

Example 1 Extended

We first load the RMariaDB. The installation line is commented out, because we assume that you have already installed this package while watching the analogous video.

```
# install.packages("RMariaDB")
library(RMariaDB)
```

Now we make a connection to the elections database on Scholar.

```
connection<-dbConnect(RMariaDB::MariaDB(),
                      host="scholar-db.rcac.purdue.edu",
                      db="elections",
                      user="elections_user",
                      password="Dataelect!98")
```

We query the campaign contributions made by people who work at Purdue University.

```
myDF <- dbGetQuery(connection, "SELECT * FROM elections WHERE employer='PURDUE UNIVERSITY'")
```

Here are the first six of these donations.

```
head(myDF)
```

```
##      cmte_id amndt_ind rpt_tp transaction_pgi  image_num transaction_tp
## 1 C00006486      N      Q2                80031592213          15
## 2 C00122176      A      MY                81020041596          15
## 3 C00006486      A      Q1                84033080815          15
## 4 C00193854      A      YE                86033984599          15
## 5 C00003558      N      M7                86034242154          15
## 6 C00122176      A      MY                87020063442          15
##      entity_tp      name      city state zip_code
## 1      SULLIVAN, GLENN H DR WEST LAFAYETTE  IN  47906
## 2      SULLIVAN, GLENN H DR      W LAFAYETTE  IN  47906
## 3      BUTZ, EARL L WEST LAFAYETTE  IN  47906
## 4      CHRISTIAN, JOHN WEST LAFAYETTE  IN  47906
## 5      BABB, EMERSON M MR      ALACHUA  FL  32615
## 6      DUNKELBERG, WILLIAM C WEST LAFAYETTE  IN  47906
##      employer occupation transaction_dt transaction_amt other_id tran_id
## 1 PURDUE UNIVERSITY          1980-06-19          300
## 2 PURDUE UNIVERSITY          1981-06-24          500
## 3 PURDUE UNIVERSITY          1984-02-22         1100
## 4 PURDUE UNIVERSITY          1985-10-17          500
## 5 PURDUE UNIVERSITY          1986-06-30          500
## 6 PURDUE UNIVERSITY          1987-04-15          500
##      file_num memo_cd memo_text      sub_id
## 1      0          3.06192e+18
## 2      0          3.06192e+18
## 3      0          3.06192e+18
## 4      0          3.06192e+18
## 5      0          3.06192e+18
```

```
## 6      0      3.06192e+18
```

Now we display the number of rows and columns in the result. The number of rows is the number of donations made by people who work at Purdue University. The number of columns is the number of variables that we have in this dataset.

```
dim(myDF)
```

```
## [1] 5768  21
```

Finally, we extract the cities where people made the donations. We tabulate the results, and then sort this table. Among the donations made by employees of Purdue University, this shows the cities in which the donations were most frequently made.

```
sort(table(myDF$city))
```

```
##
##          ALACHUA      BATESVILLE      BOULDER
##          1          1          1          1
##    BUCK CREEK    CHARLOTTE      CHILTON    ELIZABETHTOWN
##          1          1          1          1
##          EUGENE      EVANSTON    FLOYDS KNOBS    FORT COLLINS
##          1          1          1          1
##    FOUNTAIN VALLEY    FRANCESVILLE    GREENFIELD      HAMMOND
##          1          1          1          1
##          LALAYETTE    LAWRENCE    LOUISVILLE      MEQUON
##          1          1          1          1
##          NANTUCKET    NASHVILLE    NEEDHAM HGTS    NORTH PLAINFIELD
##          1          1          1          1
##          PLAINFIELD    SCHERERVILLE    THE WOODLANDS      W. LFAYETTE
##          1          1          1          1
##          WARSAW          ADA          ANN ARBOR      DURHAM
##          1          2          2          2
##    FORT LAUDERDALE    MELBOURNE    MONROEVILLE      MUNSTER
##          2          2          2          2
##          ROCKVILLE    SPRINGDALE    STERLING      STOW
##          2          2          2          2
##          WATERTOWN    WESTLAFAYETTE    ANDERSON      CAMBRIDGE
##          2          2          3          3
##          CINCINNATI    CRAWFORDSVILLE    EARL PARK      FORT MYERS
##          3          3          3          3
##    GOODLETTSVILLE    GROVE CITY      KOKOMO    MISSION VIEJO
##          3          3          3          3
##          OAK PARK      PITTSBURGH    SANTA FE      VALPARAISO
##          3          3          3          3
##          WEST LAFAYETE    BEAVERCREEK      DYER      HAIKU
##          3          4          4          4
##          IN      MOUNT PLEASANT    PARKVILLE    WHITESTOWN
##          4          4          4          4
##          WILLOWBROOK      GLENCOE    GRAND RAPIDS    JAMAICA PLAIN
##          4          5          5          5
##          LOWELL      PHILADELPHIA    THORNTOWN      WESTPOINT
##          5          5          5          5
##          BROWNSBURG    West Lafayette    WILLIAMSPORT    BATTLE GROUND
##          6          6          6          7
##          FISHERS      KATY      LIVONIA      MONROVIA
```

