

A New Approach to the Parallel Coordinates Method for Large Data Sets

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What Is Parallel Coordinates Visualization?

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What Is Parallel Coordinates Visualization?

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- If have k variables, draw k vertical axes.

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- If have k variables, draw k vertical axes. Each data point maps to a polygonal line connecting the value of each variable.
- Very old idea (late 1800s!).

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- But only popularized 100 years later.

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- Available in **lattice**, **MASS**, **GGally** etc. —

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Example

Example

Example: Height/weight/age data.

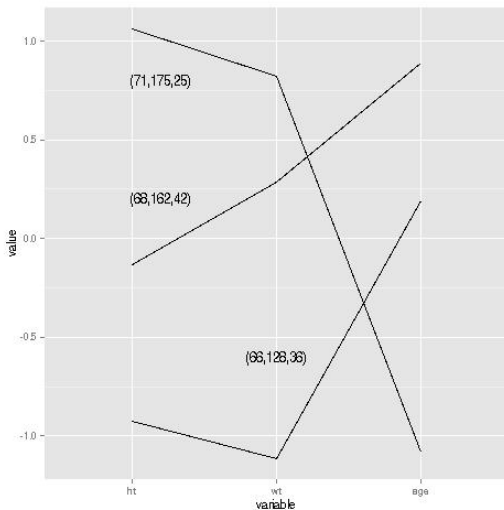
Example

Example: Height/weight/age data.

```
> d
  ht wt age
1 71 175 25
2 66 128 36
3 68 162 42
> library(GGally)
> p <-
+ ggparcoord(d,...)
> p <- p + annotate(...
...

```

Vertical axes
use centered,
scaled values.



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Problems with Parallel Coordinates

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Problems with Parallel Coordinates

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- Highly cluttered, “black screen” problem.

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- Highly cluttered, “black screen” problem.
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- **But the larger n , the less effective these solutions are**, especially with large p .

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A New Approach

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- Our solution: Plot only a few “typical” lines, based on estimated multivariate density.

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- Our solution: Plot only a few “typical” lines, based on estimated multivariate density.
- Clutter does NOT increase with n .

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- Our solution: Plot only a few “typical” lines, based on estimated multivariate density.
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- Very versatile.

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(General analysis.)

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 - What ht/wt/age combinations are “locally typical”?

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 - Bonus: Regression diagnostics.

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 - What ht/wt/age combinations are rare? **(Outlier hunting.)**
 - What ht/wt/age combinations are “locally typical”? **(Cluster hunting.)**
 - Bonus: Regression diagnostics.
- Implemented in a package **freqparcoord** on CRAN.

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Example: Taxi Data

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 - **data:** passenger_count, trip_time_in_secs, trip_distance, pickup_longitude, pickup_latitude, dropoff_longitude, dropoff_latitude, pickuptime
 - **fare:** fare_amount, surcharge, mta_tax, tip_amount, tolls_amount, total_amount, cmt, crd (paid with credit card), tippc, booltip (tip, yes or no), pickuptime, daytime

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Outlier Hunting First

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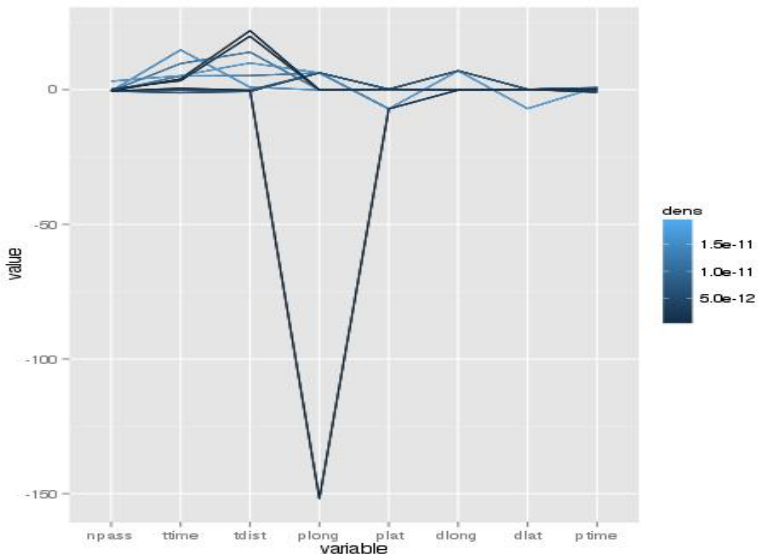
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p <- freqparcoord(d100, -10, c(8:15), keepidxs=8)
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Outliers, cont'd.

```
> p$xdisp[,11:14]
      plong      plat      dlong      dlat
-74.00399  40.742107 -73.94696  40.81335
  0.00000   0.000000 -73.96590  40.80481
-74.00748  40.703709 -74.07885  40.43142
  0.00000  40.783333   0.00000  40.79044
  0.00000  40.835121   0.00000  40.84693
  0.00000  40.733334   0.00000  40.74148
-73.88925  40.769035 -73.94363  40.75264
-1837.04530  0.041667 -73.96226  40.76774
-73.98628  40.752365 -73.77634  40.64601
  0.00000   0.000000   0.00000   0.00000
```

