Statistical Analysis of Corpus Data with R

Distributional properties of Italian NN compounds: An Exploration with R

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Outline

NN Compounds

- Part of work carried out by Marco Baroni with Emiliano Guevara (U Bologna) and Vito Pirrelli (CNR/ILC, Pisa)
- Three-way classification inspired by theoretical (Bisetto and Scalise, 2005) and psychological work (e.g., Costello and Keane, 2001)
  - **Relational** (*computer center*, *angolo bambini*)
  - **Attributive** (*swordfish*, *esperimento pilota*)
  - **Coordinative** (*singer-songwriter*, *bar pasticceria*)

Relational compounds

- Express relation between two entities
- Heads are typically information containers, organizations, places, aggregators, pointers, etc.
- **M** “grounds” generic meaning of, or fills slot of **H**
- E.g., *stanza server* (“server room”), *fondo pensioni* (“pension fund”), *centro città* (“city center”)

Attributive compounds

- Interpretation of **M** is reduced to a “salient” property of its full semantic content, and this property is *attributed* to **H**:
- *presidente fantoccio* (“puppet president”), *progetto pilota* (“pilot project”)

Coordinative compounds

- Head and modifier denote similar/compatible entities, compound has coordinative reading
- **HM** is both **H** and **M**
- *viaggio spedizione* ("expedition travel"), *cantante attore* ("singer actor")
- Ignored here

Ongoing exploration

- Data-set of frequent compounds: 24 **ATT** / 100 **REL**
- All **ATT** and **REL** compounds with freq $\geq 1,000$ in itWaC (2 billion token Italian Web-based corpus)
- Will the distinction between **ATT** and **REL** emerge from combination of distributional cues (also extracted from itWaC)?

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- All **ATT** and **REL** compounds with freq $\geq 1,000$ in itWaC (2 billion token Italian Web-based corpus)
- Will the distinction between **ATT** and **REL** emerge from combination of distributional cues (also extracted from itWaC)?
- Cues:
  - Semantic similarity between head and modifier
  - Explicit syntactic link
  - Relational properties of head and modifier
  - “Specialization” of head and modifier

Outline

The data

H Compound head (Italian compounds are left-headed!)

M Modifier

TYPE attributive or relational

COS Cosine similarity between **H** and **M**

DELLL Log-likelihood ratio score for comparison between observed frequency of ***H*** *del* ***M*** (“**H** of the **M**”) and expected frequency under independence

HDELPROP Proportion of times **H** occurs in context ***H*** *del NOUN* over total occurrences of **H**

DELMPROP Proportion of times **M** occurs in context *NOUN DEL M* over total occurrences of **M**

HNPROP Proportion of times **H** occurs in context *H NOUN* over total occurrences of **H**

NMPROP Proportion of times **M** occurs in context *NOUN M* over total occurrences of **M**

Cue statistics

- Read the file `comp.stats.txt` into a data-frame named `d` and "attach" the data-frame
  - ☞ load file with `read.delim()` function as recommended
  - ☞ use option `encoding="UTF-8"` on Windows
- Compute basic statistics
- Look at the distribution of each cue among compounds of type attributive (`at`) vs. relational (`re`)
- Find out for which cues the distinction between attributive and relational is significant (using a *t*-test or Mann-Whitney ranks test)
- Also, which cues are correlated? (use `cor()` on the subset of the data-frame that contains the cues)

Outline

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Clustering

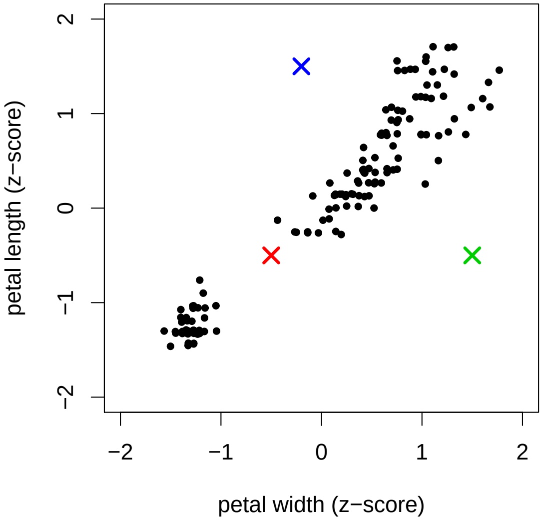
- *k-means*: one of the simplest and most widely used hard flat clustering algorithms
- For more sophisticated options, see the *cluster* and *e1071* packages