##	7	7	7	7
##	SAN DIEGO	TRAIL CREEK	WASHINGTON	OGDEN DUNES
##	7	7	7	8
##	WEST LAFAYETT	BLOOMINGTON	HIGHLAND	LA PORTE
##	8	9	9	9
##	CHESTERTON	OTTERBEIN	SOUTH BEND	WOODLAND HILLS
##	10	10	10	10
##	EAST LONGMEADOW	LONG BEACH	SHEBOYGAN	EL SEGUNDO
##	12	12	12	13
##	WESTFIELD	NYACK	CROWN POINT	GRABILL
##	13	15	16	17
##	WEST LAFYETTE	NOBLESVILLE	CHAPIN	PORTAGE
##	17	18	23	24
##	W. LAFAYETTE	ZIONSVILLE	CARMEL	CHICAGO
##	24	30	36	36
##	VEEDERSBURG	LAKE FOREST	FORT WAYNE	ATTICA
##	55	67	97	133
##	W LAFAYETTE	INDIANAPOLIS	LAFAYETTE	WEST LAFAYETTE
##	159	329	1306	2980

Here are some more examples from the elections database:

Most of the Purdue employees (who are making donations) are from the State of Indiana.

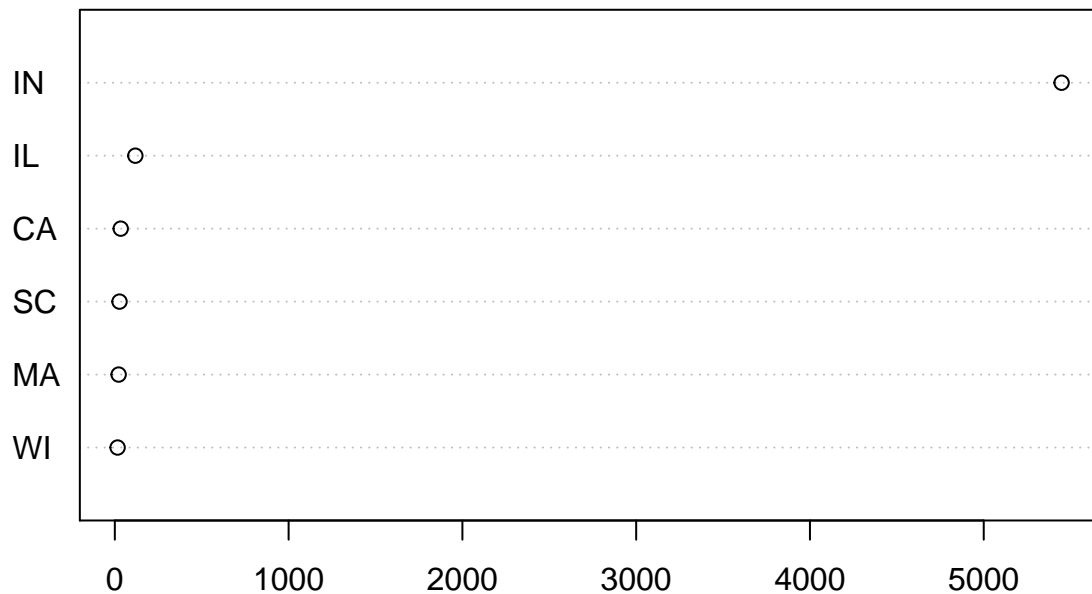
```
sort(table(myDF$state))
```

```
##
##  KS  NJ  OR  AR  CO  KY  NC  NM  HI  MO  TN  DC  FL  TX  PA  OH
##   1   1   1   2   2   2   3   3   4   4   4   7   8   8  10  13
##  MI  NY  WI  MA  SC  CA  IL  IN
##  15  15  16  22  27  34 118 5448
```

