution

Here is an implementation of the normalizeColumn method:

```
def normalizeColumn(self, columnNumber):
  """given a column number, normalize that column in self.data"""
  # first extract values to list
  col = [v[1][columnNumber] for v in self.data]
  median = self.getMedian(col)
  asd = self.getAbsoluteStandardDeviation(col, median)
  #print("Median: %f   ASD = %f" % (median, asd))
  self.medianAndDeviation.append((median, asd))
  for v in self.data:
     v[1][columnNumber] = (v[1][columnNumber] - median) / asd
```

You can see I also store the median and absolute standard deviation of each column in the list `medianAndDeviation`. I use this information when I want to use the classifier to predict the class of a new instance. For example, suppose I want to predict what sport is played by Kelly Miller, who is 5 feet 10 inches and weighs 170. The first step is to convert her height and weight to Modified Standard Scores. That is, her original attribute vector is [70, 140].

After processing the training data, the value of meanAndDeviation is

```
[(65.5, 5.95), (107.0, 33.65)]
```

meaning the data in the first column of the vector has a median of 65.5 and an absolute standard deviation of 5.95; the second column has a median of 107 and a deviation of 33.65.

I use this info to convert the original vector [70,140] to one containing Modified Standard Scores. This computation for the first attribute is

$$mss = \frac{x_i - \tilde{x}}{asd} = \frac{70 - 65.5}{5.95} = \frac{4.5}{5.95} = 0.7563$$

and the second:

$$mss = \frac{x_i - \tilde{x}}{asd} = \frac{140 - 107}{33.65} = \frac{33}{33.65} = 0.98068$$

The python method that does this is:

```
    def normalizeVector(self, v):
        """We have stored the median and asd for each column.
        We now use them to normalize vector v"""
        vector = list(v)
        for i in range(len(vector)):
            (median, asd) = self.medianAndDeviation[i]
            vector[i] = (vector[i] - median) / asd
        return vector
```

The final bit of code to write is the part that predicts the class of a new instance—in our current example, the sport a person plays. To determine the sport played by Kelly Miller, who is 5 feet 10 inches (70 inches) and weighs 170 we would call

```
      classifier.classify([70, 170])
```

In my code, `classify` is just a wrapper method for `nearestNeighbor`:

```
 def classify(self, itemVector):
   """Return class we think item Vector is in"""
   return(self.nearestNeighbor(self.normalizeVector(itemVector))[1][0])
```

code it

Can you write the nearestNeighbor method? (For my solution, I wrote an additional method, manhattanDistance.)

Yet again, download the template classifyTemplate.py to write and test this method at guidetodatamining.com.

Solution

The implementation of the `nearestNeighbor` methods turns out to be very short.

```
def manhattan(self, vector1, vector2):
   """Computes the Manhattan distance."""
   return sum(map(lambda v1, v2: abs(v1 - v2), vector1, vector2))


def nearestNeighbor(self, itemVector):
   """return nearest neighbor to itemVector"""
   return min([ (self.manhattan(itemVector, item[1]), item)
                for item in self.data])
```

That's it!!!

We have written a nearest neighbor classifier in roughly 200 lines of Python.

In the complete code which you can download from our website, I have included a function, `test`, which takes as arguments a training set file and a test set file and prints out how well the classifier performed. Here is how well the classifier did on our athlete data:

```
>>> test("athletesTrainingSet.txt", "athletesTestSet.txt")
-        Track  Aly Raisman       Gymnastics  62    115
+   Basketball  Crystal Langhorne Basketball  74    190
+   Basketball  Diana Taurasi     Basketball  72    163
<snip>
-        Track  Hannah Whelan     Gymnastics  63    117
+   Gymnastics  Jaycie Phelps     Gymnastics  60    97
80.00% correct
```

As you can see, the classifier was 80% accurate. It performed perfectly on predicting basketball players but made four errors between track and gymnastics.