k-means

- The basic algorithm
  1. Start from k random points as cluster centers
  2. Assign points in data-set to cluster of closest center
  3. Re-compute centers (means) from points in each cluster
  4. Iterate cluster assignment and center update steps until configuration converges
- Given random nature of initialization, it pays off to repeat procedure multiple times (or to start from "reasonable" initialization)

Illustration of the *k*-means algorithm

See `help(iris)` for more information about the data set used



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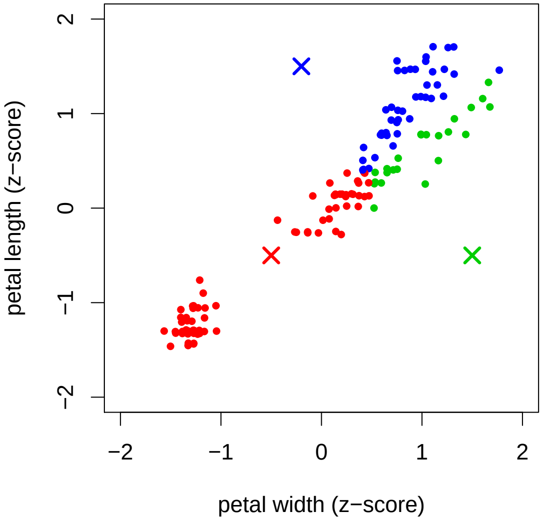

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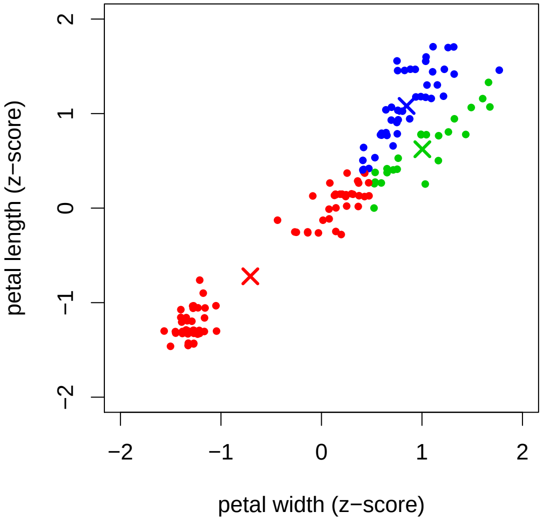

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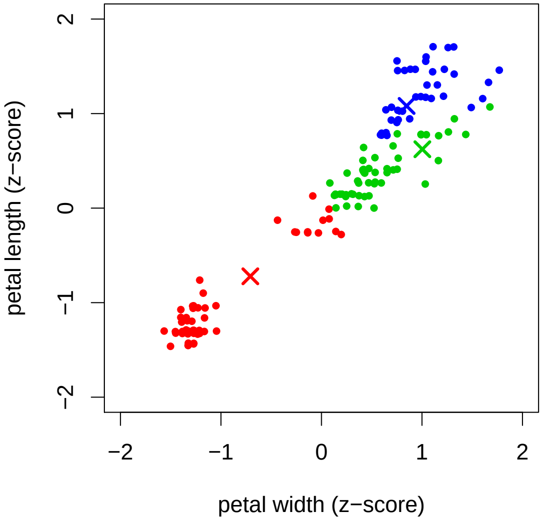

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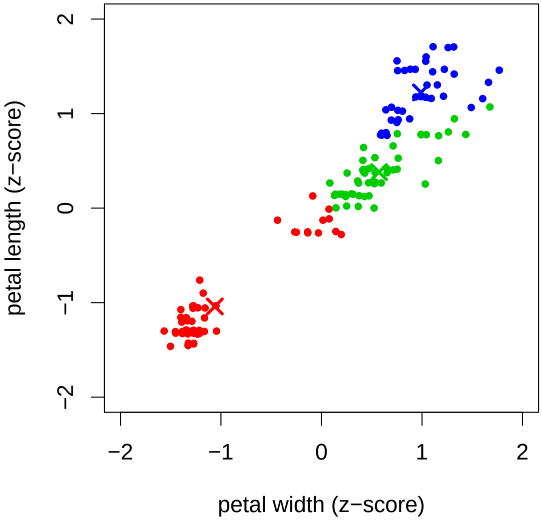