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      plong      plat      dlong      dlat
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Bad cases (-1800, 0s) removed (IDs in **p\$xdisp** but not shown here).

Outliers, cont'd.

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Illustrates another advantage of displaying just a few “typical” cases.

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General Analysis

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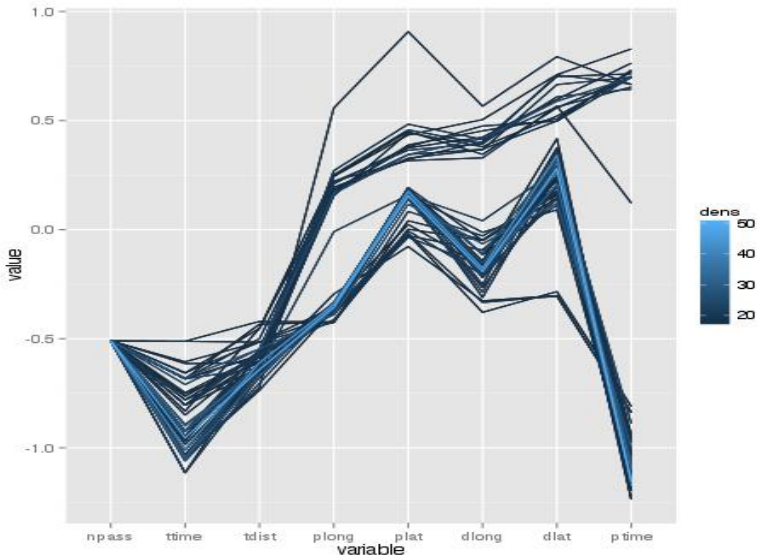
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What do we see?

- Already see at least two clusters, largely differing on pickup/dropoff location and time of day.

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- Note there is much more variation in trip time than in trip distance—due to variation in traffic.

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Cluster Analysis

Cluster Analysis

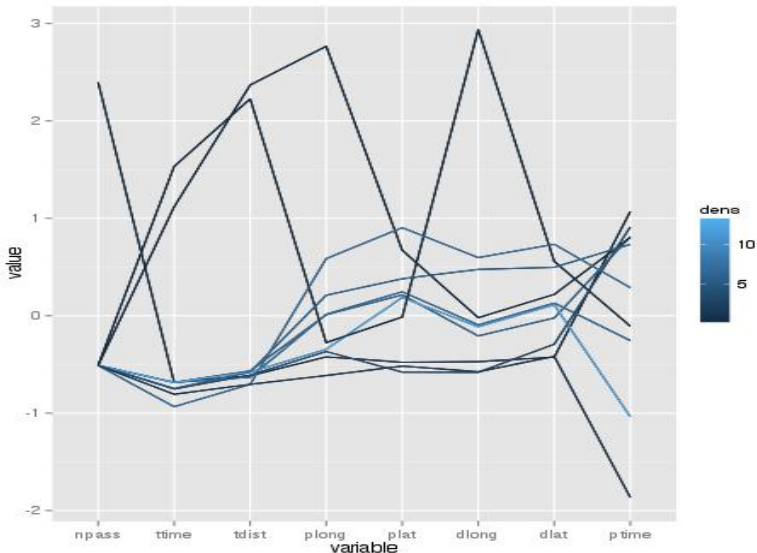
```
p <- freqparcoord(d100,1,c(8:15),method="locmax",klm=1000,  
  cls=c14,keepidxs=15)
```

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Cluster Analysis

```
p <- freqparcoord(d100,1,c(8:15),method="locmax",klm=1000,  
cls=cl4,keepidxs=15)
```



A New
Approach to
the Parallel
Coordinates
Method for
Large Data
Sets

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Clustering, cont.d

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- We see perhaps 8-9 clusters.