Irises Data Set

I also tested our simple classifier on the Iris Data Set, arguably the most famous data set used in data mining. It was used by Sir Ronald Fisher back in the 1930s. The Iris Data Set consists of 50 samples for each of three species of Irises (Iris Setosa, Iris Virginica, and Iris Versicolor). The data set includes measurements for two parts of the Iris's flower: the sepal (the green covering of the flower bud) and the petals.

Sir Fisher was a remarkable person. He revolutionized statistics and Richard Dawkins called him "the greatest biologist since Darwin."

All the data sets described in the book are available on the book's website: guidetodatamining.com. This allows you to download the data and experiment with the algorithm. Does normalizing the data improve or worsen the accuracy? Does having more data in the training set improve results? What effect does switching to Euclidean Distance have?

REMEMBER: Any learning that takes place happens in your brain, not mine. The more you interact with the material in the book, the more you will learn.

The Iris data set looks like this (species is what the classifier is trying to predict):

Sepal length	Sepal width	Petal Length	Petal Width	Species
5.1	3.5	1.4	0.2	I.setosa
4.9	3.0	1.4	0.2	I setosa

There were 120 instances in the training set and 30 in the test set (none of the test set instances were in the training set).

How well did our classifier do on the Iris Data Set?

```
>>> test('irisTrainingSet.data', 'irisTestSet.data')

93.33% correct
```

Again, a fairly impressive result considering how simple our classifier is. Interestingly, without normalizing the data the classifier is 100% accurate. We will explore this normalization problem in more detail in a later chapter.

miles per gallon.

Finally, I tested our classifier on a modified version of another widely used data set, the Auto Miles Per Gallon data set from Carnegie Mellon University. It was initially used in the 1983 American Statistical Association Exposition. The format of the data looks like this

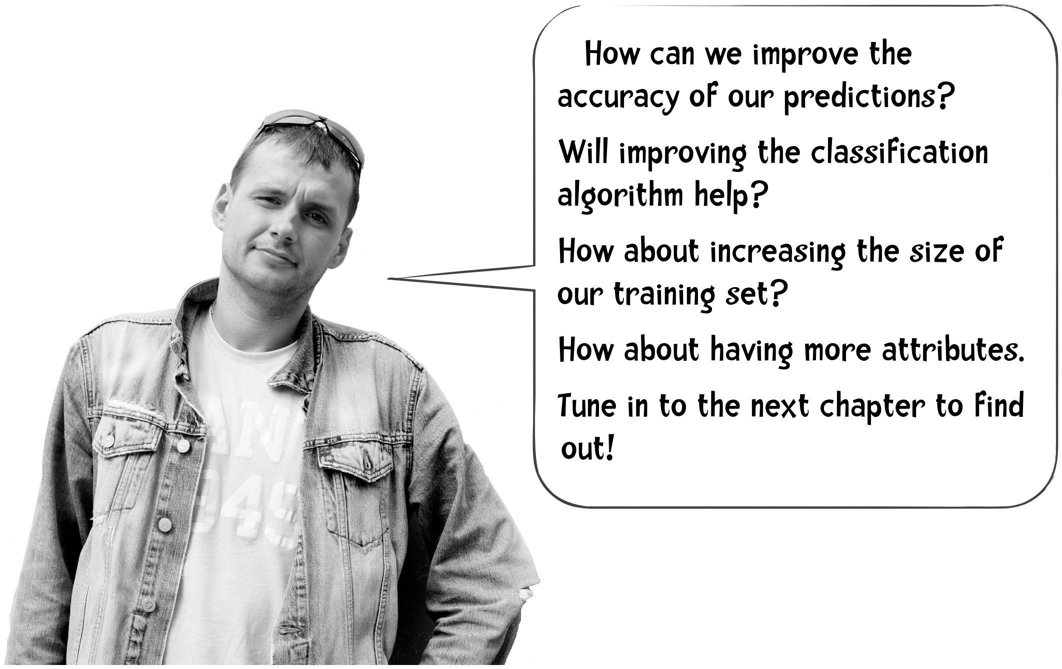
mpg	**cylinders**	**c.i.**	**HP**	**weight**	**secs. 0-60**	**make/model**
30	4	68	49	1867	19.5	fiat 128
45	4	90	48	2085	21.7	vw rabbit (diesel)
20	8	307	130	3504	12	chevrolet chevelle malibu

In the modified version of the data, we are trying to predict mpg, which is a discrete category (with values 10, 15, 20, 25, 30, 35, 40, and 45) using the attributes cylinders, displacement, horsepower, weight, and acceleration.