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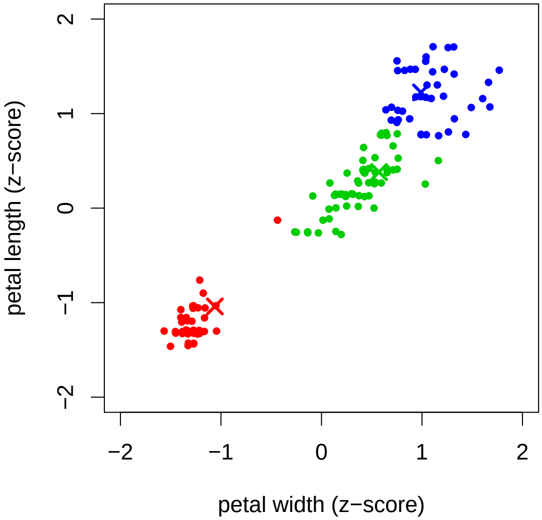

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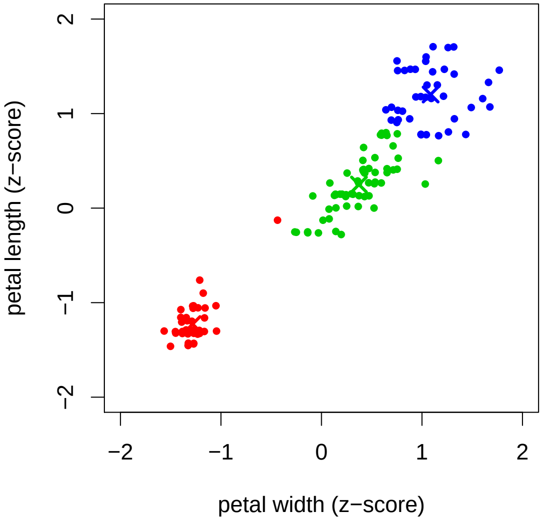

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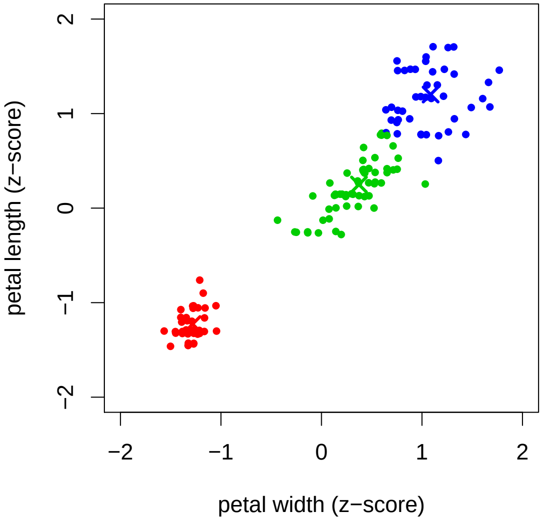

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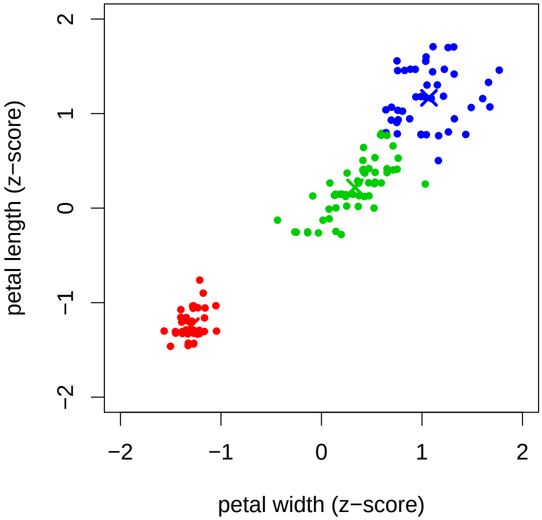