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Clustering, cont.d

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- Varying in short vs. long trip distance, pickup/dropoff location, time of day.

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- “Changing of the guard,” 2 top lines:
 - Around 1:45 p.m., mid-Manhattan → La Guardia Airport.

Clustering, cont.d

- We see perhaps 8-9 clusters.
- Varying in short vs. long trip distance, pickup/dropoff location, time of day.
- “Changing of the guard,” 2 top lines:
 - Around 1:45 p.m., mid-Manhattan → La Guardia Airport.
 - Around 7:30 p.m., La Guardia Airport → mid-Manhattan.

Clustering, cont.d

- We see perhaps 8-9 clusters.
- Varying in short vs. long trip distance, pickup/dropoff location, time of day.
- “Changing of the guard,” 2 top lines:
 - Around 1:45 p.m., mid-Manhattan → La Guardia Airport.
 - Around 7:30 p.m., La Guardia Airport → mid-Manhattan.
 - **Good example of the use of viewing variables together, rather than individually.**

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Group by # of Passengers

Group by # of Passengers

```
p <- freqparcoord(d100,50,c(9:15),grpvar=8)
```

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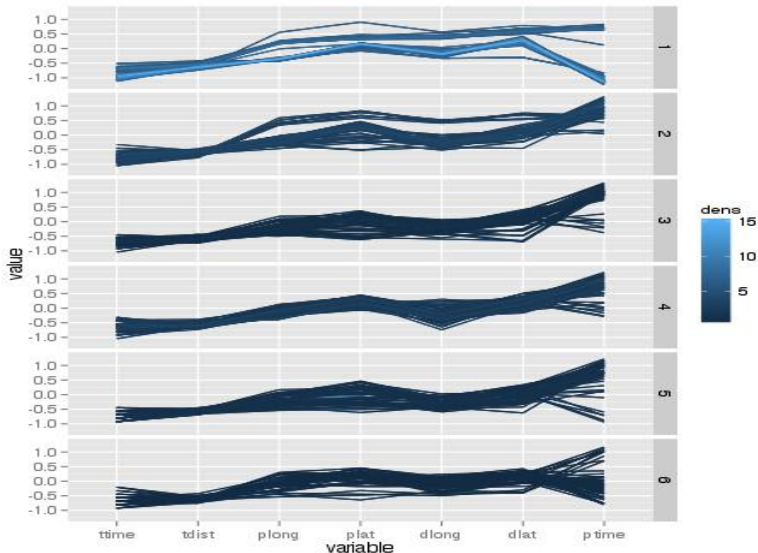
A New Approach to the Parallel Coordinates Method for Large Data Sets

Group by # of Passengers

```
p <- freqparcoord(d100,50,c(9:15),grpvar=8)
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of Passengers, cont'd.

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of Passengers, cont'd.

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- The 1-passenger trips tend to be earlier in the day, some late.

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- The 1-passenger trips tend to be earlier in the day, some late.
- The 2-4-passenger trips tend to be later in the day.

of Passengers, cont'd.

- The 1-passenger trips tend to be earlier in the day, some late.
- The 2-4-passenger trips tend to be later in the day.
- The 5-6 passenger trips (families?) more diverse in time.

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Credit Card vs. Cash

Credit Card vs. Cash