Here is a visualization of the number of donations made by Purdue University employees, grouped according to State. We are only showing the 6 most popular States, by this measure.

```
dotchart(tail(sort(table(myDF$state))))
```

```
## Warning in dotchart(tail(sort(table(myDF$state)))): 'x' is neither a vector nor
## a matrix: using as.numeric(x)
```



Note: A warning appears, letting us know that R will treat the data as numeric.

Making one simple change, namely, switching state to name, we can see who has made the largest number of donations. Note: This is not the largest monetary amount of donations! Instead, this is the greatest number of times that donations were made.

```
tail(sort(table(myDF$name)))
```

```
##
##  SAHLEY, CHRISTIE      JONES, ELIJAH    KIRCHUBEL, LINDA TEEGARDEN, DOROTHY
##                92                95                106                119
##  MAY, CHRISTOPHER    BODNER, GEORGE
##                207                583
```

As before, we can plot this data.

```
dotchart(tail(sort(table(myDF$name))))
```

```
## Warning in dotchart(tail(sort(table(myDF$name)))): 'x' is neither a vector nor a
## matrix: using as.numeric(x)
```

BODNER, GEORGE

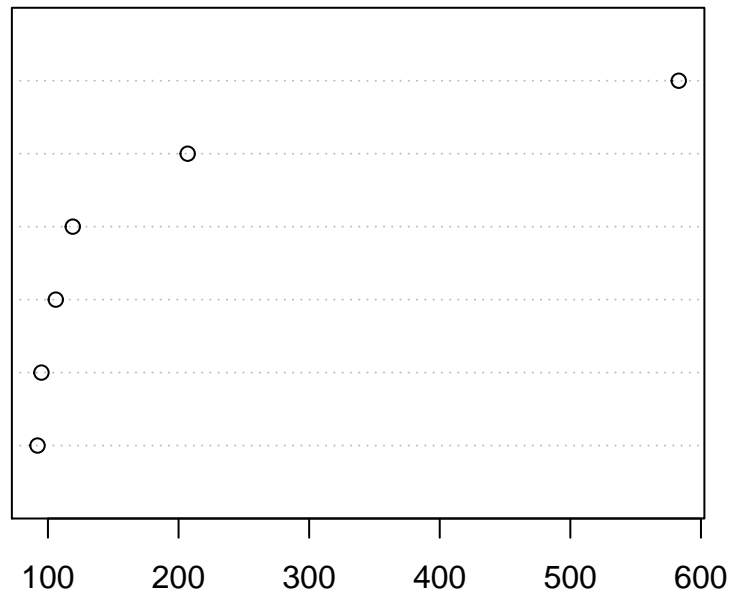
MAY, CHRISTOPHER

TEEGARDEN, DOROTHY

KIRCHUBEL, LINDA

JONES, ELIJAH

SAHLEY, CHRISTIE



With this plot in mind, we see why we put the names on the y-axis and the number of donations on the x-axis. (If the names were on the x-axis, we would not have been able to squeeze all of the names in!)

In the questions above, note that we made 1 SQL query (namely, to get the data from people who work at Purdue), and we stored this data in a data frame called myDF. Then we did some analysis based on this data frame.