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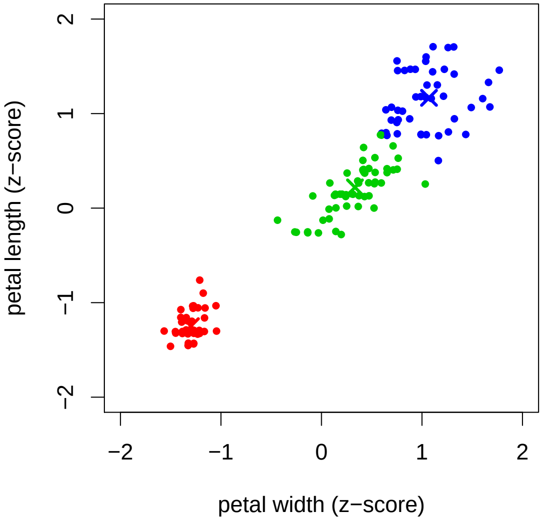

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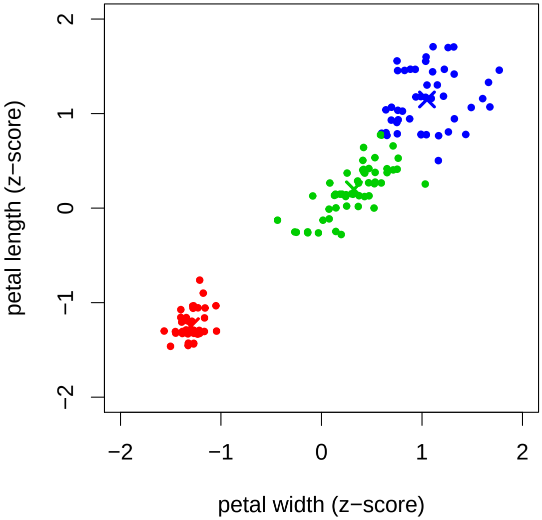


k-means, first try

```
# cues are in columns 4 to 9

> km <- kmeans(d[,4:9], 2, nstart=10)
> km

# problem: extreme DELLL values dominate the clustering
# (relevant small cluster might be cluster 2 in your solution)

> DELLL[km$cluster==1]

> head(sort(DELLL, decreasing=TRUE))
```

Scaling and trying again

```
> scaled <- scale(d[,4:9])
> summary(d[4:9])    # distribution of original data
> summary(scaled)    # after scaling

> km <- kmeans(scaled, 2, nstart=10)
> km

> table(km$cluster, d$TYPE)  # confusion matrix
```

Outline

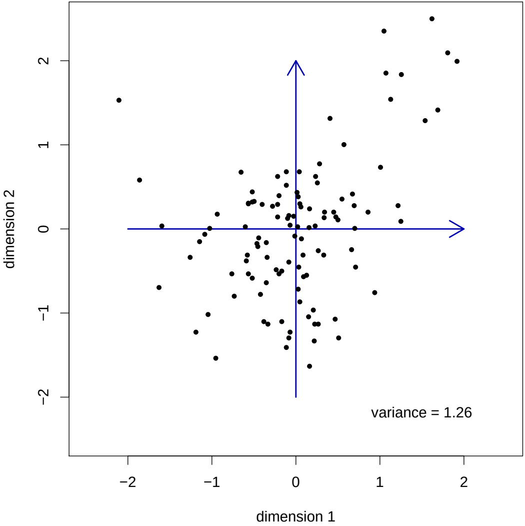
Dimensionality reduction

- To find “latent” variables
- To reduce random noise
- For easier visualization

Principal component analysis (PCA)

- Find a set of orthogonal dimensions such that the first dimension “accounts” for the most *variance* in the original data-set, the second dimension accounts for as much as possible of the remaining variance, etc.
- The top k dimensions (principal components) are the best sub-set of k dimensions to approximate the spread in the original data-set
- Principal components represent correlations of original variables ➪ might reveal interesting underlying patterns