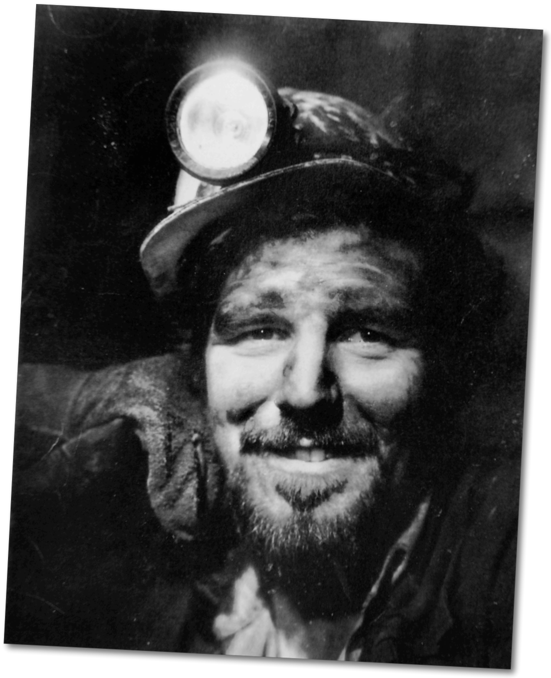
There are 342 instances of cars in the training set and 50 in the test set. If we just predicted the miles per gallon randomly, our accuracy would be 12.5%.

```
>>> test('mpgTrainingSet.txt', 'mpgTestSet.txt')

56.00% correct
```

Without normalization the accuracy is 32%.


How can we improve the accuracy of our predictions?
Will improving the classification algorithm help?
How about increasing the size of our training set?
How about having more attributes.
Tune in to the next chapter to find out!

odds and ends



Heads Up on Normalization

In this chapter we talked the importance of normalizing data. This is critical when attributes have drastically different scales (for example, income and age). In order to get accurate distance measurements, we should rescale the attributes so they all have the same scale.

While most data miners use the term 'normalization' to refer to this rescaling, others make a distinction between 'normaliza-tion' and 'standardization.' For them, normalization means scaling values so they lie on a scale from 0 to 1. Standardization, on the other hand, refers to scaling an attribute so the average (mean or median) is 0, and other values are deviations from this average (standard deviation or absolute standard deviation). So for these data miners, Standard Score and Modified Standard Score are examples of standardization.

Recall that one way to normalize an attribute on a scale between 0 and 1 is to find the minimum (min) and maximum (max) values of that attribute. The normalized value of a value is then

$$\frac{value - \min}{\max - \min}$$

Let's compare the accuracy of a classifer that uses this formula over one that uses the Modified Standard

You say normalize and I say standardize You say tomato and I say tomato

code it

Can you modify our classifier code so that it normalizes the attributes using the formula on our previous page?

You can test its accuracy with our three data sets:

	classifier built		
data set	using no normalization	using the formula on previous page	using Modified Standard Score
Athletes	80.00%	?	80.00%
Iris	100.00%	?	93.33%
MPG	32.00%	?	56.00%

my results

Here are my results:

	classifier built		
data set	using no normalization	using the formula on previous page	using Modified Standard Score
Athletes	80.00%	60.00%	80.00%
Iris	100.00%	83.33%	93.33%
MPG	32.00%	36.00%	56.00%

Hmm. These are disappointing results compared with using Modified Standard Score.

It is fun playing with data sets and trying different methods. I obtained the Iris and MPG data sets from the UCI Machine Learning Repository (archive.ics.uci.edu/ml). I encourage you to go there, download a data set or two, convert the data to match data format, and see how well our classifier does.