Now we make another query. This time, we lookup all of the donations across all of the years. We sum the amounts of the donations, grouping the amounts of the donations, according to the state where the donor lives.

```
myDF <- dbGetQuery(connection, "SELECT SUM(transaction_amt), state FROM elections GROUP BY state")
myDF
```

```
##      SUM(transaction_amt) state
## 1          652941123
## 2              500      'H
## 3              600      'U
## 4              250      (A
## 5              500      -0
## 6             1614      00
## 7             1814      01
## 8               0      03
## 9               0      06
## 10              0      09
## 11             1000       1
## 12               0      10
## 13              75      11
## 14               0      15
## 15             600      17
## 16              -5      19
## 17             750      20
## 18               0      28
## 19               0      29
## 20               0      32
## 21             210      36
## 22               0      46
```

## 23	0	53
## 24	0	55
## 25	1000	60
## 26	0	64
## 27	500	67
## 28	0	72
## 29	80	75
## 30	0	77
## 31	0	78
## 32	500	79
## 33	2000	7E
## 34	167	81
## 35	5471	85
## 36	0	87
## 37	500	90
## 38	0	91
## 39	0	92
## 40	0	94
## 41	0	95
## 42	-141	98
## 43	1250	<
## 44	2650	??
## 45	1320	A
## 46	678578	AA
## 47	19553	AB
## 48	1405541	AE
## 49	250	AF
## 50	1000	AI
## 51	69577306	AK
## 52	304041321	AL
## 53	500	AN
## 54	250	AO
## 55	681851	AP
## 56	262243128	AR
## 57	397614	AS
## 58	511	AT
## 59	4612	AU
## 60	532637404	AZ
## 61	1000	B
## 62	14896	BA
## 63	86064	BC
## 64	250	BD
## 65	14107	BE
## 66	151	BK
## 67	250	BL
## 68	505	BO
## 69	4600	BR
## 70	7000	BS
## 71	500	BU
## 72	400	BW
## 73	2000	BX
## 74	4938	C
## 75	5843659325	CA
## 76	500	CD

## 77	725	CE
## 78	6919	CH
## 79	3250	CI
## 80	2500	CM
## 81	17661	CN
## 82	651796668	CO
## 83	2000	CR
## 84	841002706	CT
## 85	950	CZ
## 86	1250	D
## 87	500	D.
## 88	2614794626	DC
## 89	124615709	DE
## 90	3280	DF
## 91	1000	DI
## 92	1000	DL
## 93	500	DP
## 94	500	DU
## 95	1750	EA
## 96	210	EE
## 97	250	EG
## 98	1000	EL
## 99	200	EM
## 100	104140	EN
## 101	426	ES
## 102	110	EU
## 103	1318	F
## 104	4000	FA
## 105	1600	FC
## 106	294424	FF
## 107	1250	FI
## 108	2330169028	FL
## 109	135736	FM
## 110	1000	FO
## 111	250	FP
## 112	30948	FR
## 113	5659	FS
## 114	1875	G
## 115	747525201	GA
## 116	1243	GB
## 117	7171	GE
## 118	2722	GL
## 119	40	GP
## 120	2000	GR
## 121	900	GT
## 122	4306645	GU
## 123	300	GY
## 124	364	H
## 125	1290	HA
## 126	6640	HE
## 127	102228962	HI
## 128	5250	HK
## 129	1000	HM
## 130	6555	HO

## 131	1350	HU
## 132	198590085	IA
## 133	2000	IB
## 134	77527183	ID
## 135	1739757415	IL
## 136	9250	IM
## 137	414889271	IN
## 138	7200	IO
## 139	1048182	IR
## 140	1750	IS
## 141	18250	IT
## 142	2085	JA
## 143	1500	JN
## 144	2425	JP
## 145	39	K
## 146	2150	KA
## 147	300	KE
## 148	250	KI
## 149	500	KO
## 150	252134601	KS
## 151	2064	KU
## 152	1000	KX
## 153	317402936	KY
## 154	100	L
## 155	400073166	LA
## 156	885	LE
## 157	27	LL
## 158	250	LN
## 159	18855	LO
## 160	500	LU
## 161	450	LX
## 162	2058	M
## 163	1236991169	MA
## 164	6822	MB
## 165	3000	MC
## 166	874546900	MD
## 167	119437063	ME
## 168	16965	MH
## 169	795915409	MI
## 170	1900	MJ
## 171	489863090	MN
## 172	534339055	MO
## 173	916011	MP
## 174	148489537	MS
## 175	96255694	MT
## 176	2801	MX
## 177	1500	MY
## 178	5650	N
## 179	12525	N/
## 180	127168	NA
## 181	9486	NB
## 182	597318167	NC
## 183	56477858	ND
## 184	177995925	NE