Preserving variance: examples



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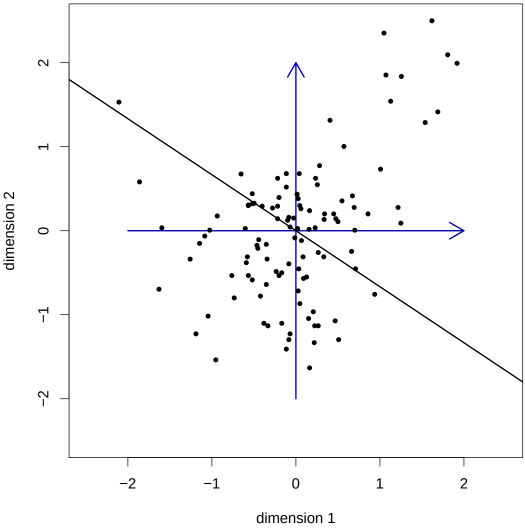

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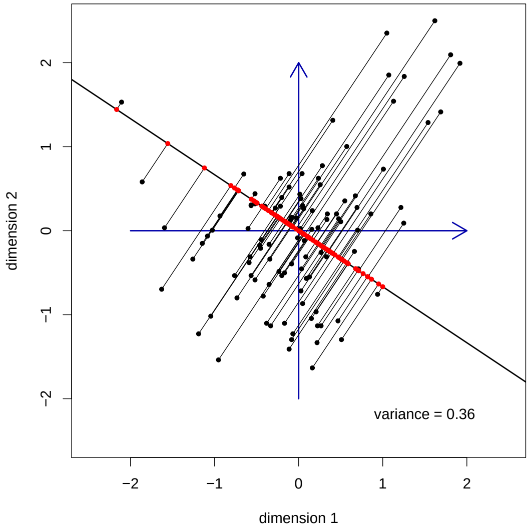

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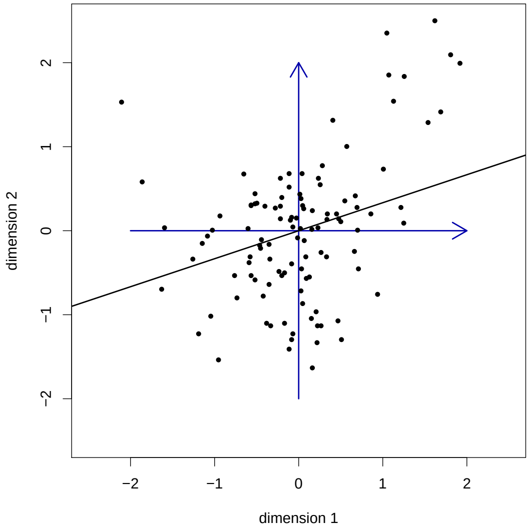

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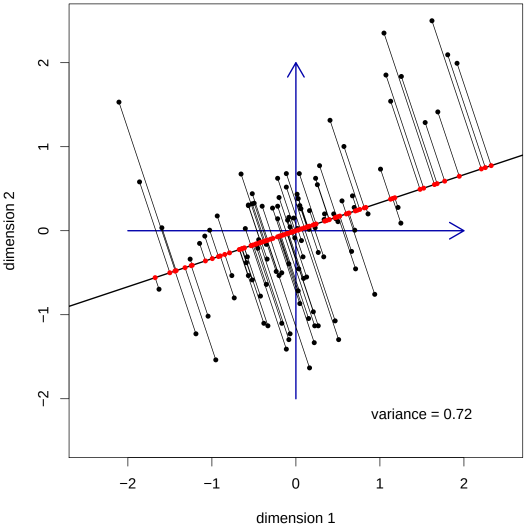

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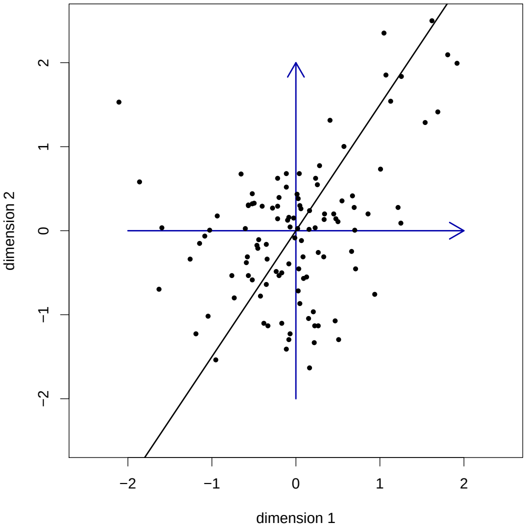