```
p <- freqparcoord(fare100,10,c(6,7,9:12,14:17),grpvar=13)
```

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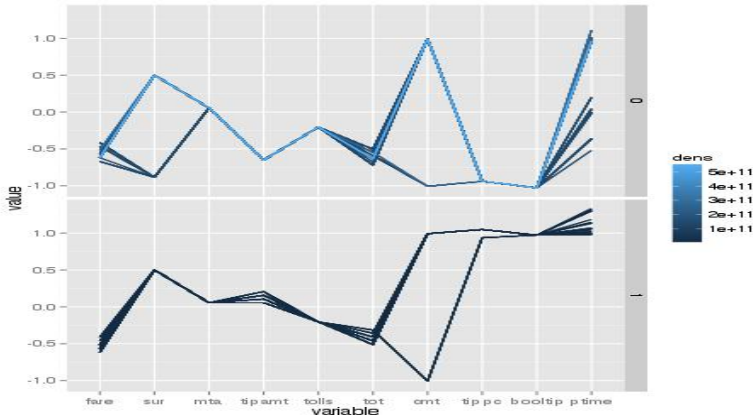
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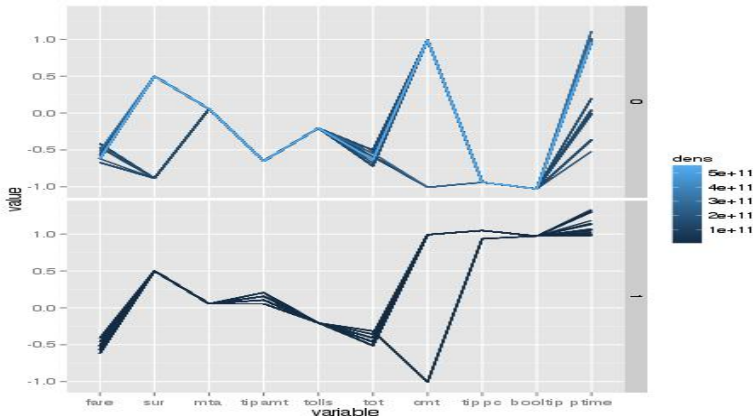
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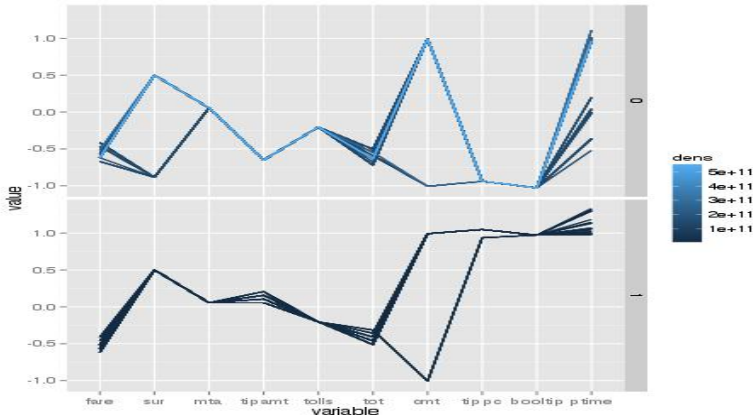
Not much difference, e.g. in base fare.

Credit Card vs. Cash

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p <- freqparcoord(fare100,10,c(6,7,9:12,14:17),grpvar=13)
```

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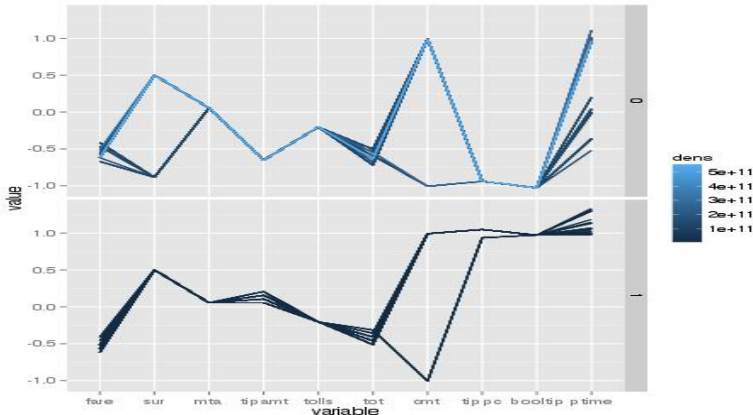
Not much difference, e.g. in base fare. Some difference in time of day.

Credit Card vs. Cash

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p <- freqparcoord(fare100,10,c(6,7,9:12,14:17),grpvar=13)
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Not much difference, e.g. in base fare. Some difference in time of day. But stark difference in tips!

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Application: Regression Diagnostics

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Application: Regression Diagnostics

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- Compute *divergences* (not residuals):

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Application: Regression Diagnostics

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- Compute *divergences* (not residuals):

$$div_i = param_est_i - nonparam_est_i$$

- Use **fregparcoord()** on the divergences,

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- Compute *divergences* (not residuals):

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- Use **fregparcoord()** on the divergences, to identify regions of predictor space in which there is systematic over- or underestimation of the true regression function.

Application: Regression Diagnostics

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- Compute *divergences* (not residuals):

$$div_i = param_est_i - nonparam_est_i$$

- Use **freqparcoord()** on the divergences, to identify regions of predictor space in which there is systematic over- or underestimation of the true regression function.
- See our **useR! 2014** slides, at <http://heather.cs.ucdavis.edu/freqparcoord/UseR2014Slides.pdf>.

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Conclusions

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- Location of these slides:
<http://heather.cs.ucdavis.edu/freqparcoord/BosSlides.pdf>