## 185	165	NF
## 186	146933211	NH
## 187	1004221945	NJ
## 188	3851	NL
## 189	198249938	NM
## 190	20472	NO
## 191	1050	NR
## 192	13192	NS
## 193	16626	NT
## 194	34306	NU
## 195	677671421	NV
## 196	5327197118	NY
## 197	1676	NZ
## 198	22555	O
## 199	966562414	OH
## 200	24500	OJ
## 201	298419110	OK
## 202	172161	ON
## 203	273321583	OR
## 204	1000	OS
## 205	2750	OT
## 206	250	OV
## 207	1350	P
## 208	1259313542	PA
## 209	1652	PE
## 210	3044	PH
## 211	2200	PN
## 212	1000	PO
## 213	69402832	PR
## 214	500	PU
## 215	6610	PW
## 216	200	Q
## 217	27530	QC
## 218	2250	QU
## 219	250	RH
## 220	94373994	RI
## 221	80	RJ
## 222	6000	RM
## 223	2250	RO
## 224	6009	SA
## 225	245366225	SC
## 226	73622367	SD
## 227	4750	SE
## 228	1250	SH
## 229	3050	SI
## 230	533	SJ
## 231	1665	SK
## 232	250	SO
## 233	15202	SP
## 234	210	SR
## 235	1450	ST
## 236	13619	SU
## 237	25170	SW
## 238	40	SY

## 239	500	SZ
## 240	900	T
## 241	1500	TA
## 242	1500	TC
## 243	3975	TE
## 244	500	TH
## 245	500	TI
## 246	4200	TM
## 247	537204492	TN
## 248	10296	TO
## 249	250	TU
## 250	50	TW
## 251	2945587994	TX
## 252	3000	TZ
## 253	195	U*
## 254	1000	UH
## 255	83523	UK
## 256	45865	UN
## 257	1000	UR
## 258	2000	US
## 259	170795379	UT
## 260	2017	V
## 261	1375724476	VA
## 262	225	VD
## 263	1500	VE
## 264	10251026	VI
## 265	50	VR
## 266	66673746	VT
## 267	1400	W
## 268	719698705	WA
## 269	1000	WD
## 270	2580	WE
## 271	389146459	WI
## 272	500	WO
## 273	10	WP
## 274	2000	WS
## 275	500	WU
## 276	116375772	WV
## 277	126752246	WY
## 278	5750	XM
## 279	203843	XX
## 280	3263	YT
## 281	165	ZA
## 282	1818	ZH
## 283	500	ZR
## 284	1000	ZU
## 285	25192260	ZZ

In our first SQL query, we retrieved all of the information about all of the variables that met our criteria. The fact that we wanted all variables in the first query is signified by the “.”. *In general, when we see a “.” in data science, it means that we want all such items or results.*

In this second SQL query, however, we only extract two variables, namely, the sum of the transaction amounts, and the states. We also group the results from the SQL query according to the state where the donor lives.

Notice that the results have 285 rows and 2 columns.

```
head(myDF)
```

```
##      SUM(transaction_amt) state
## 1          652941123
## 2              500      'H
## 3              600      'U
## 4              250      (A
## 5              500      -0
## 6             1614      00
```

```
dim(myDF)
```

```
## [1] 285  2
```

The first column is the sum of the transactions from the state, and the second column is the state. There are many erroneous states.