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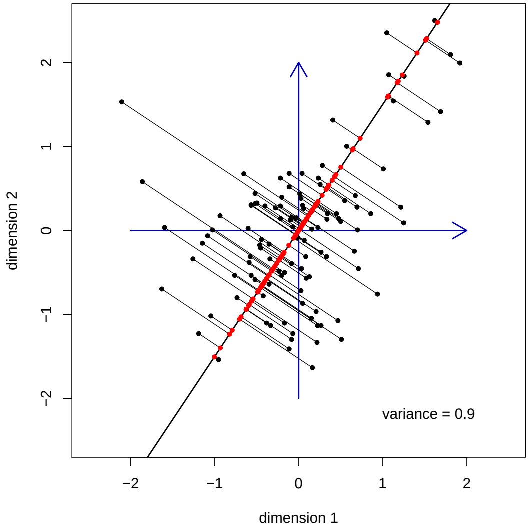
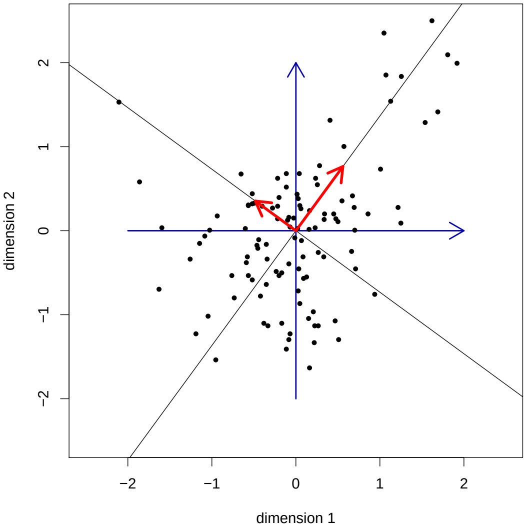


Adding an orthogonal dimension



PCA in R

```
> temp <- subset(d, select=c(HNPROP, NMPROP,
  DELLL, HDELPROP, DELMPROP, COS))

> pr <- prcomp(temp, scale=TRUE)
> pr

> plot(pr)

> biplot(pr)
> biplot(pr, xlabs=TYPE,
  xlim=c(-.25,.25), ylim=c(-.25,.25))
```

More refined plotting

```
> plot(pr$x[,1:2], type="n",
  xlim=c(min(pr$x[,1]),4),
  ylim=c(min(pr$x[,2]),4))     # only sets up plot region

> points(subset(pr$x, TYPE=="re"),
  col="blue", pch=19, lwd=2)  # blue points for type "re"

> points(subset(pr$x, TYPE=="at"),
  col="red", pch=19, lwd=2)   # red points for type "at"

> legend("topright", inset=.05,
  fill=c("red","blue"), cex=1.5,
  legend=c("ATT","REL"))       # legend explains colors
```

Adding the cues

```
> text(pr$rotation[1,1]*4, pr$rotation[1,2]*4,
  label="H N", cex=1.7)

> text(pr$rotation[2,1]*4, pr$rotation[2,2]*4,
  label="N M", cex=1.7)

> text(pr$rotation[3,1]*4, pr$rotation[3,2]*4,
  label="H DEL M", cex=1.7)

> text(pr$rotation[4,1]*4, pr$rotation[4,2]*4,
  label="H DEL", cex=1.7)

> text(pr$rotation[5,1]*4, pr$rotation[5,2]*4,
  label="DEL M", cex=1.7)

> text(pr$rotation[6,1]*4, pr$rotation[6,2]*4,
  label="COS", cex=1.7)
```

Trying k-means again

```
> km <- kmeans(pr$x[,1:4], 2, nstart=10)
> table(km$cluster, d$TYPE)
```

what happens with more/fewer dimensions?

```
> plot(pr$x[,1:2], type="n",
  xlim=c(min(pr$x[,1]),4),
  ylim=c(min(pr$x[,2]),4))

> text(pr$x[,1], pr$x[,2],
  col=km$cluster, labels=TYPE)
```

now refine this plot as on previous slides