If we save the sum of transaction amounts as `v` and give each element of `v` the name of that state

```
v <- myDF$`SUM(transaction_amt)`
names(v) <- myDF$state
```

then we are ready to sort the data, as we did before.

```
sort(v)
```

```
##      98      19      03      06      09      10      15
##     -141     -5       0       0       0       0       0
##      28      29      32      46      53      55      64
##       0       0       0       0       0       0       0
##      72      77      78      87      91      92      94
##       0       0       0       0       0       0       0
##      95      WP      LL      K      GP      SY      TW
##       0      10      27      39      40      40      50
##      VR      11      75      RJ      L      EU      BK
##      50      75      80      80     100     110     151
##      NF      ZA      81      U*      EM       Q       36
##     165     165     167     195     200     200     210
##      EE      SR      VD      (A      AF      A0      BD
##     210     210     225     250     250     250     250
##      BL      EG      FP      KI      LN      OV      RH
##     250     250     250     250     250     250     250
##      S0      TU      GY      KE      H      BW      ES
##     250     250     300     300     364     400     426
##      LX      'H      -0      67      79      90      AN
##     450     500     500     500     500     500     500
##      BU      CD      D.      DP      DU      K0      LU
##     500     500     500     500     500     500     500
##      PU      SZ      TH      TI      W0      WU      ZR
##     500     500     500     500     500     500     500
##      B0      AT      SJ      'U      17      CE      20
##     505     511     533     600     600     725     750
##      LE      GT      T      CZ      1      60      AI
##     885     900     900     950    1000    1000    1000
##       B      DI      DL      EL      FO      HM      KX
##     1000    1000    1000    1000    1000    1000    1000
```

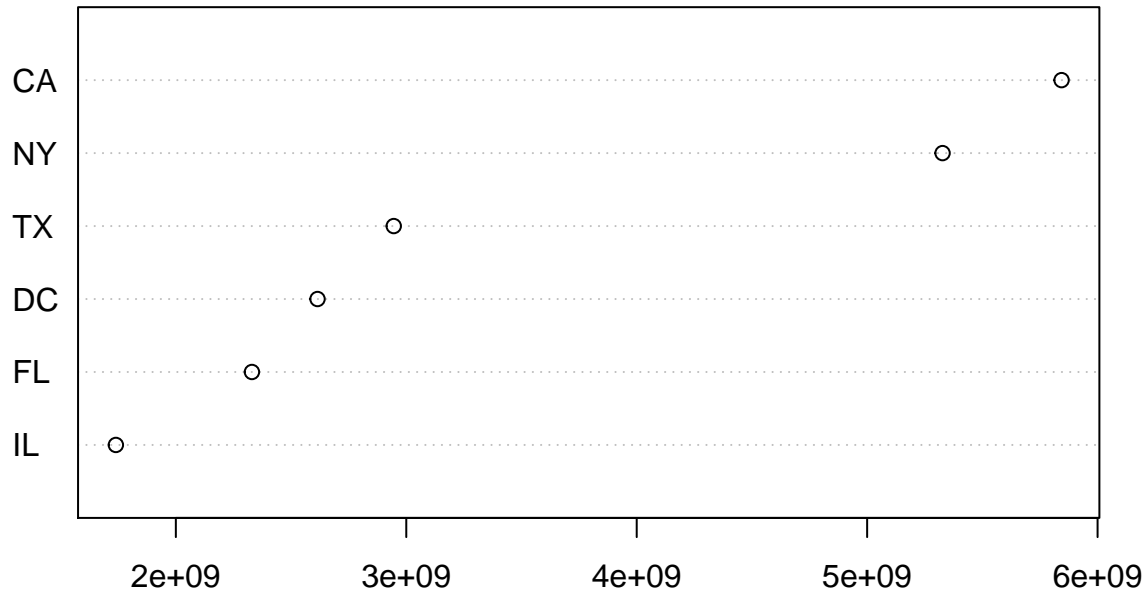
##	OS	PO	UH	UR	WD	ZU	NR
##	1000	1000	1000	1000	1000	1000	1050
##	GB	<	D	FI	SH	HA	F
##	1243	1250	1250	1250	1250	1290	1318
##	A	HU	P	W	ST	JN	MY
##	1320	1350	1350	1400	1450	1500	1500
##	TA	TC	VE	FC	OO	PE	SK
##	1500	1500	1500	1600	1614	1652	1665
##	NZ	EA	IS	O1	ZH	G	MJ
##	1676	1750	1750	1814	1818	1875	1900
##	7E	BX	CR	GR	IB	US	WS
##	2000	2000	2000	2000	2000	2000	2000
##	V	M	KU	JA	KA	PN	QU
##	2017	2058	2064	2085	2150	2200	2250
##	RO	JP	CM	WE	??	GL	OT
##	2250	2425	2500	2580	2650	2722	2750
##	MX	MC	TZ	PH	SI	CI	YT
##	2801	3000	3000	3044	3050	3250	3263
##	DF	NL	TE	FA	TM	BR	AU
##	3280	3851	3975	4000	4200	4600	4612
##	SE	C	HK	85	N	FS	XM
##	4750	4938	5250	5471	5650	5659	5750
##	RM	SA	HO	PW	HE	MB	CH
##	6000	6009	6555	6610	6640	6822	6919
##	BS	GE	IO	IM	NB	TO	N/
##	7000	7171	7200	9250	9486	10296	12525
##	NS	SU	BE	BA	SP	NT	MH
##	13192	13619	14107	14896	15202	16626	16965
##	CN	IT	LO	AB	NO	O	OJ
##	17661	18250	18855	19553	20472	22555	24500
##	SW	QC	FR	NU	UN	UK	BC
##	25170	27530	30948	34306	45865	83523	86064
##	EN	NA	FM	ON	XX	FF	AS
##	104140	127168	135736	172161	203843	294424	397614
##	AA	AP	MP	IR	AE	GU	VI
##	678578	681851	916011	1048182	1405541	4306645	10251026
##	ZZ	ND	VT	PR	AK	SD	ID
##	25192260	56477858	66673746	69402832	69577306	73622367	77527183
##	RI	MT	HI	WV	ME	DE	WY
##	94373994	96255694	102228962	116375772	119437063	124615709	126752246
##	NH	MS	UT	NE	NM	IA	SC
##	146933211	148489537	170795379	177995925	198249938	198590085	245366225
##	KS	AR	OR	OK	AL	KY	WI
##	252134601	262243128	273321583	298419110	304041321	317402936	389146459
##	LA	IN	MN	AZ	MO	TN	NC
##	400073166	414889271	489863090	532637404	534339055	537204492	597318167
##	CO		NV	WA	GA	MI	CT
##	651796668	652941123	677671421	719698705	747525201	795915409	841002706
##	MD	OH	NJ	MA	PA	VA	IL
##	874546900	966562414	1004221945	1236991169	1259313542	1375724476	1739757415
##	FL	DC	TX	NY	CA		
##	2330169028	2614794626	2945587994	5327197118	5843659325		

and this looks reasonable. The greatest monetary donations, altogether, came from California, New York,

Texas, etc.

We can plot this data. The y-axis shows the states, and the x-axis shows the total amount of donations, given in dollars.

```
dotchart(tail(sort(v)))
```



If you want to just see (for instance) the first 10 rows of a database table and all of the variables, you can limit the results.

```
myDF <- dbGetQuery(connection, "SELECT * FROM elections LIMIT 10")
myDF
```

```
##      cmte_id amndt_ind rpt_tp transaction_pgi  image_num transaction_tp
## 1  C00078279      A    M11                P 80031492155          22Y
## 2  C00078279      A    M11                79031415137           15
## 3  C00078279      A    M11                79031415137           15
## 4  C00078279      A    M11                79031415137           15
## 5  C00078287      A    Q1                79031231889           15
## 6  C00078287      A    Q1                79031231889           15
## 7  C00078287      A    Q1                79031231889           15
## 8  C00078287      A    Q1                79031231889           15
## 9  C00078287      A    Q1                79031231889           15
## 10 C00078287      A    Q1                79031231889           15
##      entity_tp      name      city state zip_code      employer
## 1              MCKENNON, K R MIDLAND  MI    00000
## 2              OREFFICE, P MIDLAND  MI    00000 DOW CHEMICAL CO
## 3              DOWNEY, J MIDLAND  MI    00000 DOW CHEMICAL CO
## 4              BLAIR, E MIDLAND  MI    00000 DOW CHEMICAL CO
## 5      BLANCHARD, JOHN A CHICAGO  IL    60685
## 6      CRAMER, JOHN H CHICAGO  IL    60685
## 7      MCHUGH, KEVIN CHICAGO  IL    60685
## 8      NOHA, EDWARD J CHICAGO  IL    60685
## 9      RYCROFT, DONALD C CHICAGO  IL    60685
## 10     VANDERSLICE, WILLIAM D CHICAGO  IL    60685
##      occupation transaction_dt transaction_amt other_id tran_id file_num memo_cd
## 1              1979-10-03              400              0
```

```
## 2          1979-10-26          1500          0
## 3          1979-10-26           300          0
## 4          1979-10-26          1000          0
## 5          1979-03-20           200          0
## 6          1979-02-28           200          0
## 7          1979-03-05           200          0
## 8          1979-03-12           300          0
## 9          1979-03-19           200          0
## 10         1979-02-27           200          0
##              memo_text      sub_id
## 1 CONTRIBUTION REF TO INDIVIDUAL 3.06202e+18
## 2                               3.06192e+18
## 3                               3.06192e+18
## 4                               3.06192e+18
## 5                               3.06192e+18
## 6                               3.06192e+18
## 7                               3.06192e+18
## 8                               3.06192e+18
## 9                               3.06192e+18
## 10                              3.06192e+18
```

Warning: Please note that you probably do NOT want to try this: If we removed the LIMIT 10, then we would pull all of the data from the entire database table, and that would take a very long time! That is not recommended.

We can also check the employers, to compute the monetary amount were made by the employees from each company.

Warning: “Here be dragons!” The new query might take (say) 15 or 20 minutes to run.

```
myDF <- dbGetQuery(connection, "SELECT SUM(transaction_amt), employer FROM elections GROUP BY employer")
```

There are 4.4 million employers listed in the database:

```
dim(myDF)
```

```
## [1] 4467789      2
```

Again, we save the sum of transaction amounts as v and give each element of v the name of that employer

```
v <- myDF$`SUM(transaction_amt)`
names(v) <- myDF$employer
```

then we are ready to sort the data, as we did before. There are too many results to see the whole list, so we look at the tail of the sorted results.

```
tail(sort(v))
```

```
## BLOOMBERG INC.          N/A    NOT EMPLOYED    SELF-EMPLOYED          RETIRED
## 1078605046      1151685215    1185574584      1739808973      2191230249
##
## 7319850748
```

and this looks reasonable. The greatest monetary donations, altogether, were either listed without an employer, or retired, or self-employed, or not employed, or N/A, or from Bloomberg Inc.

If we want to see a few more results, we can specify how many results we want to see in the tail command.

```
tail(sort(v), n=30)
```

```
## CORPORATION PALOMA PARTNERS ADVISORS, INC.
```

##	35750424	37496200
##	NOT-EMPLOYED	INVESTOR
##	41242677	47676343
##	RENAISSANCE TECHNOLOGIES	NEA
##	47869641	50639401
##	LAS VEGAS SANDS INC.	PHYSICIAN
##	52671200	66286228
##	LAS VEGAS SANDS CORPORATION	NEWSWEB CORPORATION
##	67323975	70225588
##	INFO REQUESTED	STATE OF FLORIDA
##	70539797	71432000
##	CANDIDATE	ULINE
##	82183411	98918238
##	INFORMATION REQUESTED	ADELSON DRUG CLINIC
##	106636889	108578400
##	BLOOMBERG LP	HOUSEWIFE
##	114417573	131168498
##	ATTORNEY	FAHR, LLC
##	143690457	248244304
##	HOMEMAKER	NONE
##	754539553	768247155
##	SELF EMPLOYED	SELF
##	770420301	1026722788
##	BLOOMBERG INC.	N/A
##	1078605046	1151685215
##	NOT EMPLOYED	SELF-EMPLOYED
##	1185574584	1739808973
##	RETIRED	
##	2191230249	7319850748

Notice that there are lots of missing data values, and data for which the employer was not listed. This is common with real world data, and it is something to get used to, when working on data analysis.